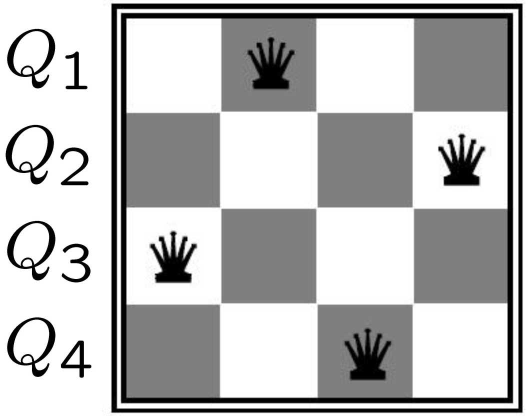
第四周

- 教学计划
  - 竞争搜索：期望最大值（上次课）
  - 小组0104，0108，0201项目1总结报告
  - 回顾约束满足问题：N王后，数独（家作2）
  - 代码练习：Python parametes, mutable vs. immutable
  - 马可夫决策过程
- 任务
  - 家作2项目2：最小最大值，期望最大值
  - 两周的时间：4月5日提交，尽早开始

CSP: N-Queens

- Formulation:
  - Variables: Q_k
  - Domains: $\{1, 2, 3, \ldots N\}$
  - Constraints:



Implicit: $\forall i, j \;\; \text{non-threatening}(Q_i, Q_j)$

Explicit: $(Q_1, Q_2) \in \{(1,3), (1,4), \ldots\}$

$\cdots$

No Conflict

```
def no_conflict(assign, j0):
    # Check columns
    if j0 in assign:
        return False
    # Check diagonals
    i0 = len(assign)
    for i, j in enumerate(assign):
        if abs(i0-i) == abs(j0-j):
            return False
    return True
```

Backtracking

```
def backtrack(assign):
    # Check whether it is the solution
    if len(assign) == N: return assign
    # Assign new value to variable
    for j in range(N):
        if no_conflict(assign, j):
            res = backtrack(assign+[j])
            if res != None:
                return res
```

Demo: N-queen problem

```
$python nqueen.py
1 []
2 [0]
3 [0, 2]
4 [0, 2, 4]
5 [0, 2, 4, 1]
6 [0, 2, 4, 1, 3]
7 [0, 2, 4, 1, 7]
8 [0, 2, 4, 6]
9 [0, 2, 4, 6, 1]
10 [0, 2, 4, 6, 1, 3]
11 [0, 2, 4, 6, 1, 3, 5]
...
113 [0, 4, 7, 5, 2, 6, 1]
114 [0, 4, 7, 5, 2, 6, 1, 3]
```

Backtracking

```
def backtrack(assign):
    # Check whether it is the solution
    if len(assign) == N: return assign
    # Assign new value to variable
    for j in range(N):
        if no_conflict(assign, j):
            res = backtrack(assign+[j])
            if res != None:
                return res
```

Digression: modify assign list

```
def backtrack(assign):
    # Check whether it is the solution
    if len(assign) == N: return assign
    # Assign new value to variable
    for j in range(N):
        if no_conflict(assign, j):
            assign.append(j) # What if I do this?
            res = backtrack(assign)
            if res != None:
                return res
```

Digression: modify assign list

```
def backtrack(assign):
    # Check whether it is the solution
    if len(assign) == N: return assign
    # Assign new value to variable
    for j in range(N):
        if no_conflict(assign, j):
            assign.append(j) # What if I do this?
            res = backtrack(assign)
            assign.pop(-1) # Will this work?
            if res != None:
                return res
```

Digression: modify assign list

```
def backtrack(assign):
    # Check whether it is the solution
    if len(assign) == N: return assign[:] #Need this
    # Assign new value to variable
    for j in range(N):
        if no_conflict(assign, j):
            assign.append(j) # What if I do this?
            res = backtrack(assign)
            assign.pop(-1) # Will this work? No
            if res != None:
                return res
```

Digression: modify assign list

```
def backtrack(assign):
    # Check whether it is the solution
    if len(assign) == N: return assign
    # Assign new value to variable
    for j in range(N):
        if no_conflict(assign, j):
            assign.append(j) # What if I do this?
            res = backtrack(assign)
            if res != None:
                return res
            assign.pop(-1) # Or put this here
```

Digression: save result in assign

```
def backtrack(assign):
    if len(assign) == N: return True
    for j in range(N):
        if no_conflict(assign, j):
            assign.append(j)
            res = backtrack(assign)
            if res:
                return res
            assign.pop(-1)
    return False
```

CSP: Sudoku

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

- Variables:
  - Each (open) square
- Domains:
  - {1,2,…,9}
- Constraints:

  9-way alldiff for each column

  9-way alldiff for each row

  9-way alldiff for each region

  (or can have a bunch of pairwise inequality constraints)

Digression: what if we modify integers?

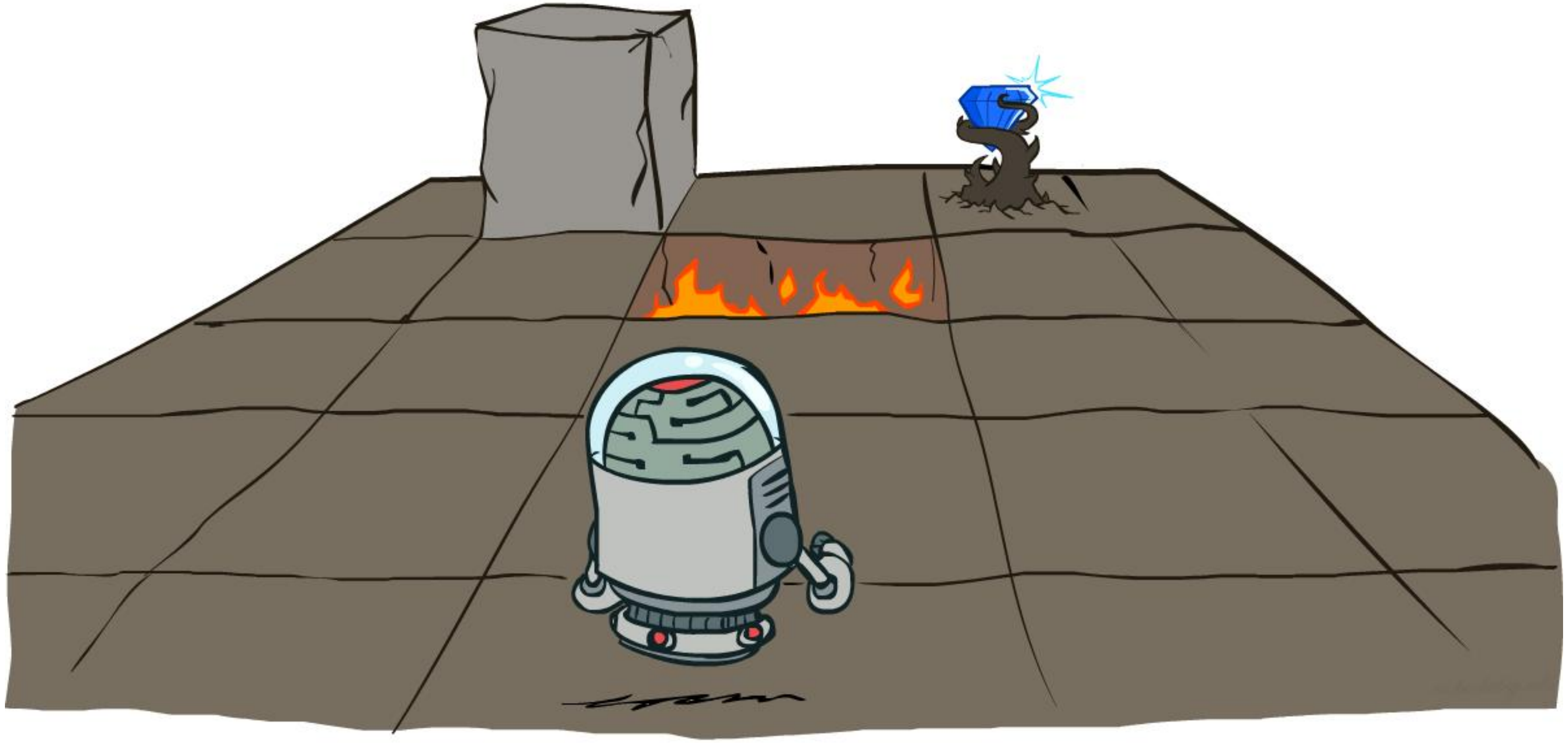
```
def backtrack(assign, i, j):
    # Check whether we have the solution
    if i == 8 and j == 8: return True

    # Find the next empty square to fill
    while assign[i,j] != 0:
        i, j = (i+1, 0) if j == 8 else (i, j+1)
        if i >= 9: return True

    # Assign value to the empty square
    for value in range(1,10): ...
```

人工智能导论

Markov Decision Processes

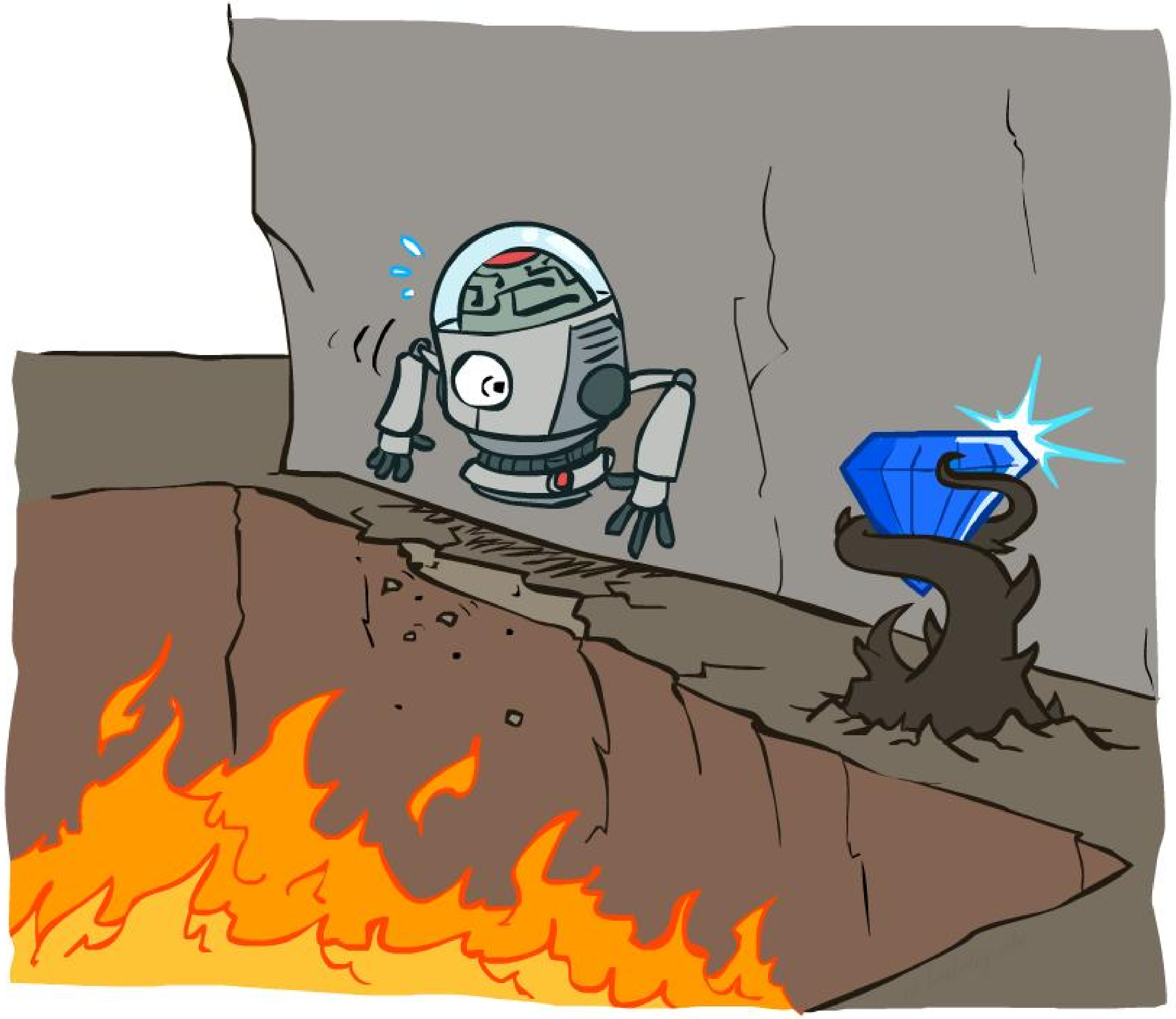


基于UC Berkeley, CS188课程

University of California, Berkeley

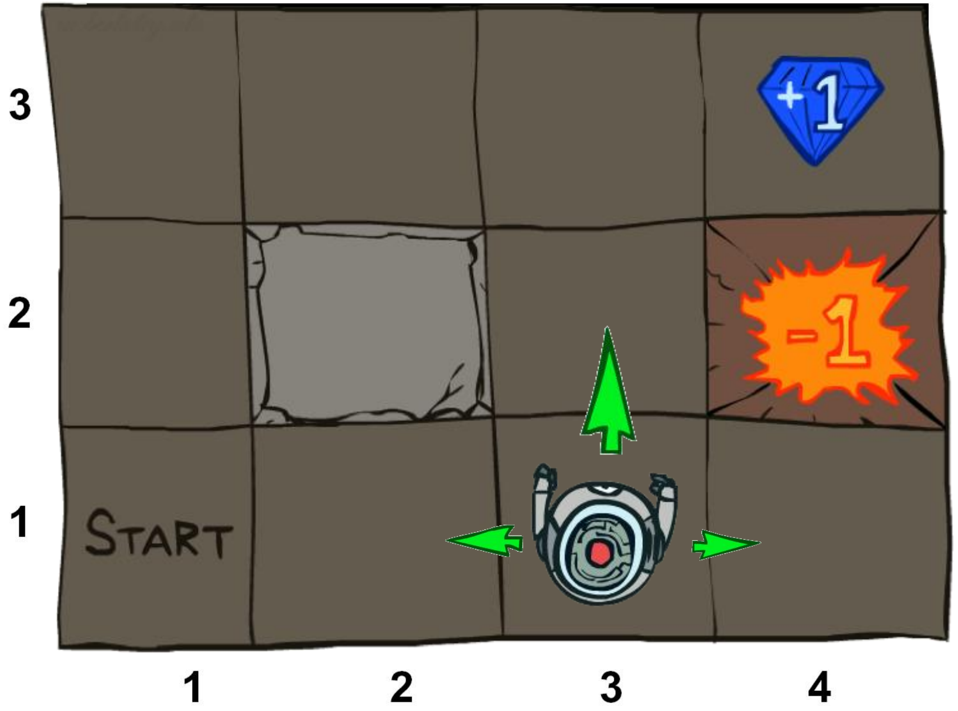
[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at http://ai.berkeley.edu.]

Non-Deterministic Search



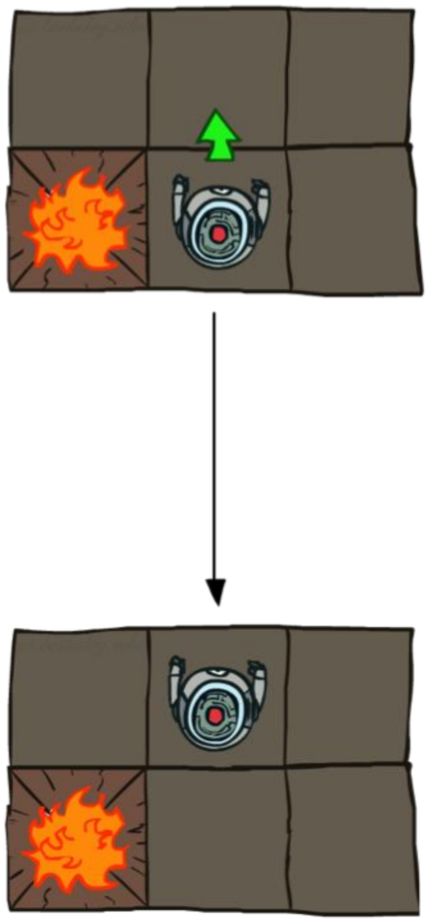
Example: Grid World

- 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 (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

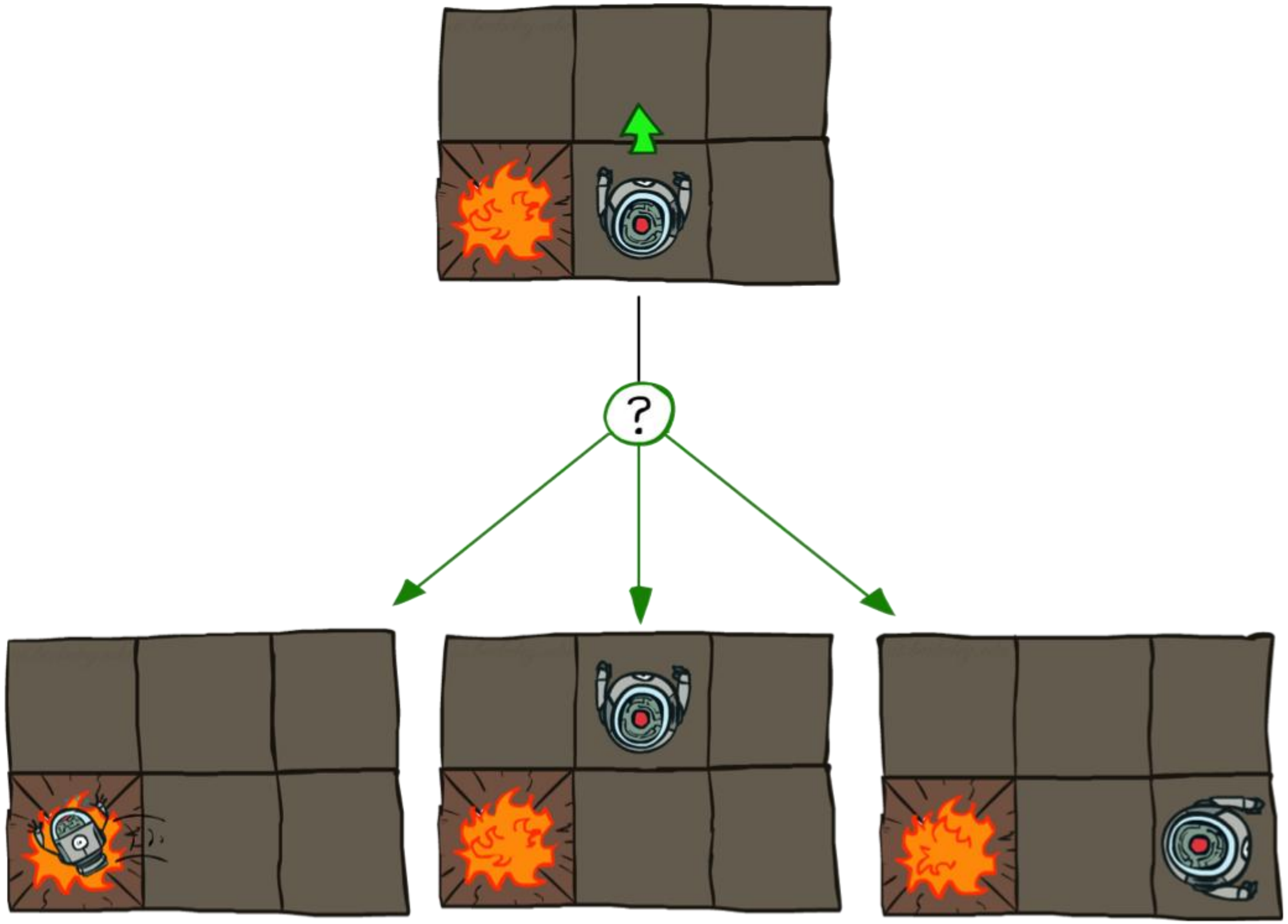


Grid World Actions

Deterministic Grid World

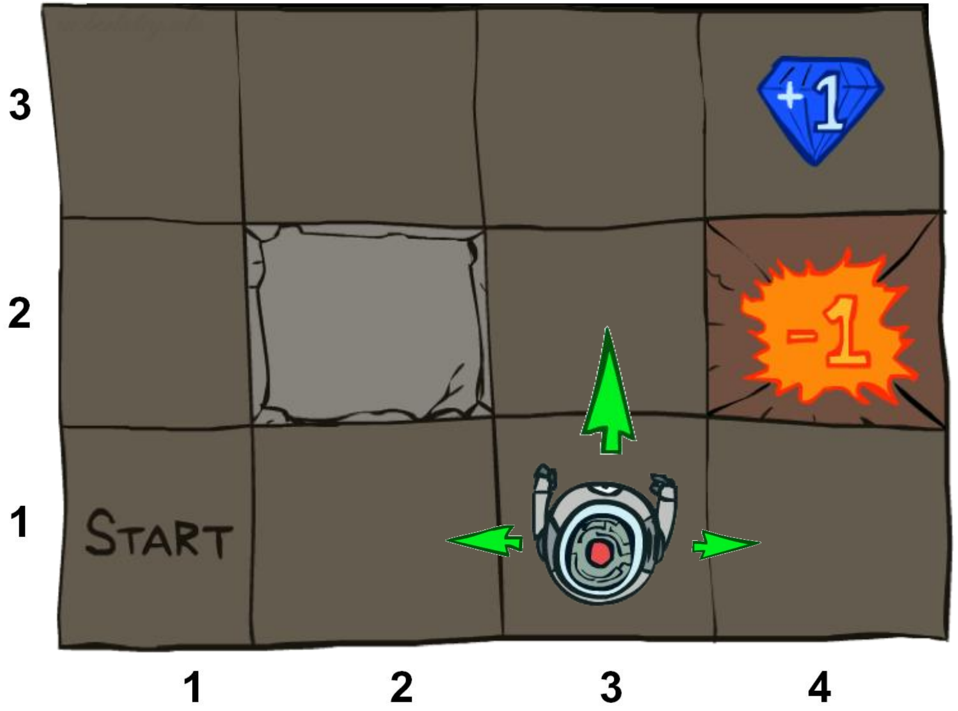


Stochastic Grid World



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')
    - Sometimes just R(s) or R(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

[Demo – gridworld manual intro (L8D1)]

Video of Demo Gridworld Manual Intro

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

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

$$=$$

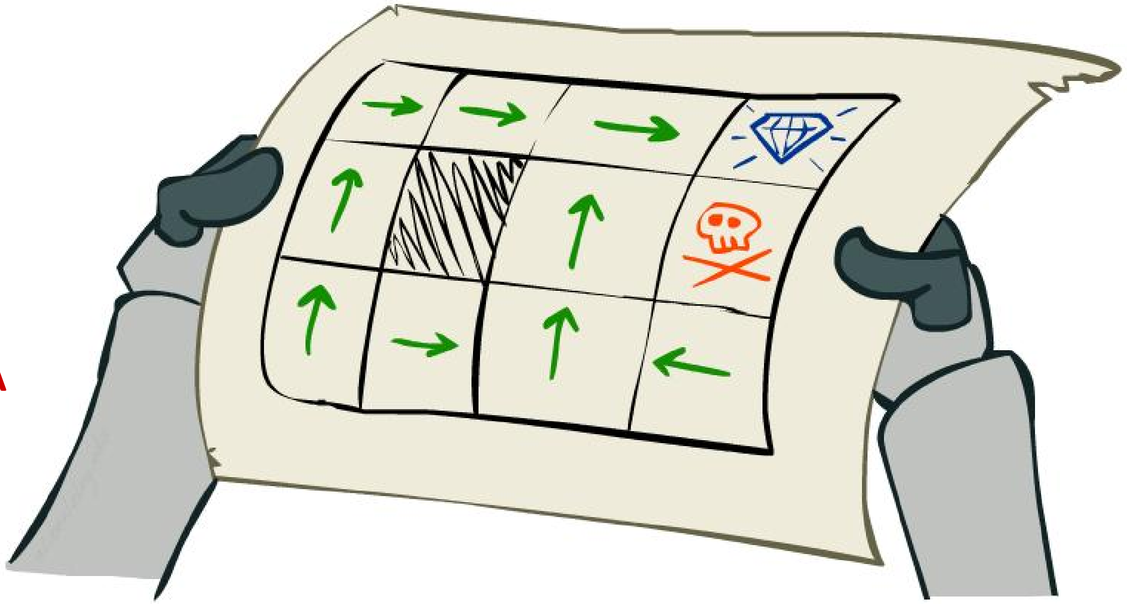
$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t)$$

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

Andrey Markov
(1856-1922)

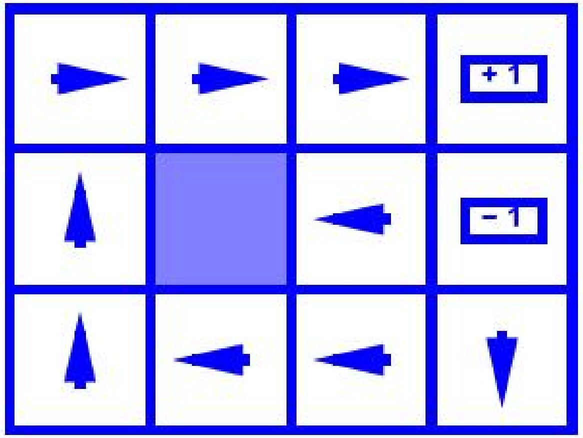
Policies

- 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

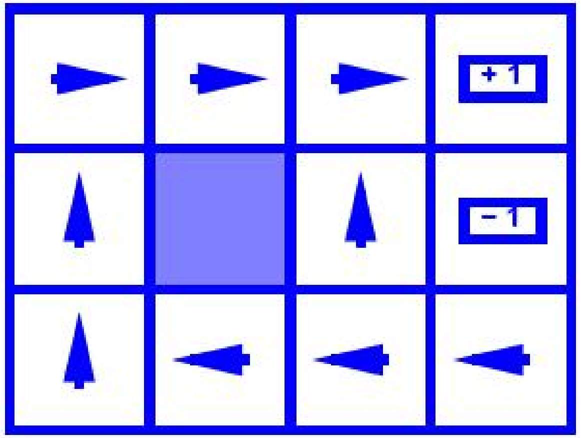


Optimal policy when R(s, a, s') = -0.03 for all non-terminals s

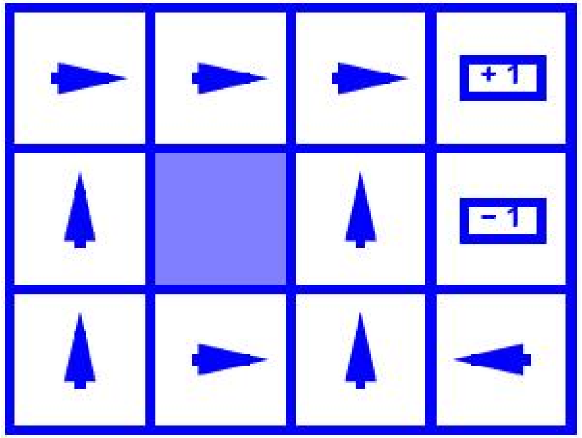
Optimal Policies



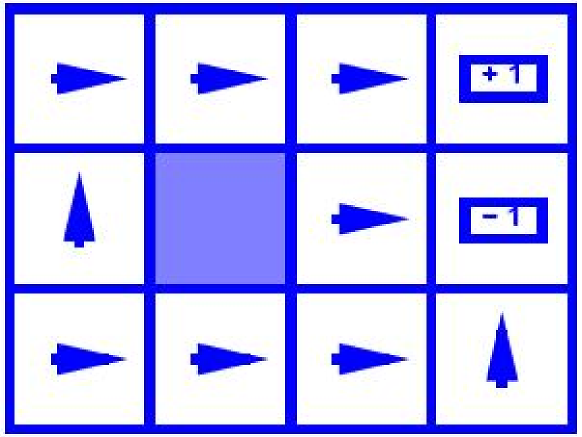
R(s) = -0.01



R(s) = -0.03

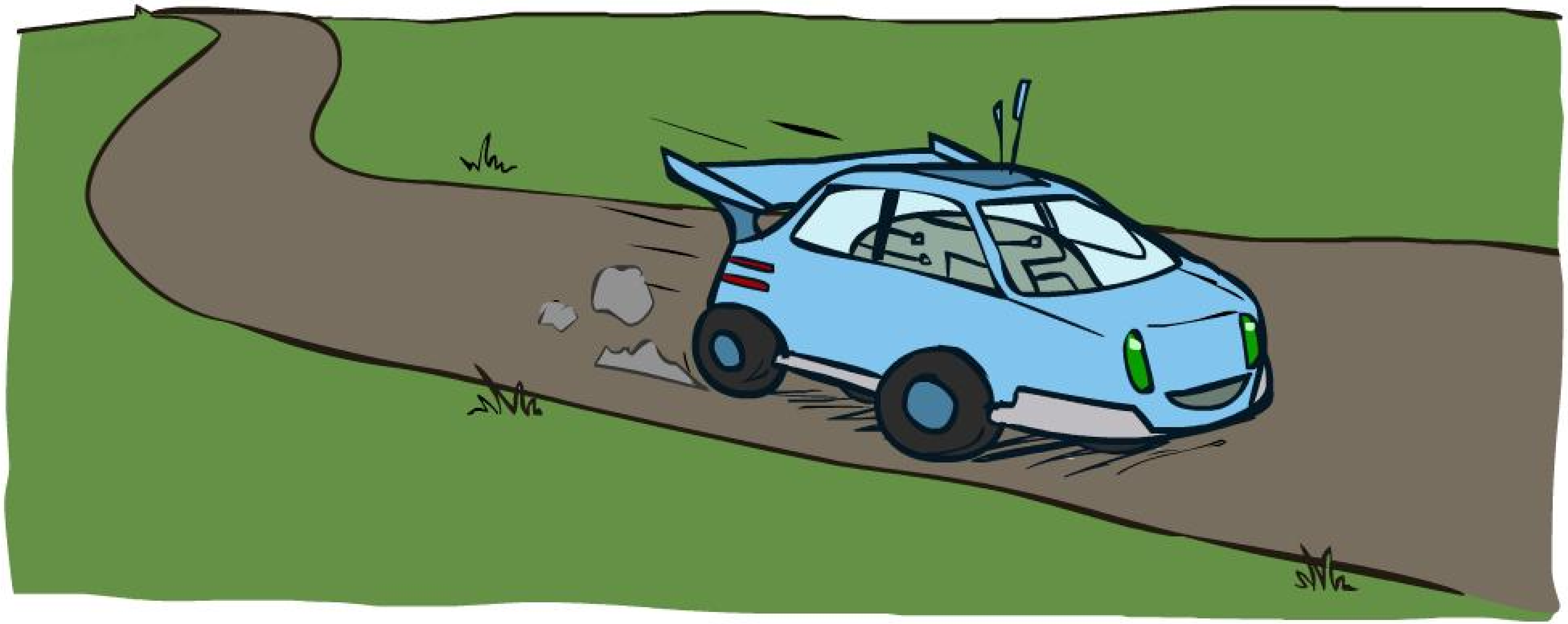


R(s) = -0.4



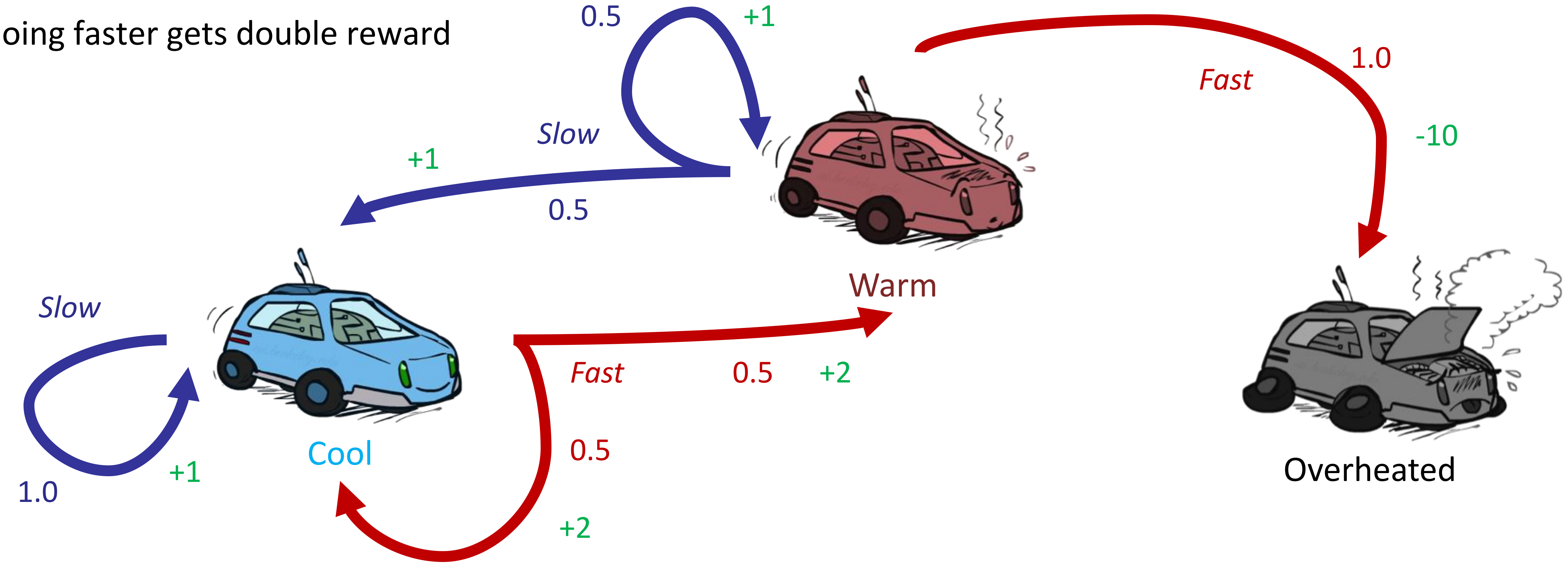
R(s) = -2.0

Example: Racing

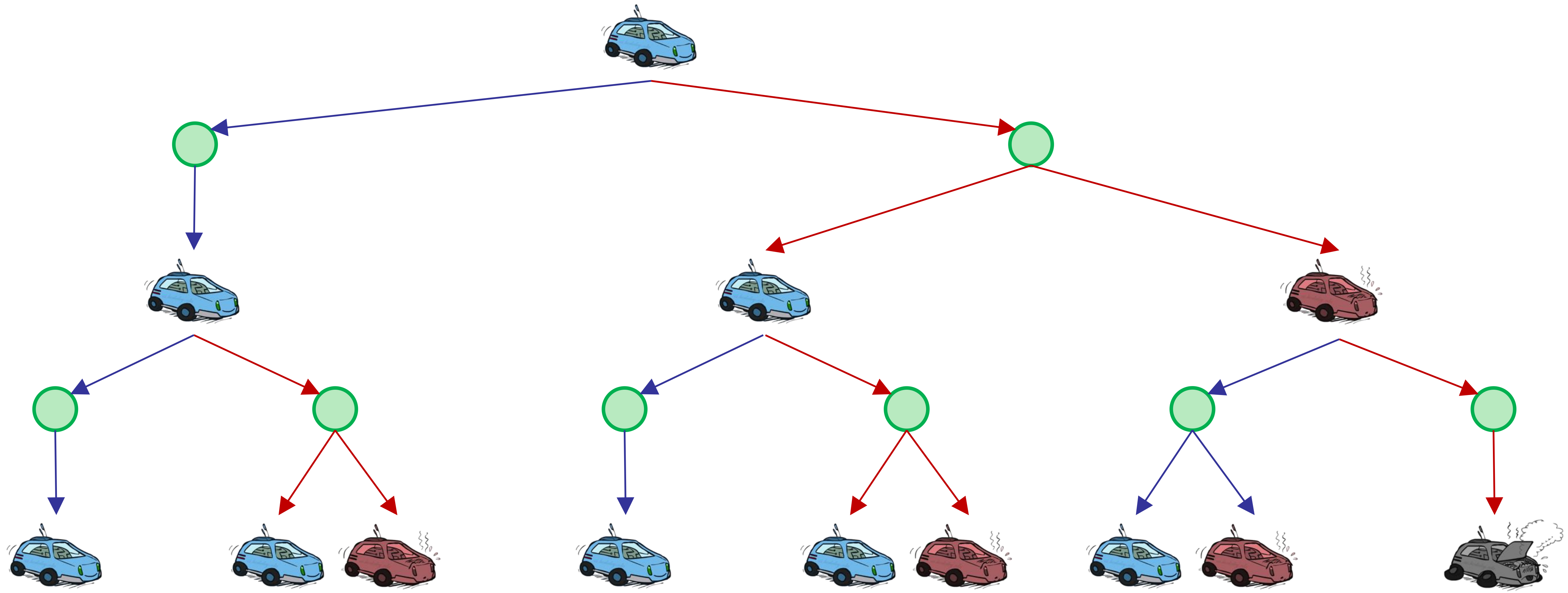


Example: Racing

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

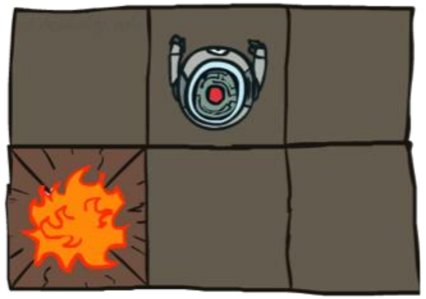


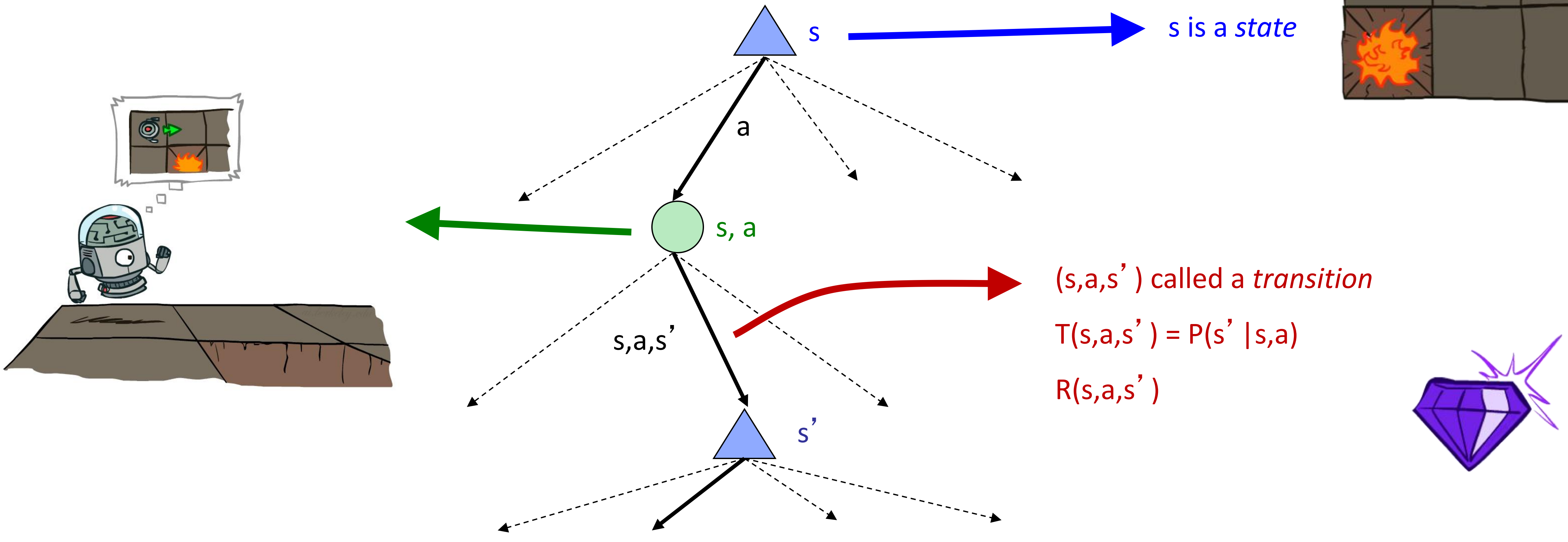
Racing Search Tree



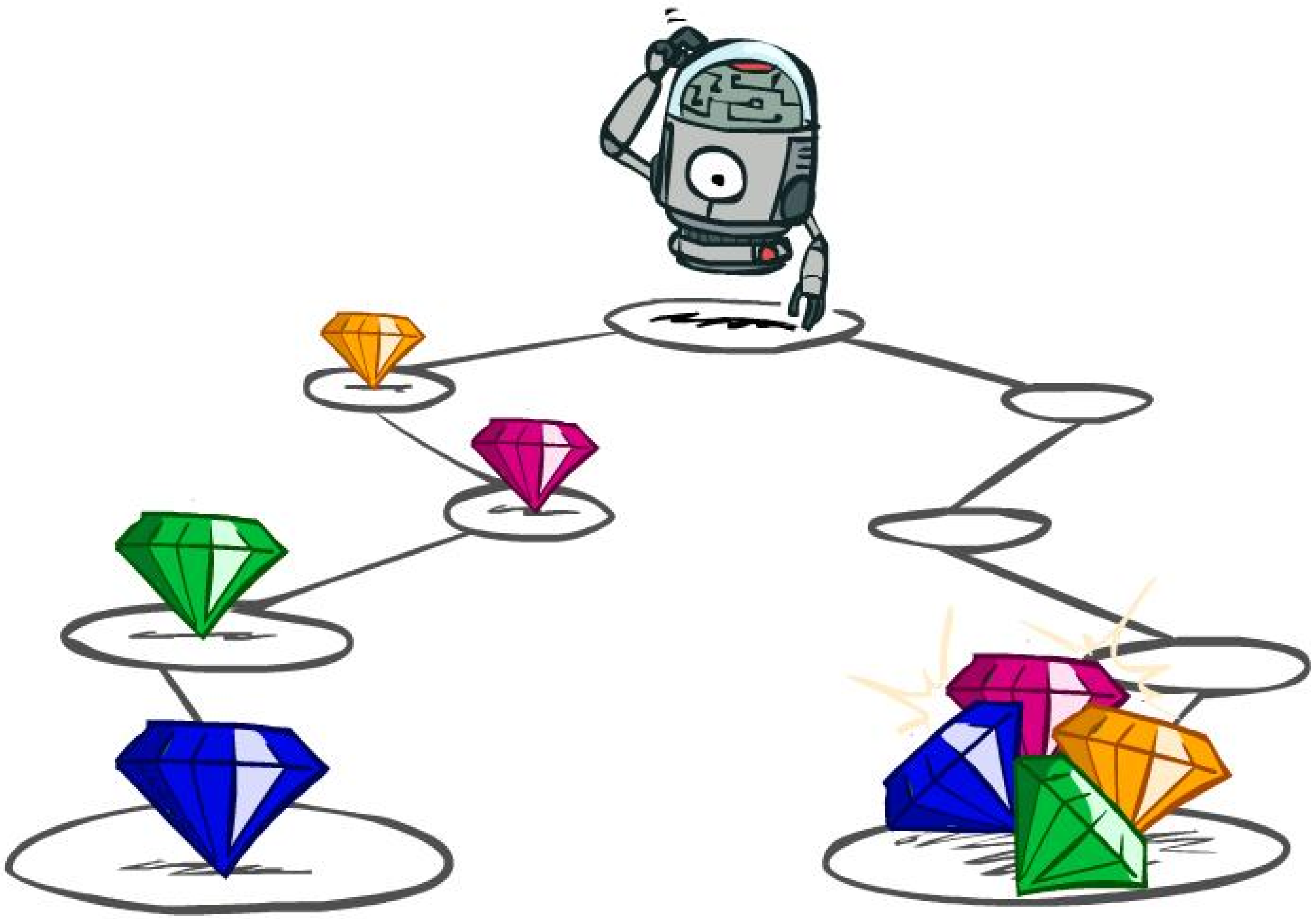
MDP Search Trees

- Each MDP state projects an expectimax-like search tree





Utilities of Sequences

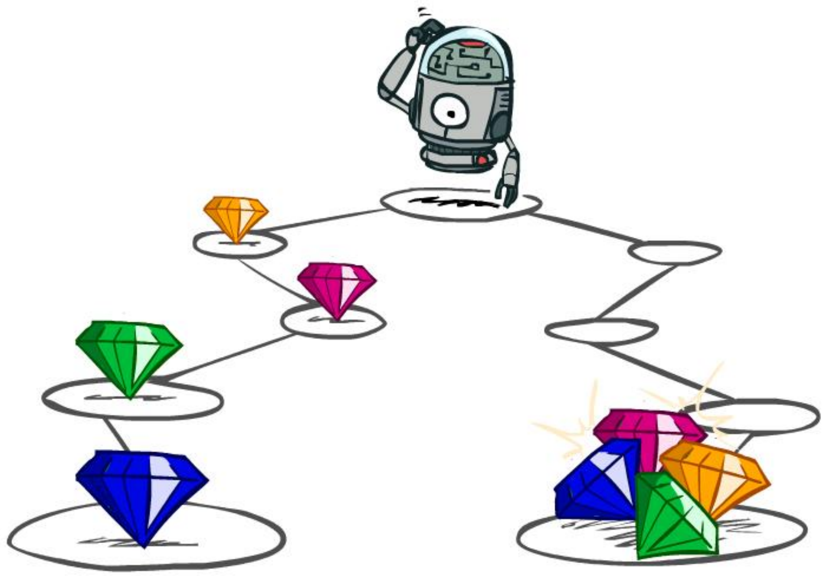


Utilities of Sequences

- 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

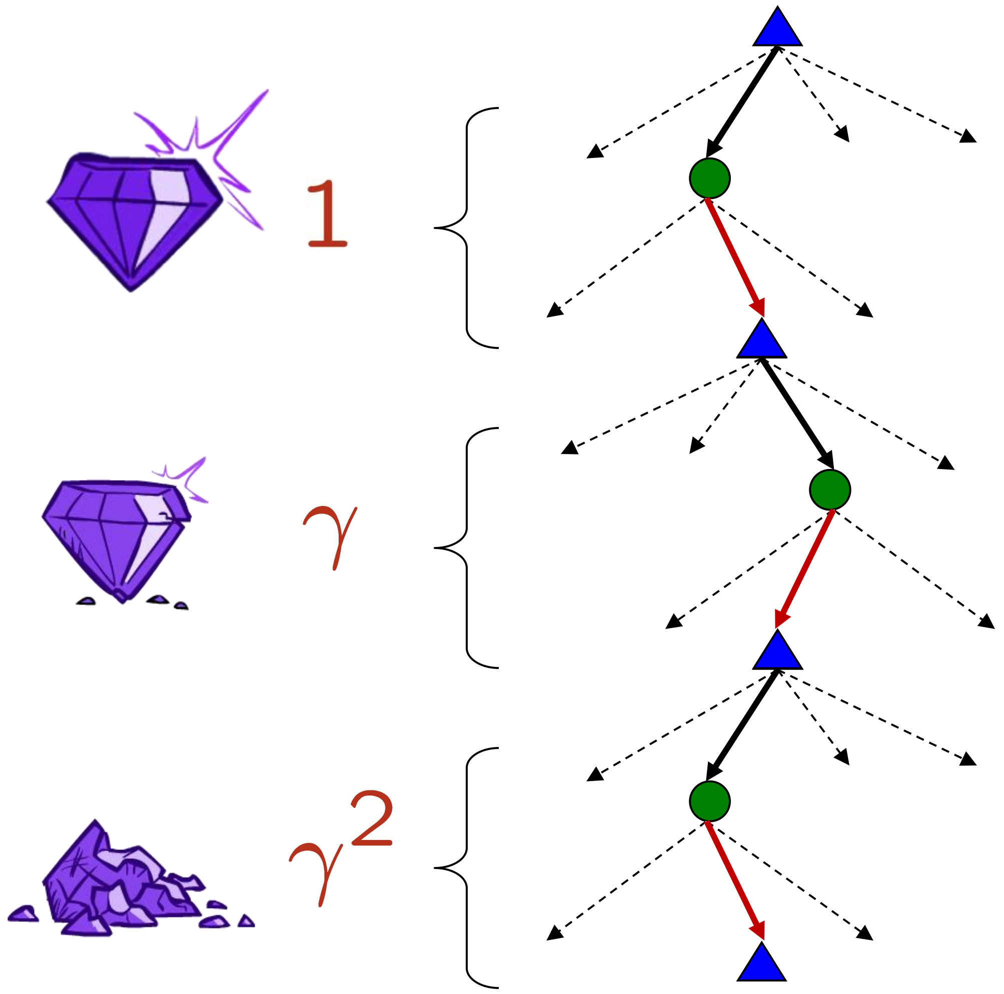
Worth Next Step

γ^2

Worth In Two Steps

Discounting

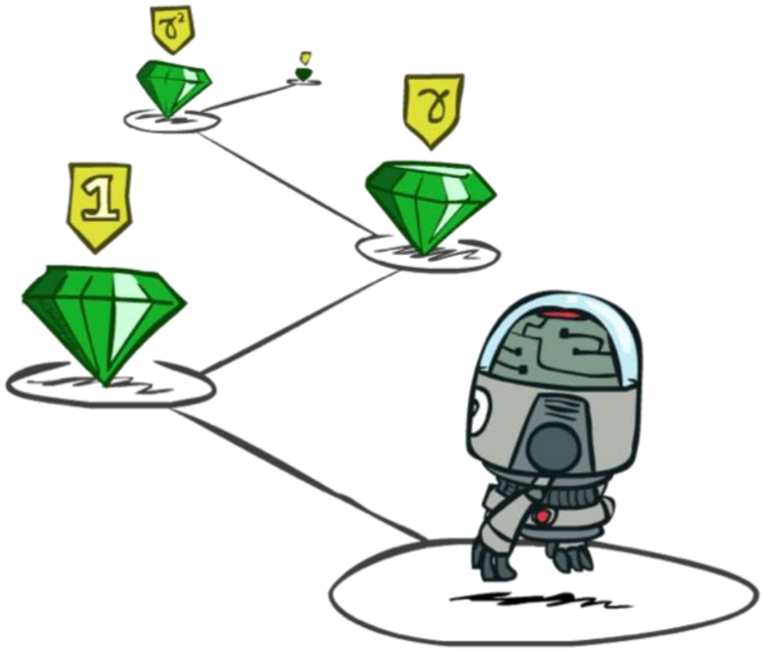
- How to discount?
  - Each time we descend a level, we multiply in the discount once
- Why discount?
  - Sooner rewards probably do have higher utility than later rewards
  - Also helps our algorithms converge
- Example: discount of 0.5
  - U([1,2,3]) = 1*1 + 0.5*2 + 0.25*3
  - U([1,2,3]) < U([3,2,1])



Stationary Preferences

- Theorem: if we assume stationary preferences:

$$[a_1, a_2, \ldots] \succ [b_1, b_2, \ldots]$$
$$\Updownarrow$$
$$[r, a_1, a_2, \ldots] \succ [r, b_1, b_2, \ldots]$$



- Then: there are only two ways to define utilities
  - Additive utility: $U([r_0, r_1, r_2, \ldots]) = r_0 + r_1 + r_2 + \cdots$
  - Discounted utility: $U([r_0, r_1, r_2, \ldots]) = r_0 + \gamma r_1 + \gamma^2 r_2 \cdots$

Quiz: Discounting

- Given:

10				1
a	b	c	d	e

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

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

10				1

- Quiz 2: For $\gamma = 0.1$, what is the optimal policy?

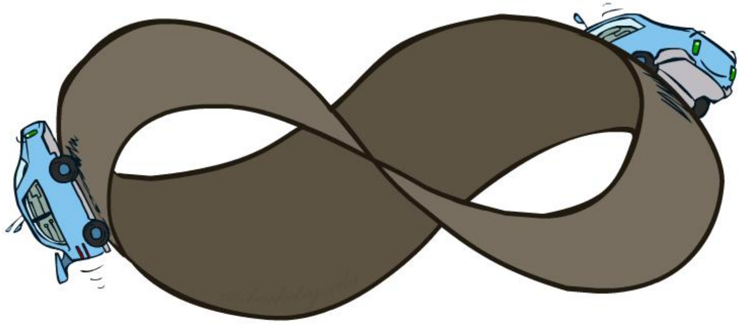
10				1

- Quiz 3: 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)
    - Gives nonstationary policies (π depends on time left)



  - Discounting: use $0 < \gamma < 1$

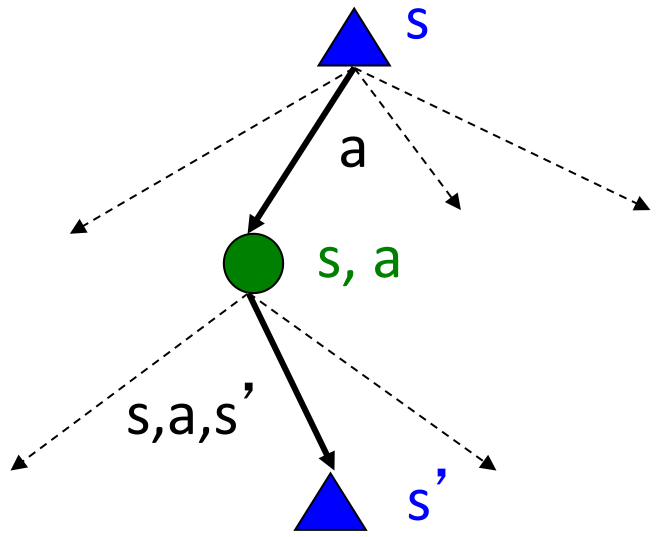
$$U([r_0, \ldots r_\infty]) = \sum_{t=0}^{\infty} \gamma^t r_t \leq R_{\max}/(1-\gamma)$$

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

  - Absorbing state: guarantee that for every policy, a terminal state will eventually be reached (like "overheated" for racing)

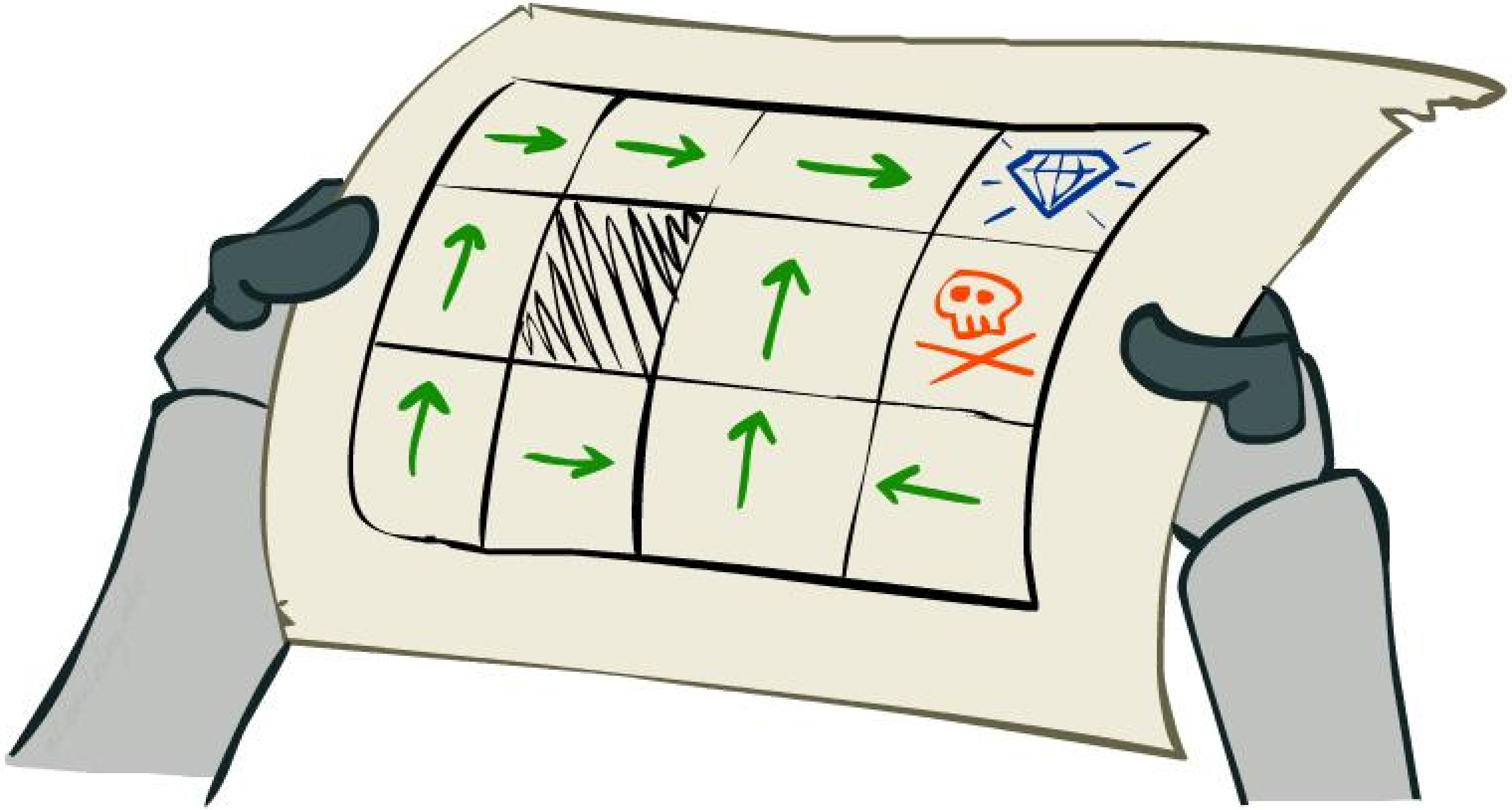
Recap: Defining MDPs

- 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:

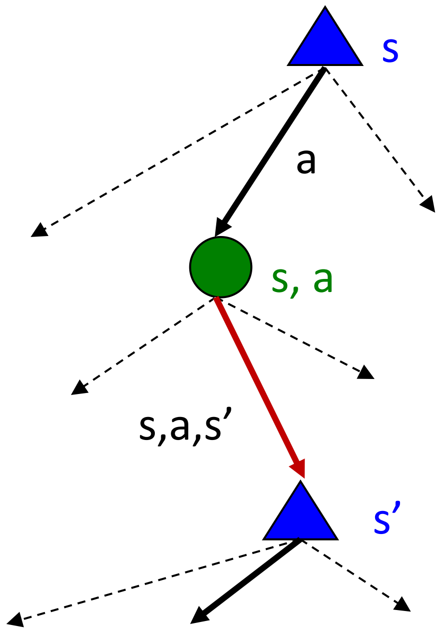
  $V^*(s)$ = expected utility starting in s and acting optimally

- 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



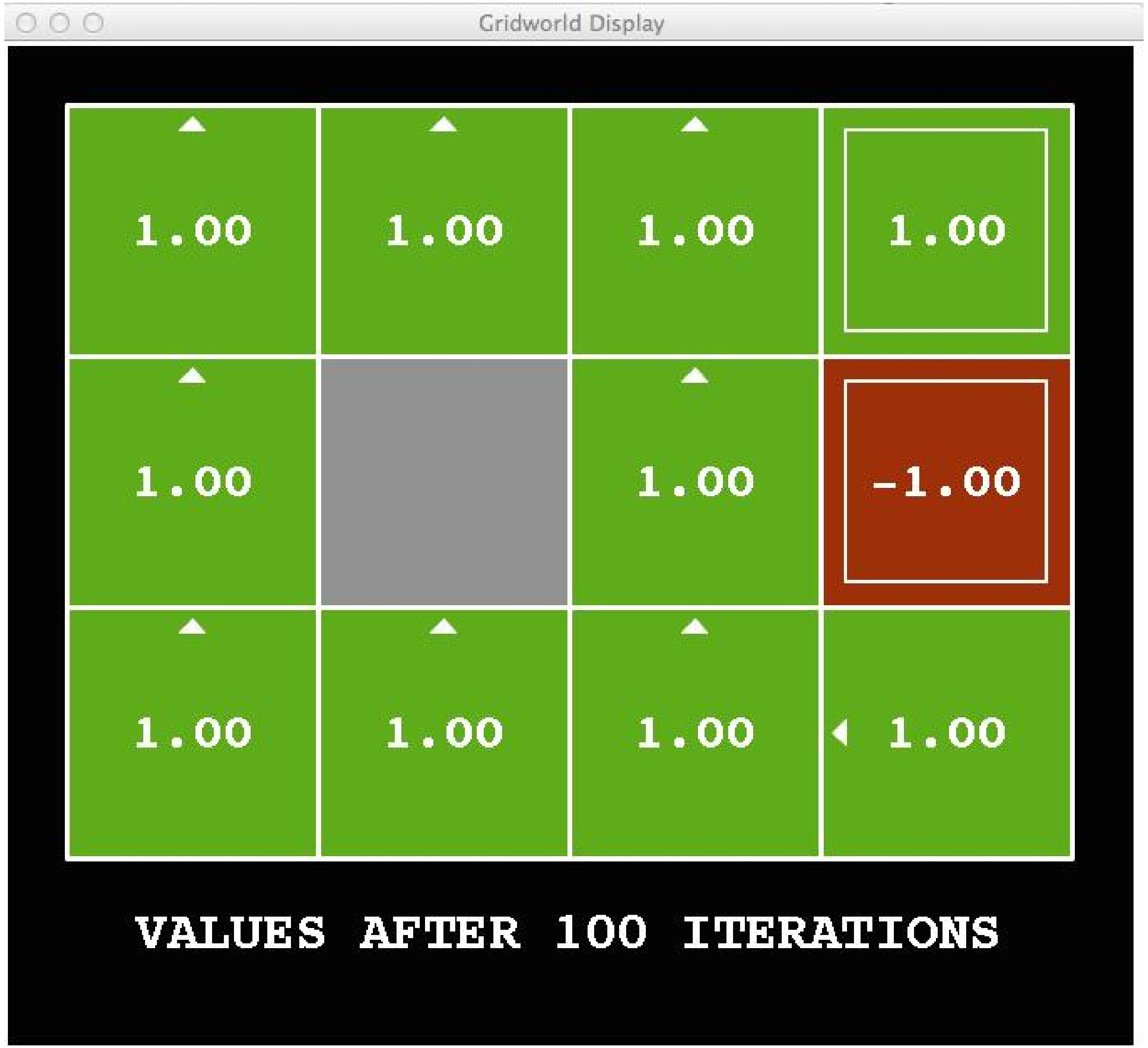
s is a *state*

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

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

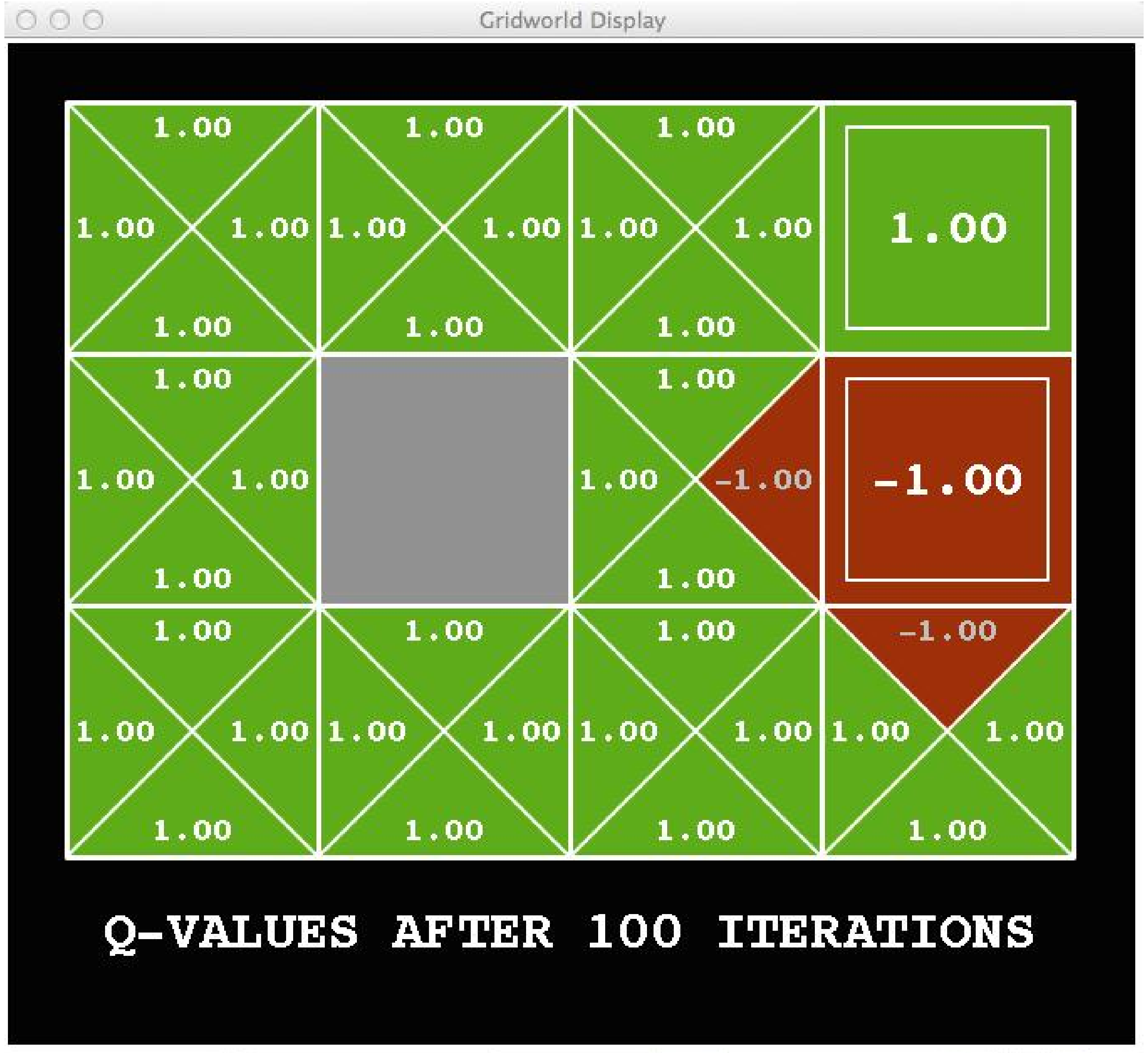
[Demo – gridworld values (L8D4)]

Snapshot of Demo – Gridworld V Values



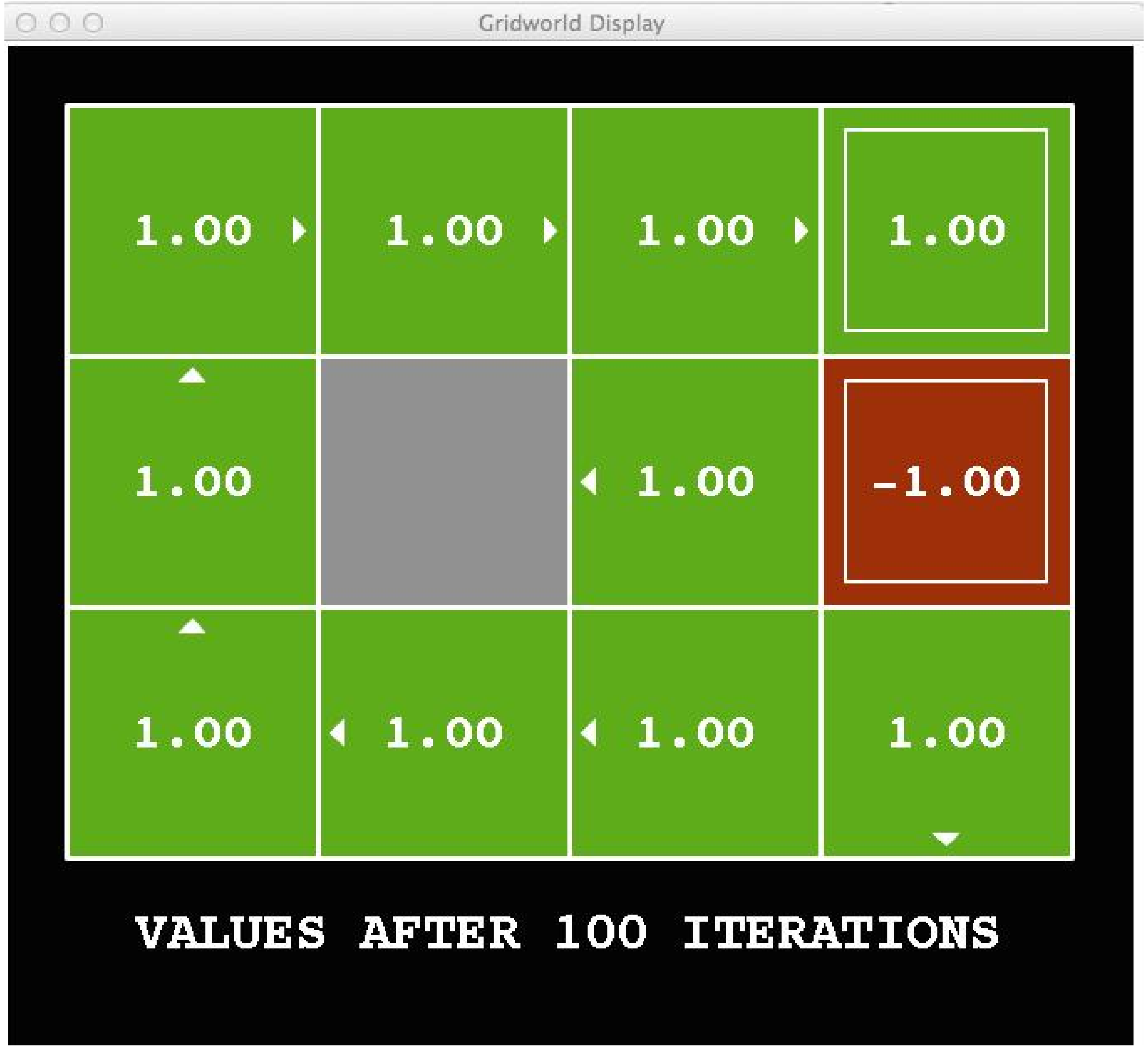
Noise = 0
Discount = 1
Living reward = 0

Snapshot of Demo – Gridworld Q Values



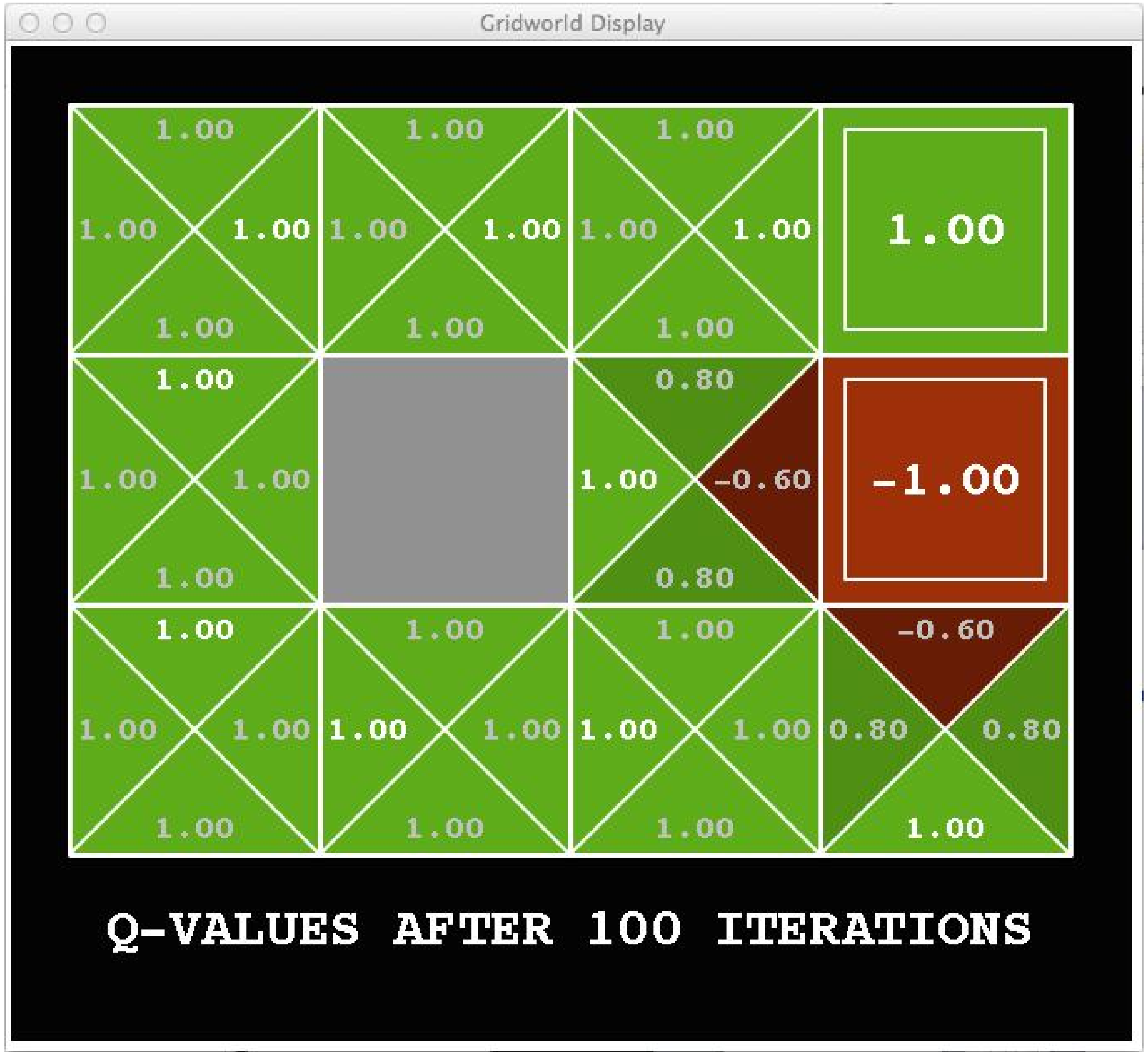
Noise = 0
Discount = 1
Living reward = 0

Snapshot of Demo – Gridworld V Values



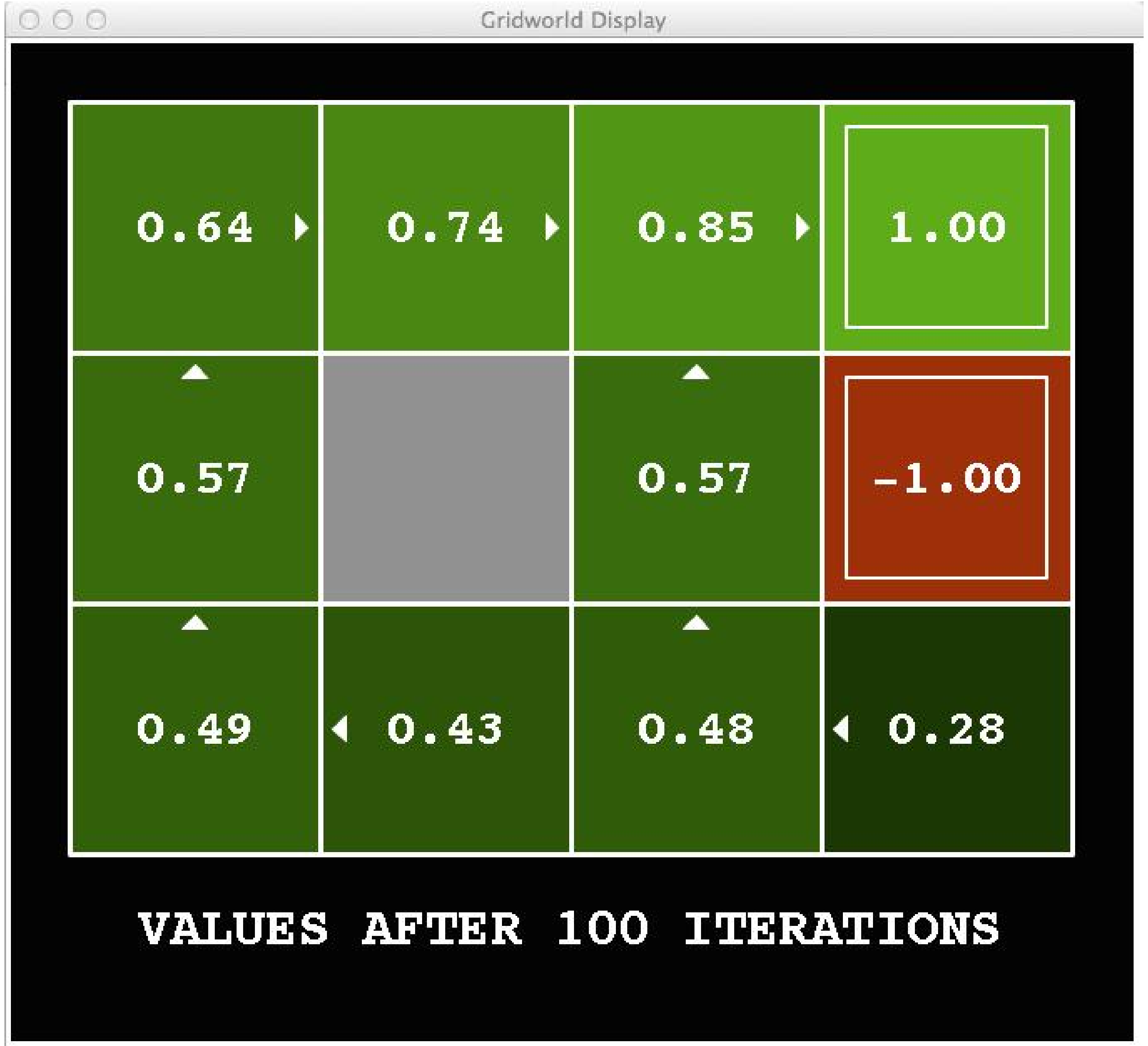
Noise = 0.2
Discount = 1
Living reward = 0

Snapshot of Demo – Gridworld Q Values



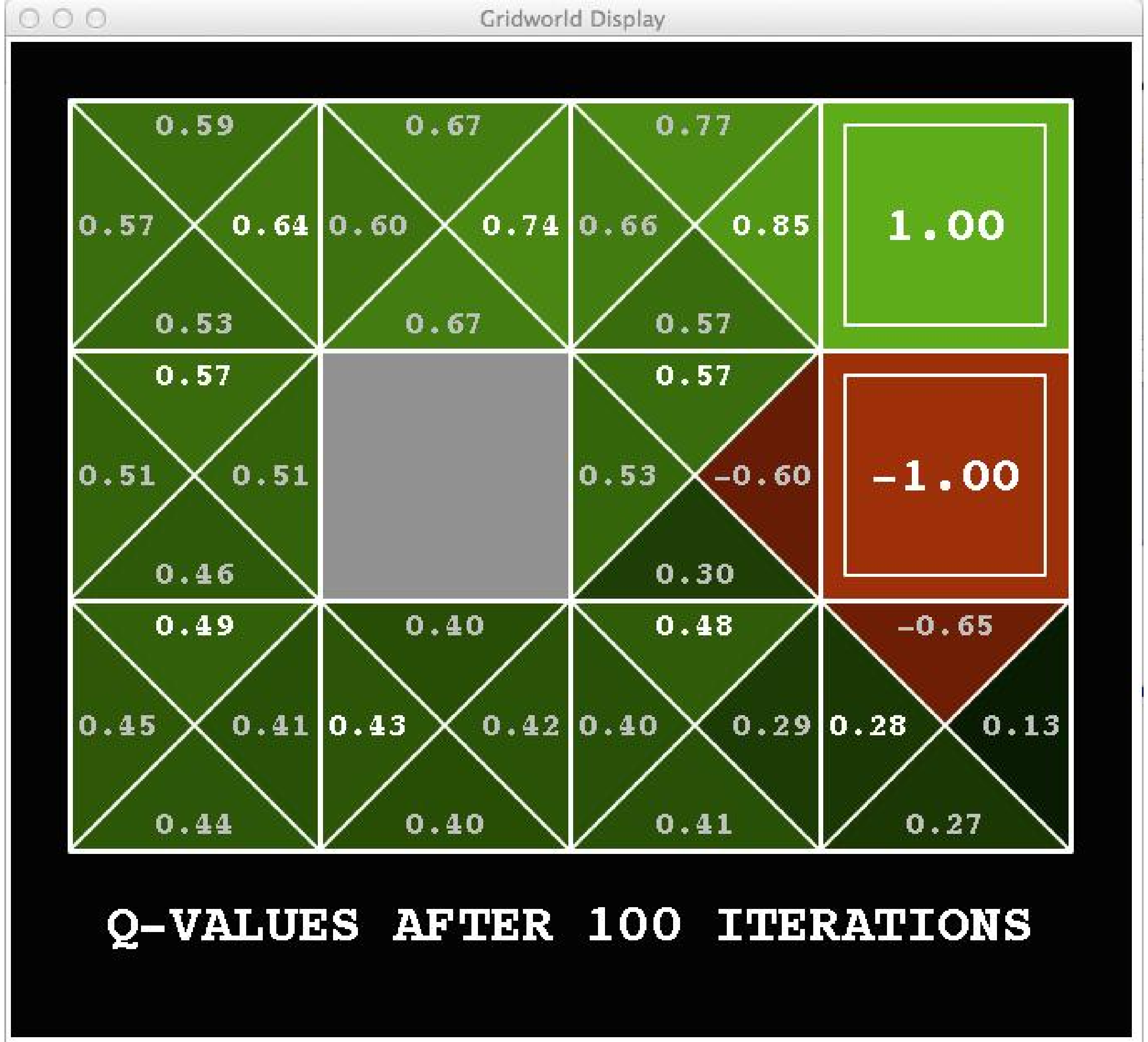
Noise = 0.2
Discount = 1
Living reward = 0

Snapshot of Demo – Gridworld V Values



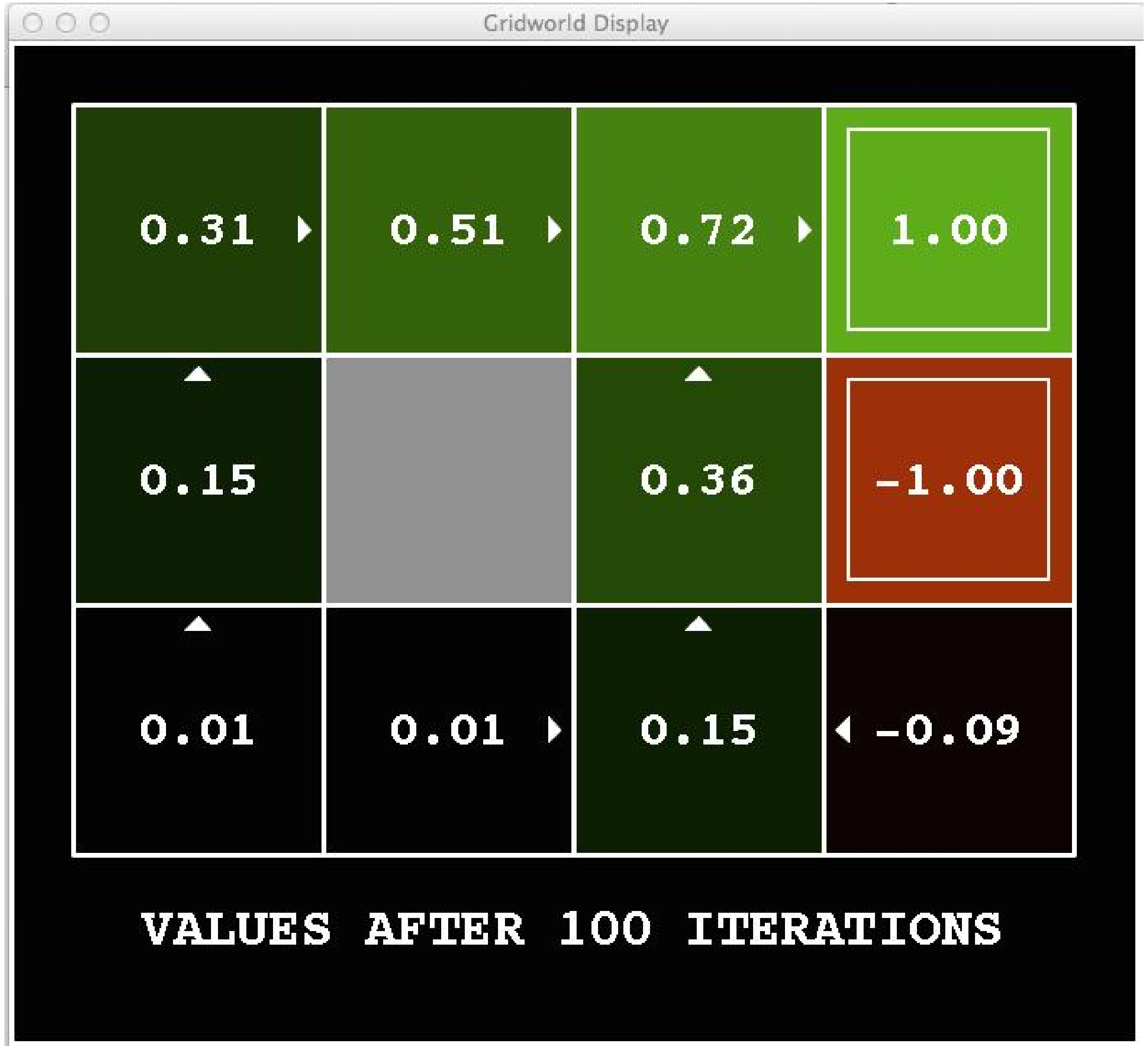
Noise = 0.2
Discount = 0.9
Living reward = 0

Snapshot of Demo – Gridworld Q Values



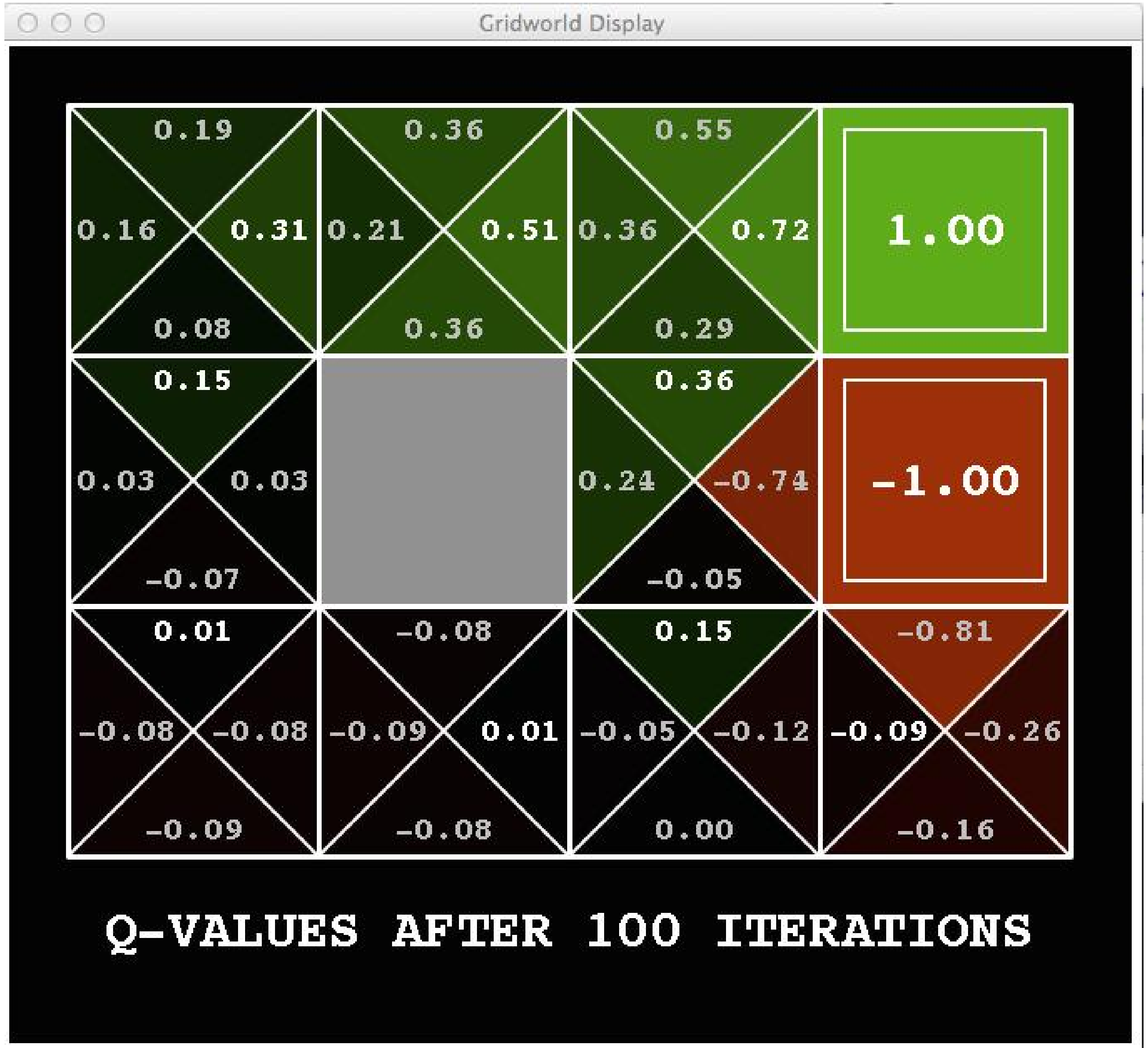
Noise = 0.2
Discount = 0.9
Living reward = 0

Snapshot of Demo – Gridworld V Values



Noise = 0.2
Discount = 0.9
Living reward = -0.1

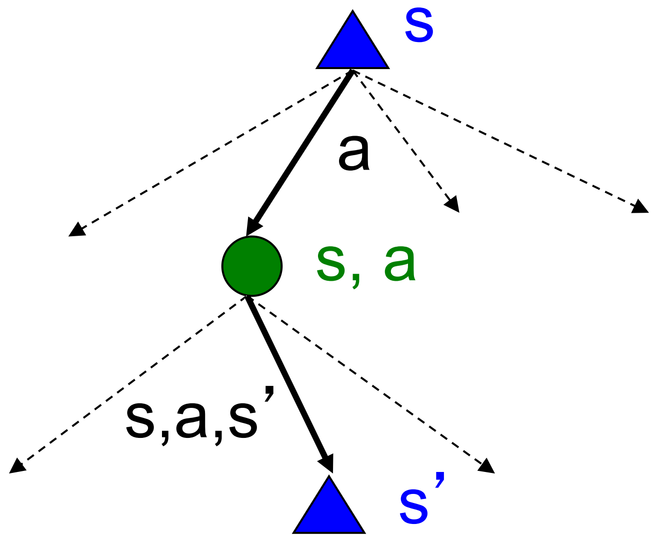
Snapshot of Demo – Gridworld Q Values



Noise = 0.2
Discount = 0.9
Living reward = -0.1

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!



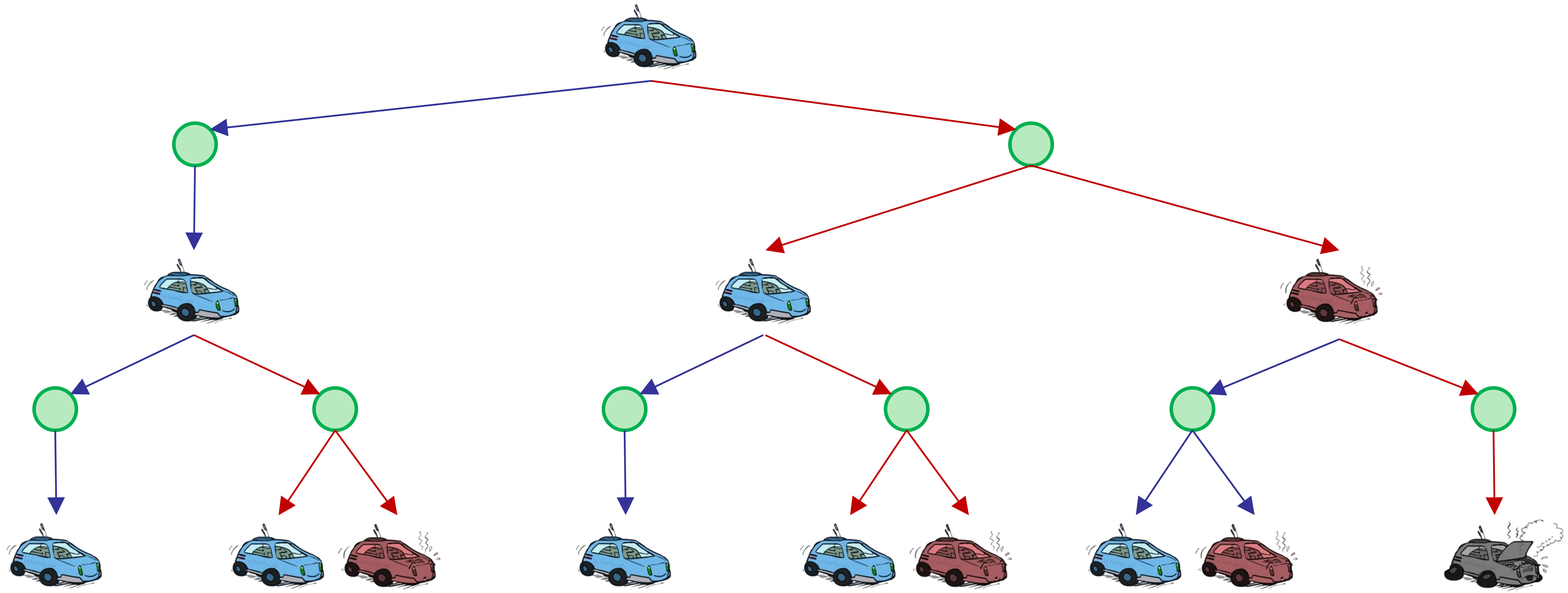
- Recursive definition of value:

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

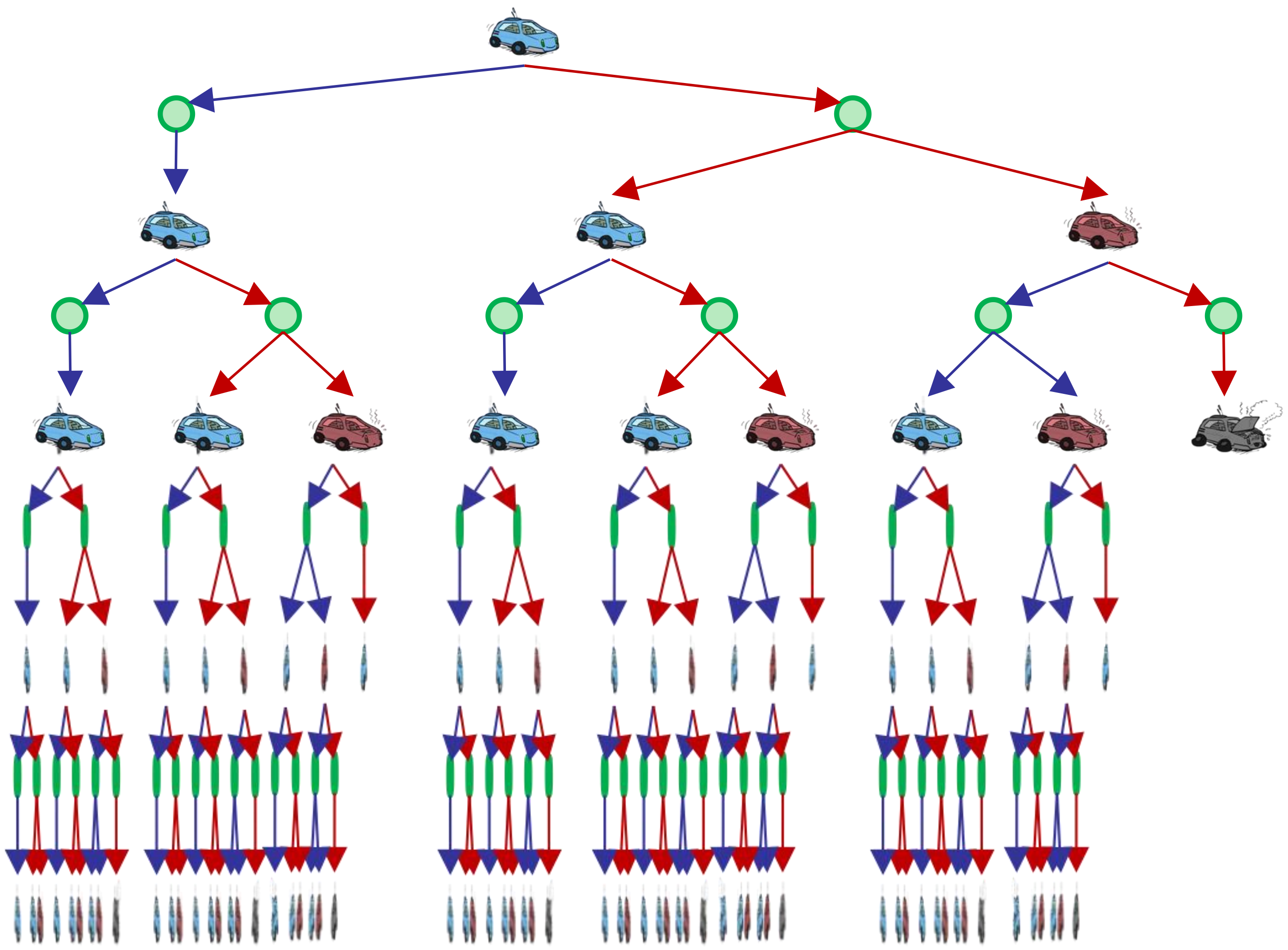
$$Q^*(s,a) = \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s')\right]$$

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

Racing Search Tree

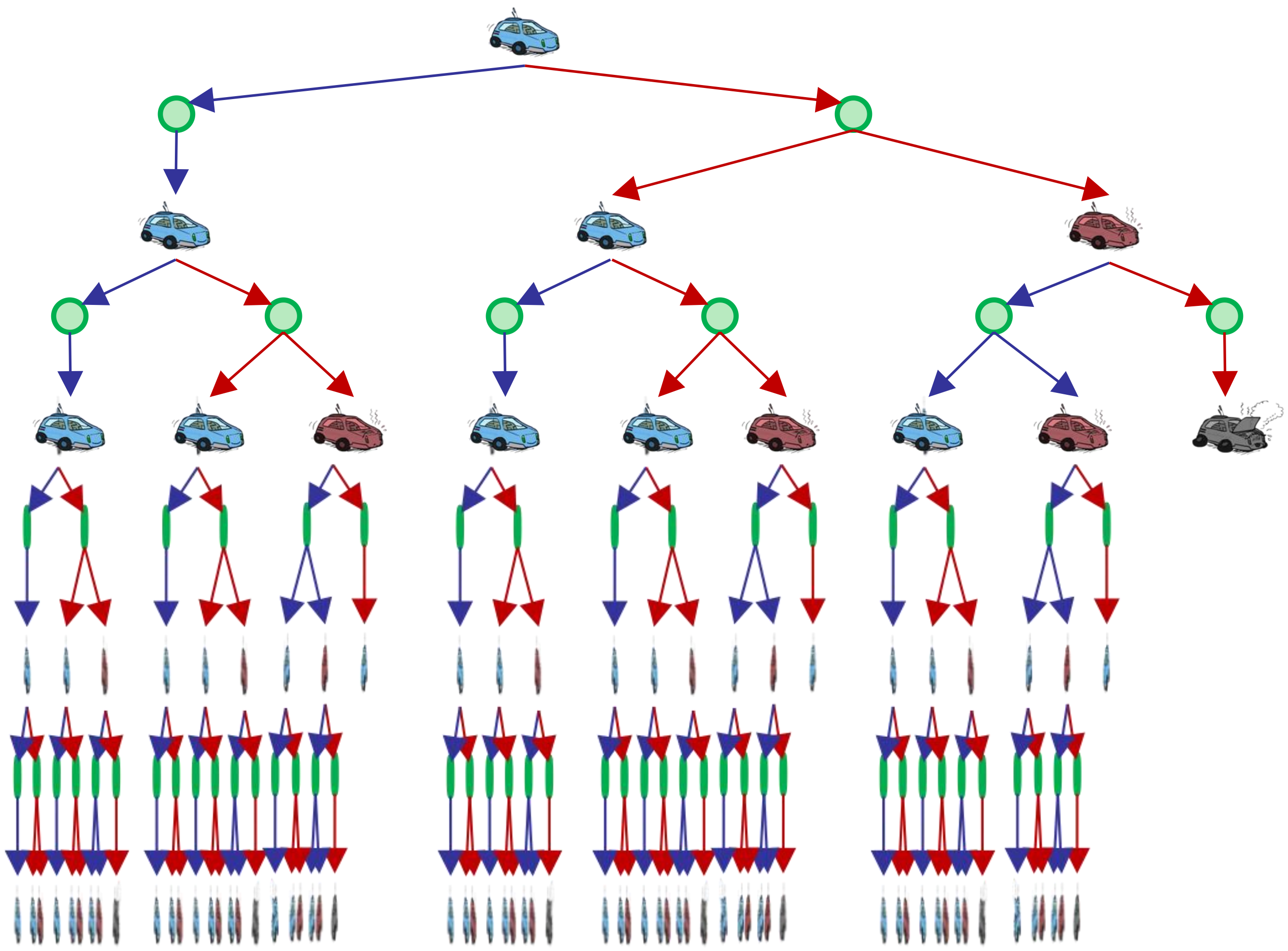


Racing Search Tree



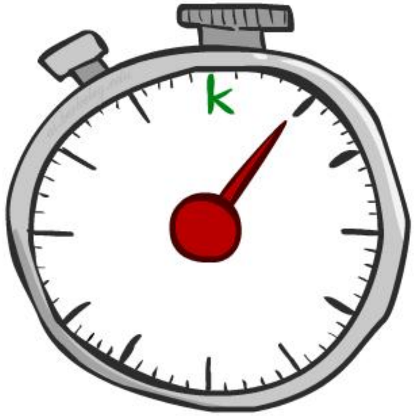
Racing Search Tree

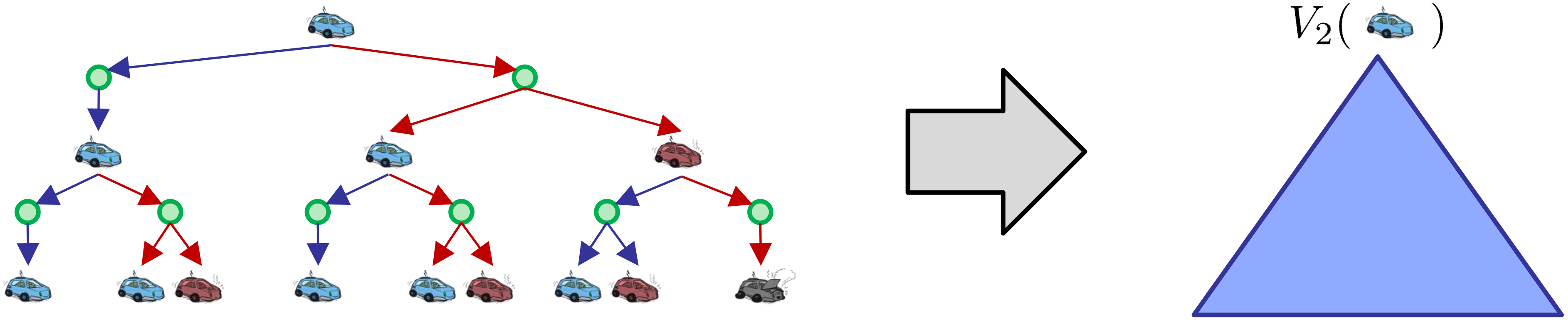
- We’re doing way too much work with expectimax!
- Problem: States are repeated
  - Idea: Only compute needed quantities once
- Problem: Tree goes on forever
  - Idea: Do a depth-limited computation, but with increasing depths until change is small
  - Note: deep parts of the tree eventually don’t matter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



Time-Limited Values

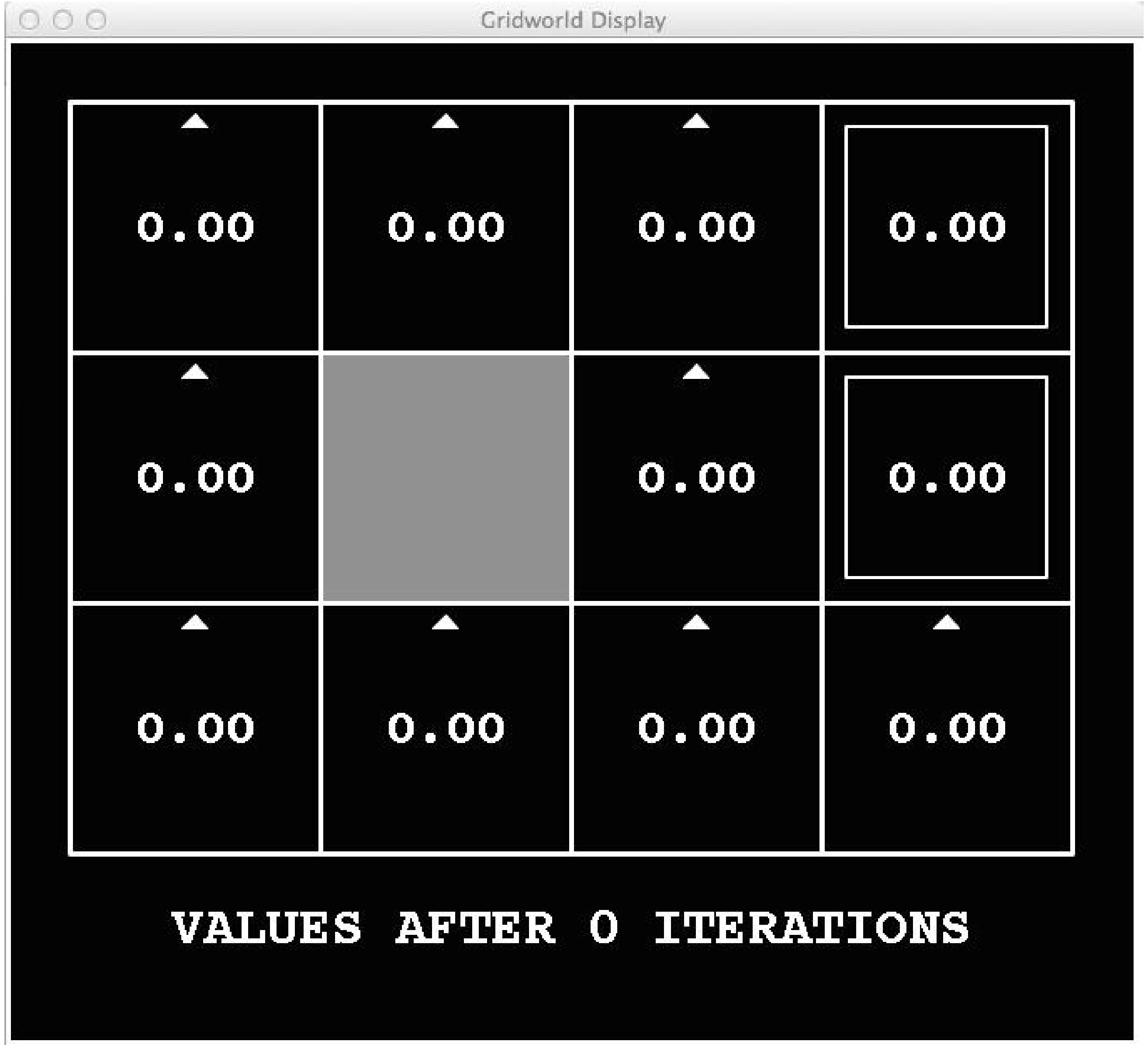
- Key idea: time-limited values
- Define $V_k(s)$ to be the optimal value of s if the game ends in k more time steps
  - Equivalently, it's what a depth-k expectimax would give from s





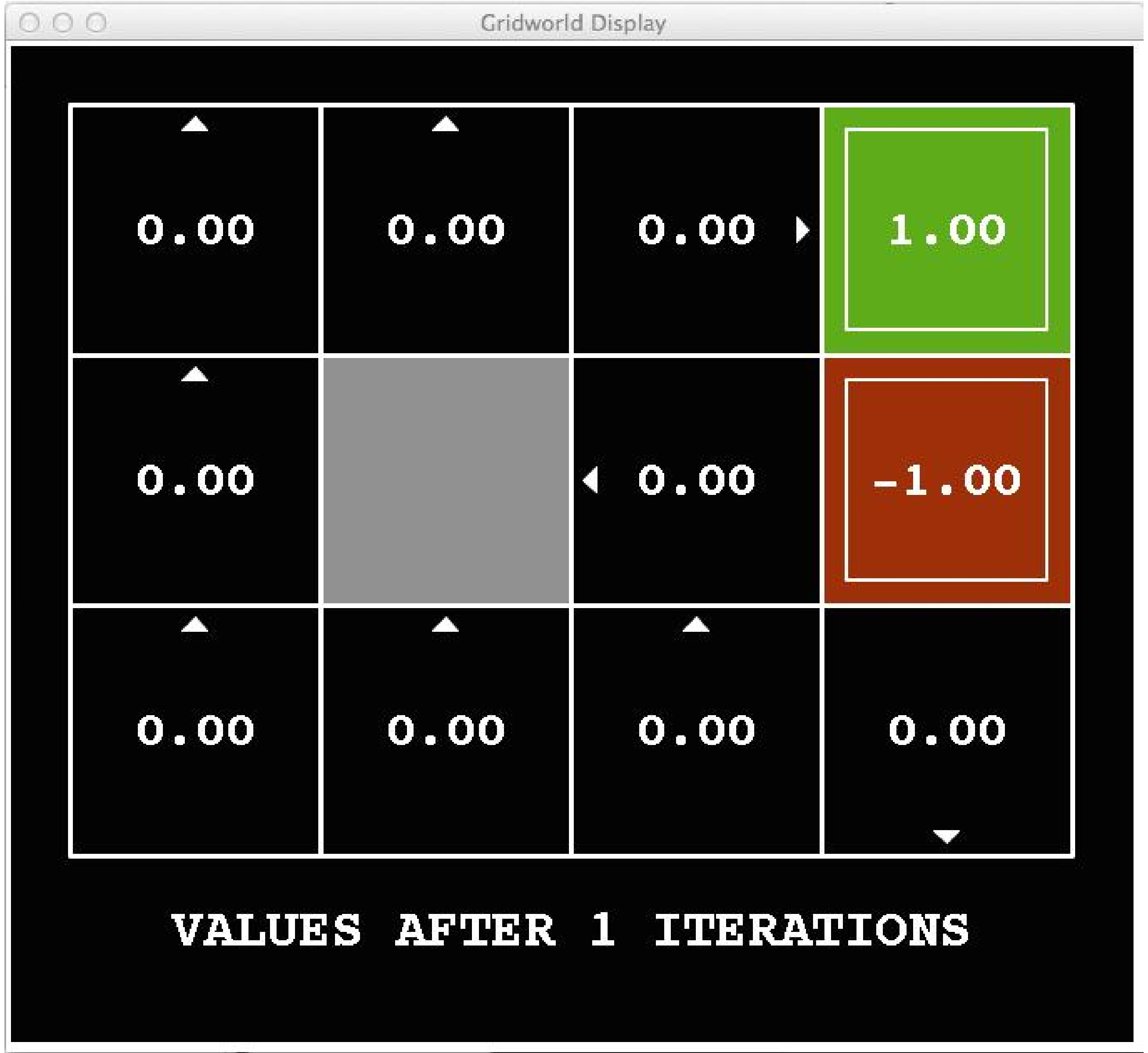
[Demo – time-limited values (L8D6)]

k=0



Noise = 0.2
Discount = 0.9
Living reward = 0

k=1



Noise = 0.2
Discount = 0.9
Living reward = 0

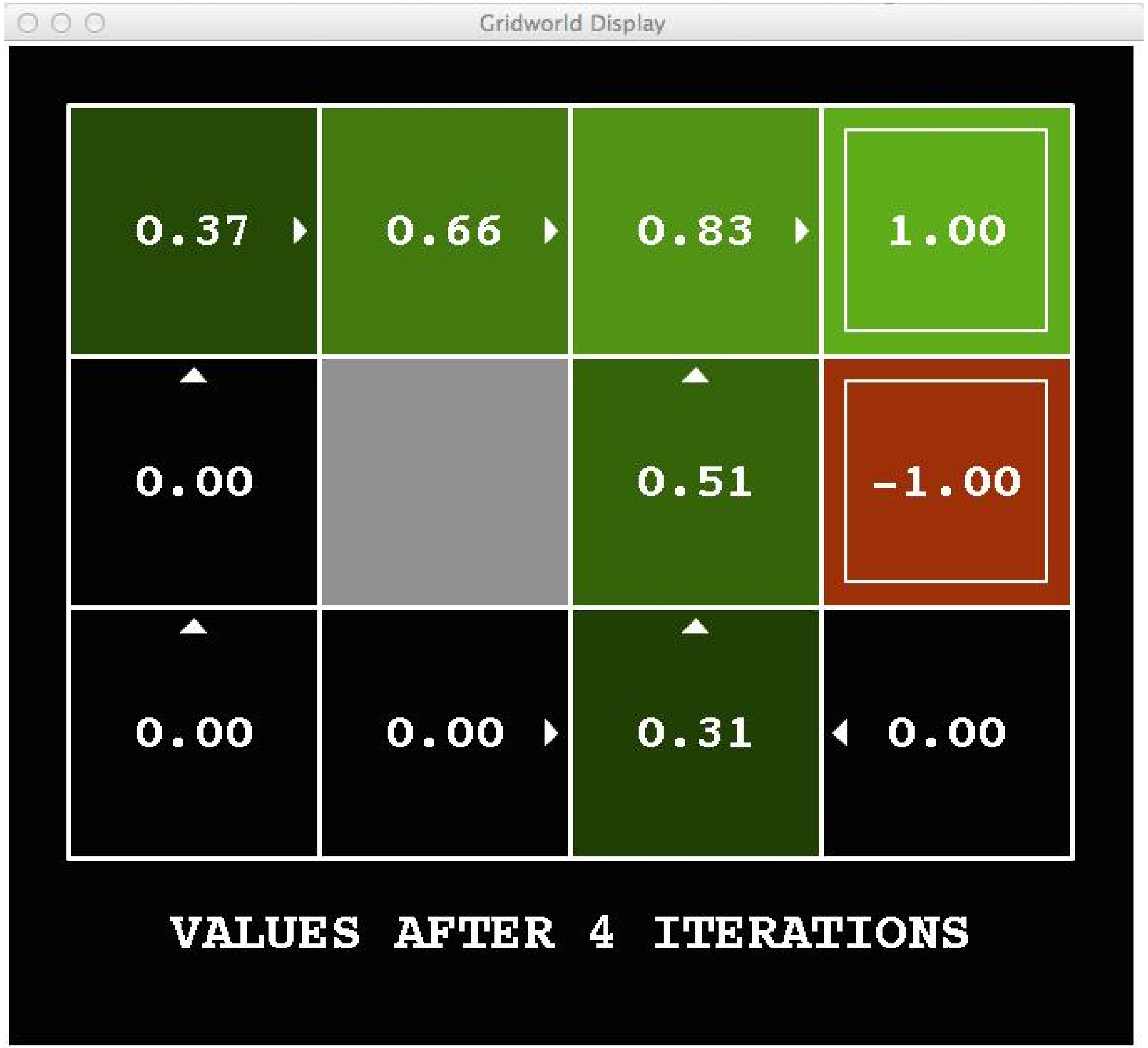
k=2

Noise = 0.2
Discount = 0.9
Living reward = 0

k=3

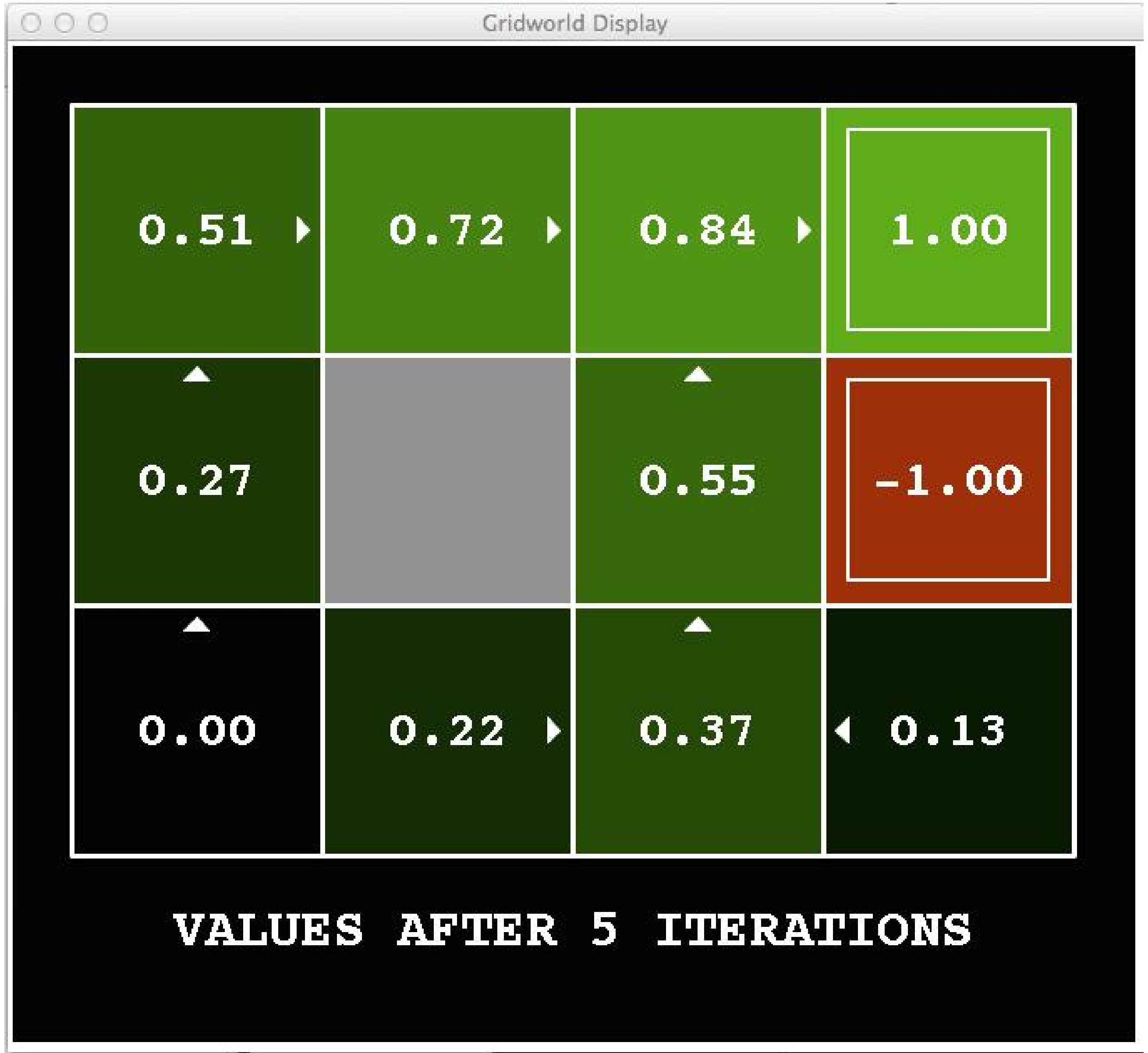
Noise = 0.2
Discount = 0.9
Living reward = 0

k=4



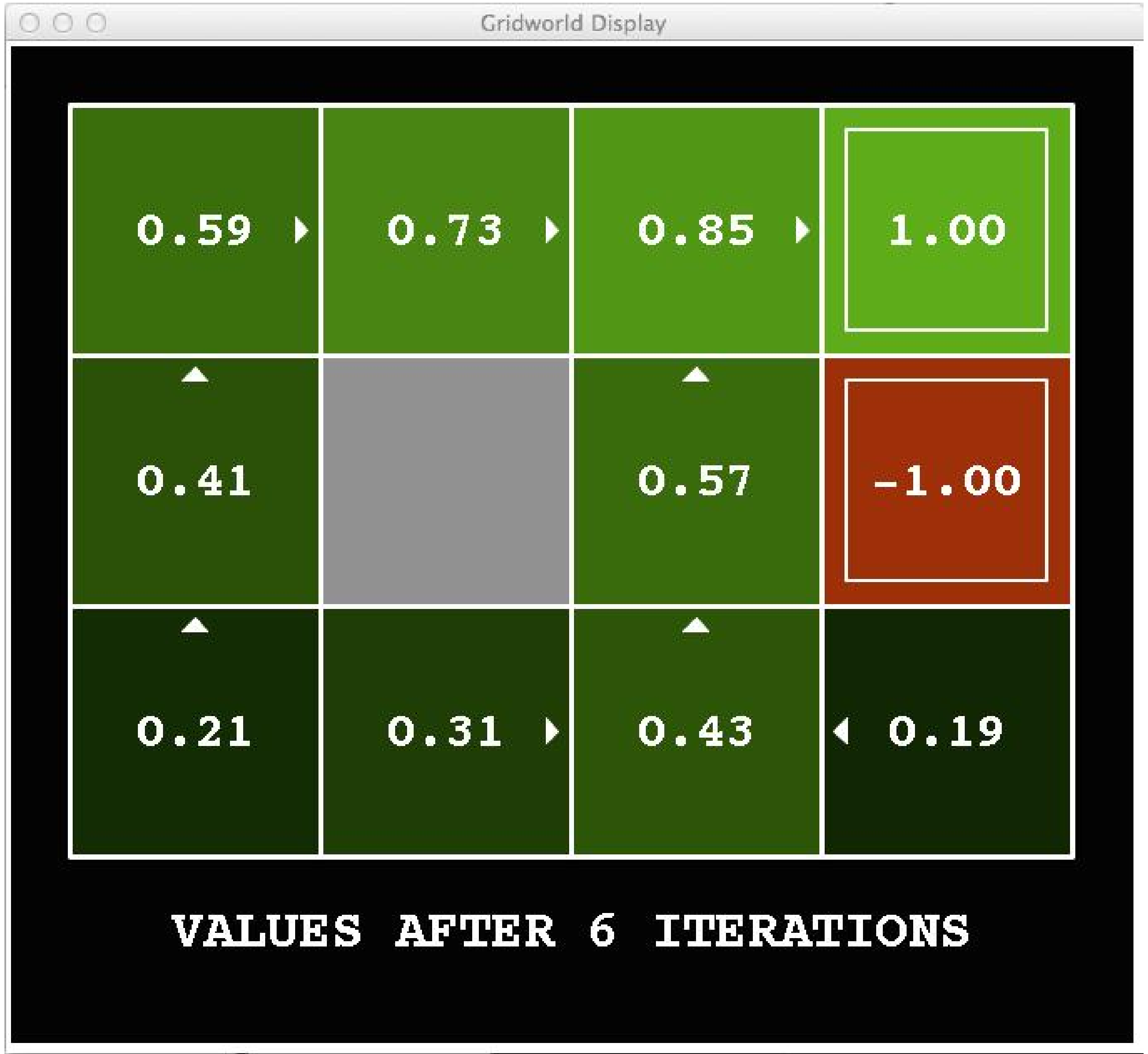
Noise = 0.2
Discount = 0.9
Living reward = 0

k=5



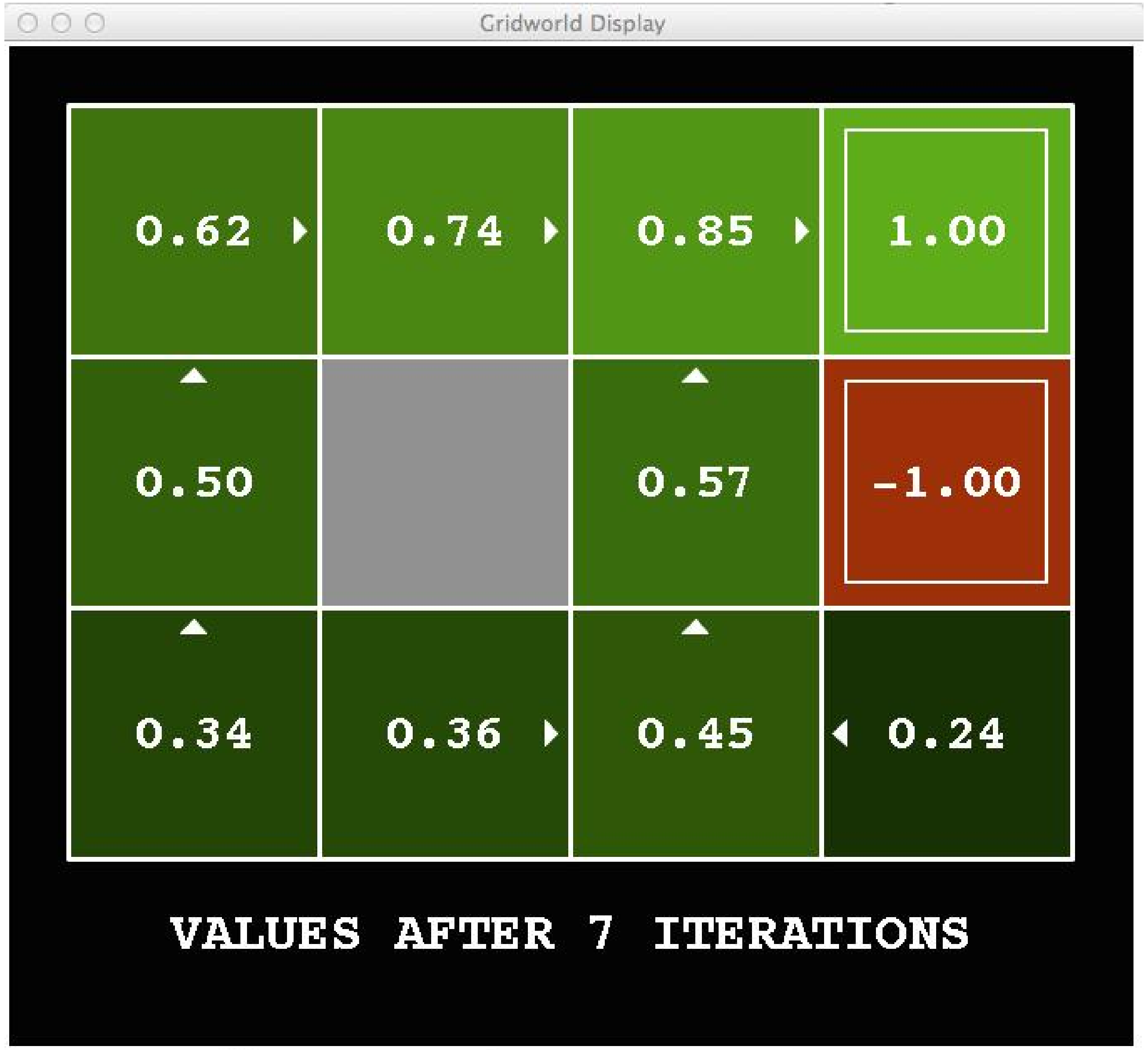
Noise = 0.2
Discount = 0.9
Living reward = 0

k=6



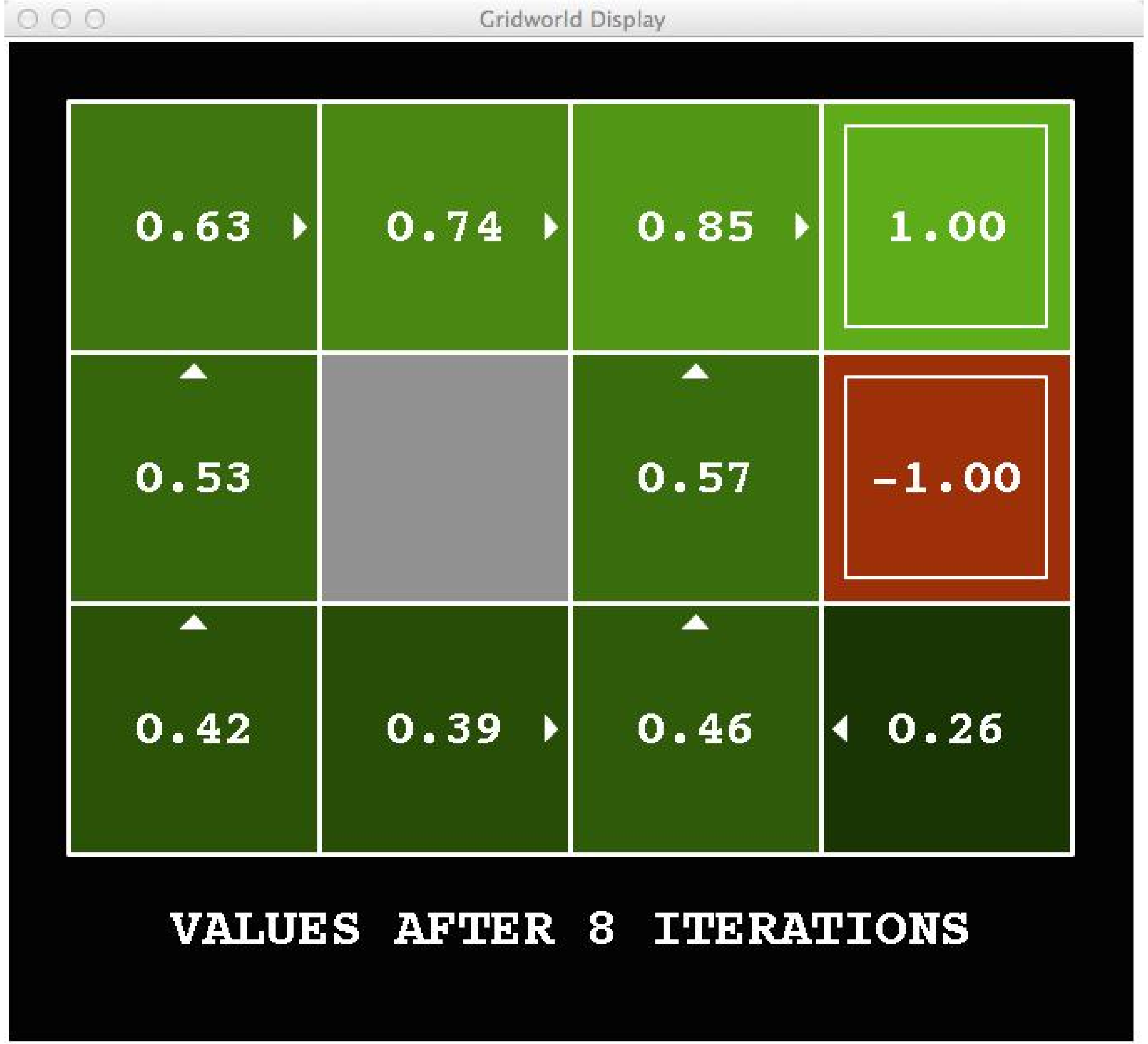
Noise = 0.2
Discount = 0.9
Living reward = 0

k=7



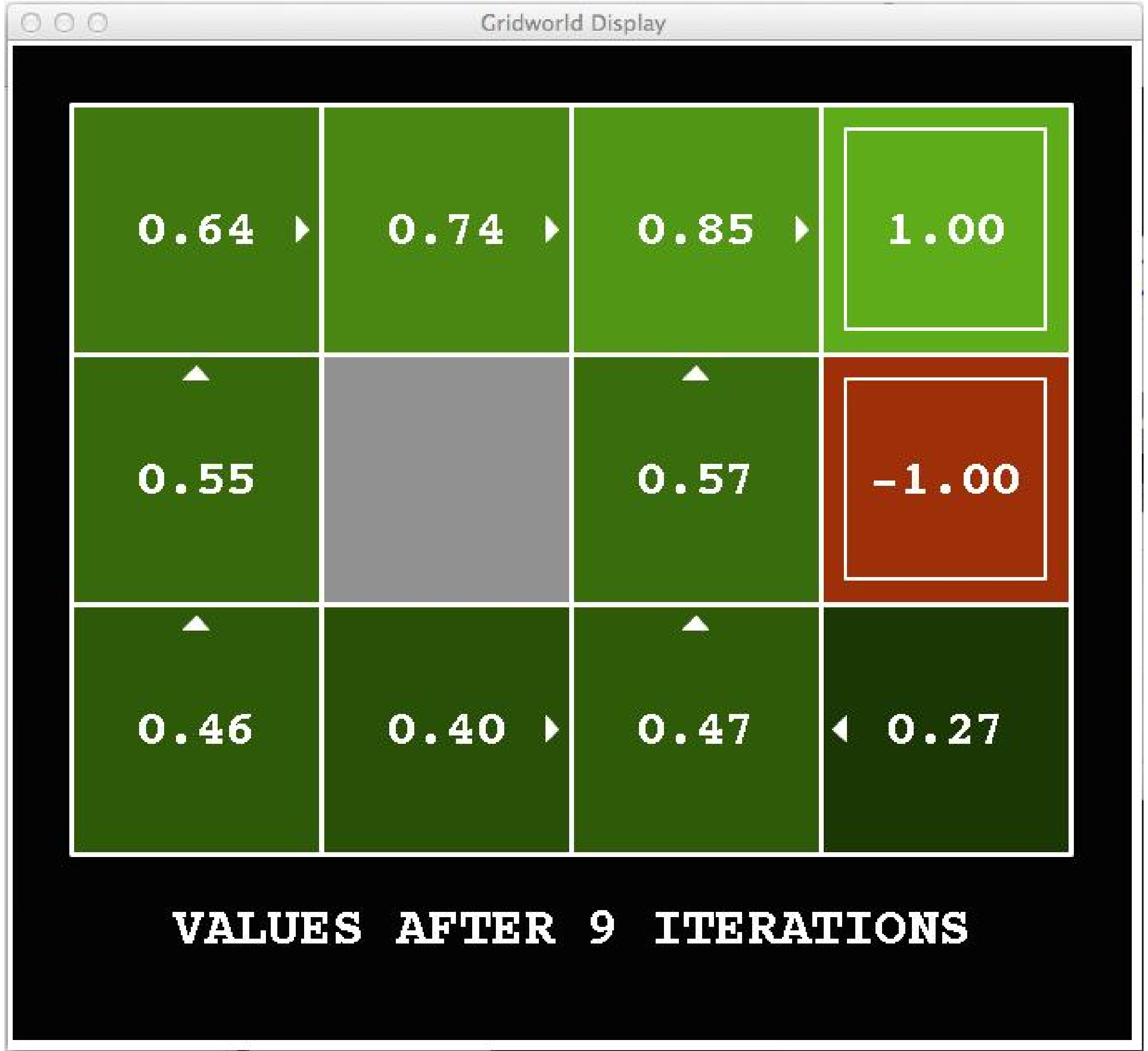
Noise = 0.2
Discount = 0.9
Living reward = 0

k=8



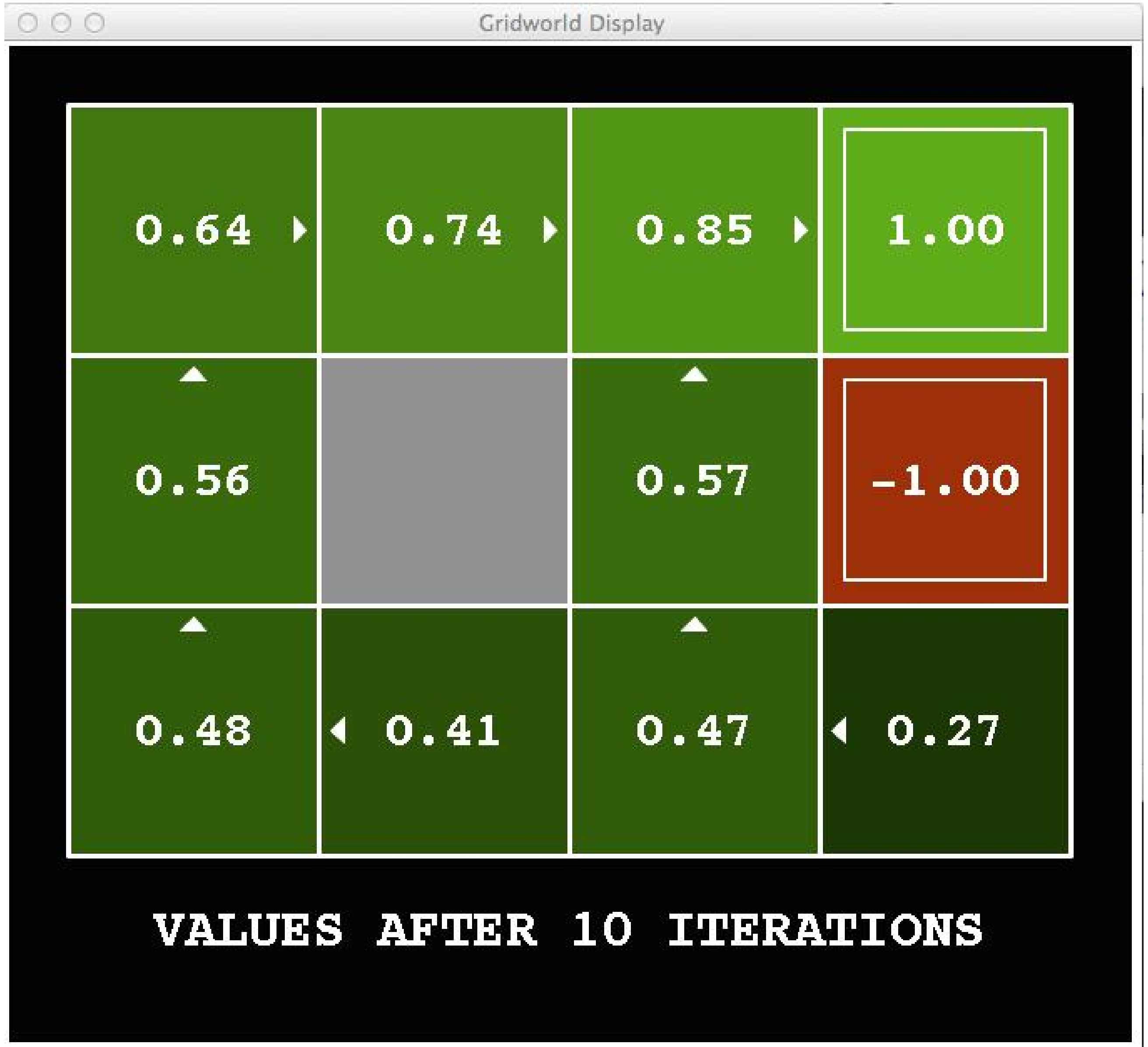
Noise = 0.2
Discount = 0.9
Living reward = 0

k=9



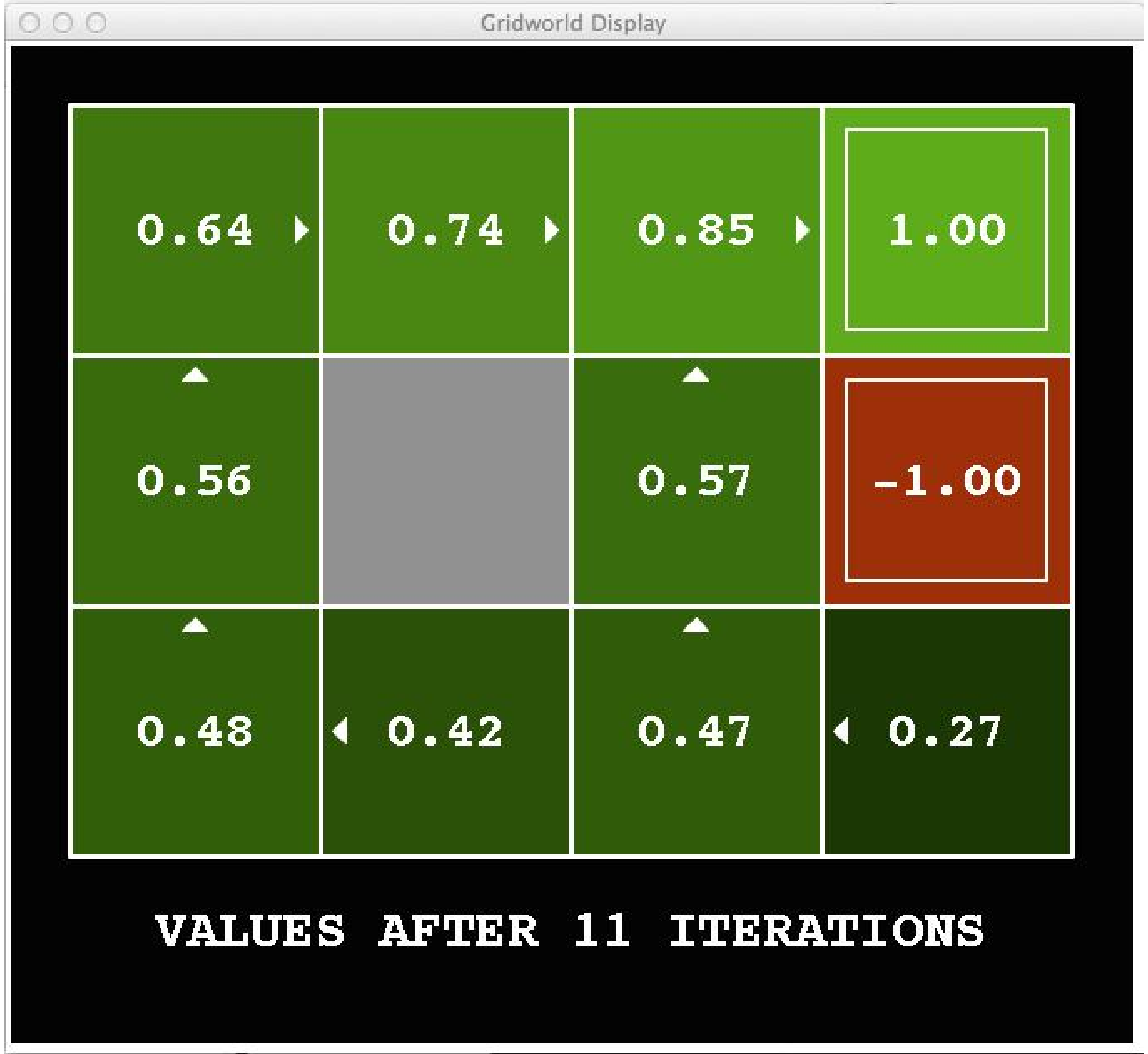
Noise = 0.2
Discount = 0.9
Living reward = 0

k=10



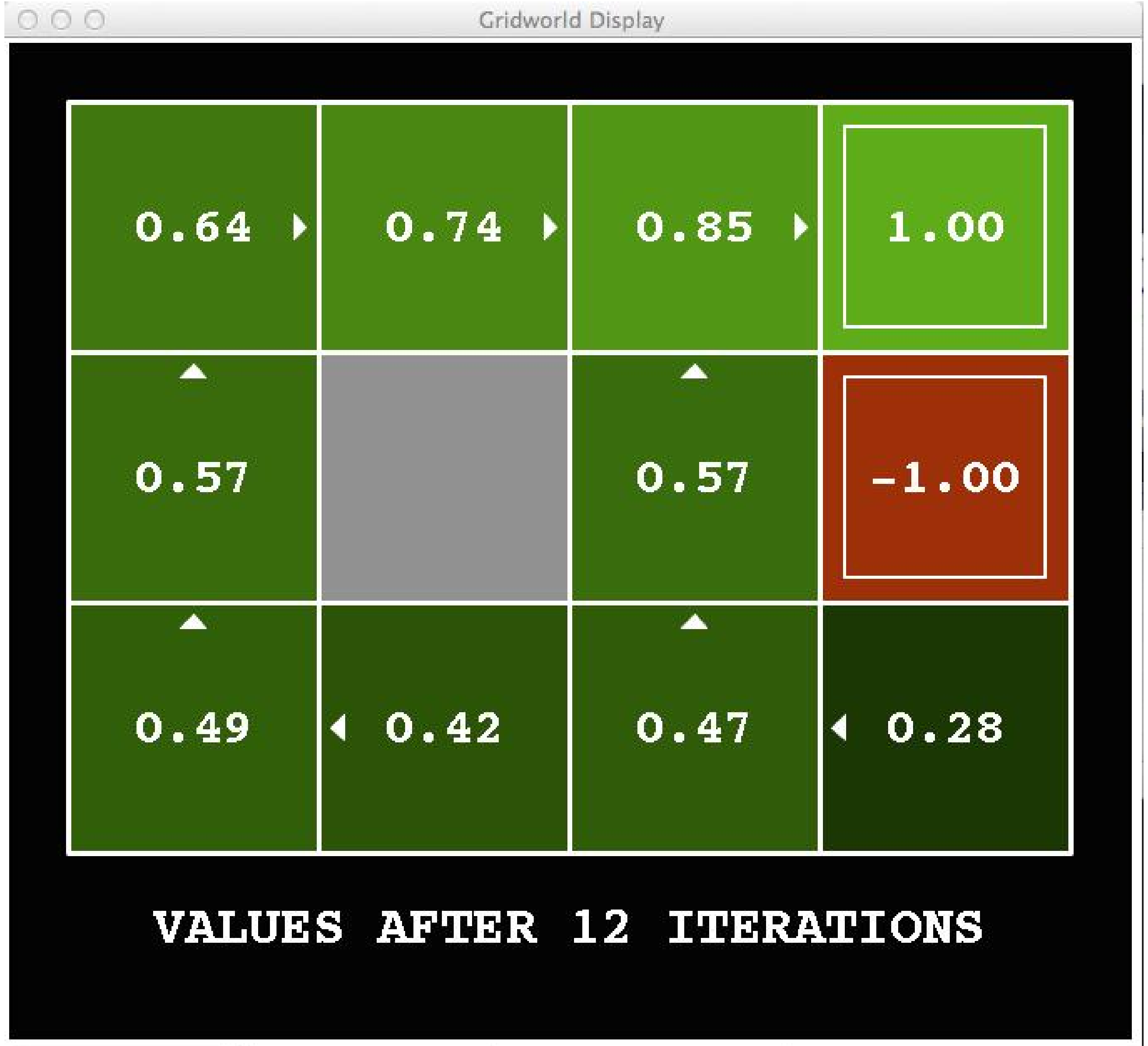
Noise = 0.2
Discount = 0.9
Living reward = 0

k=11



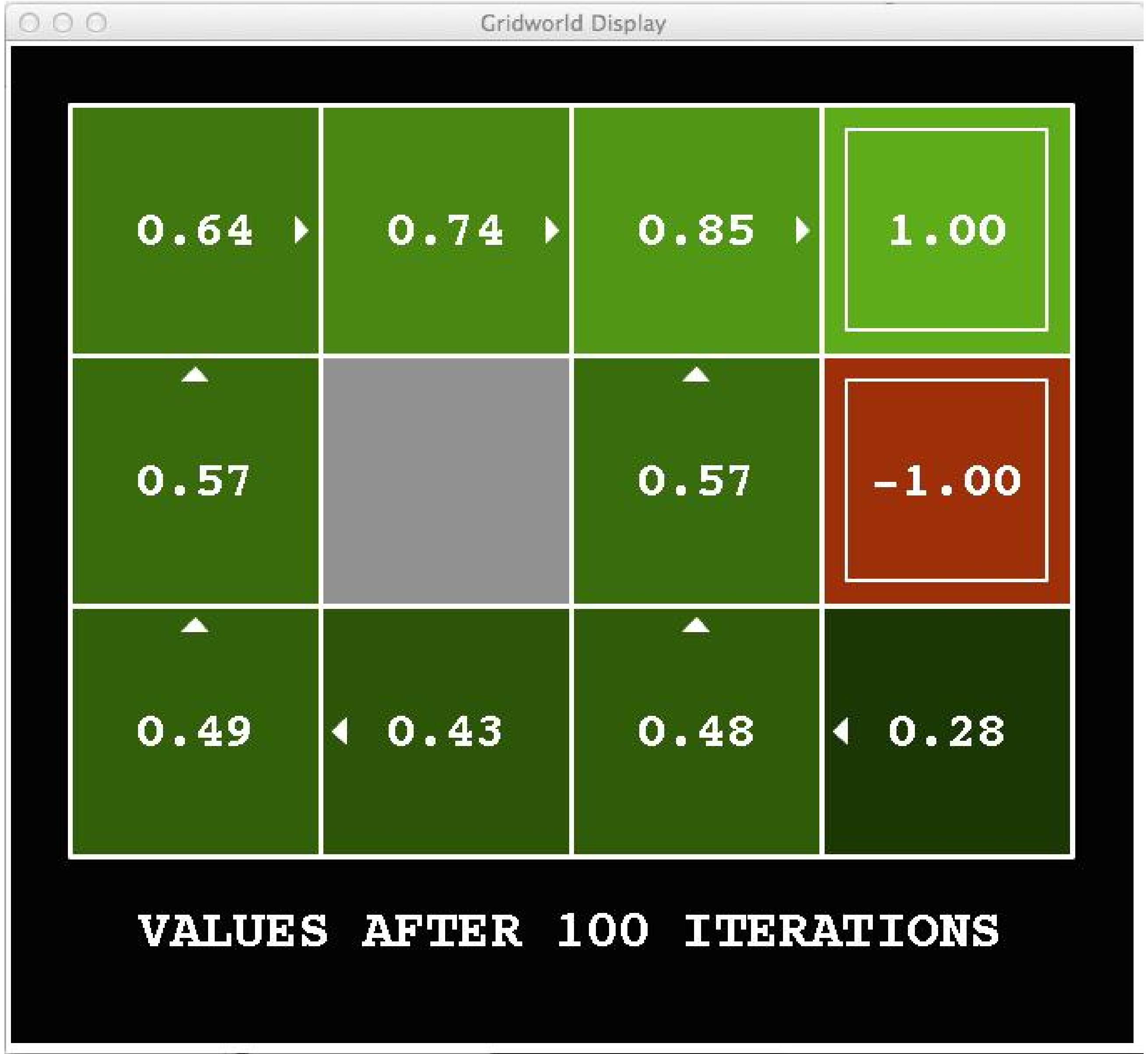
Noise = 0.2
Discount = 0.9
Living reward = 0

k=12



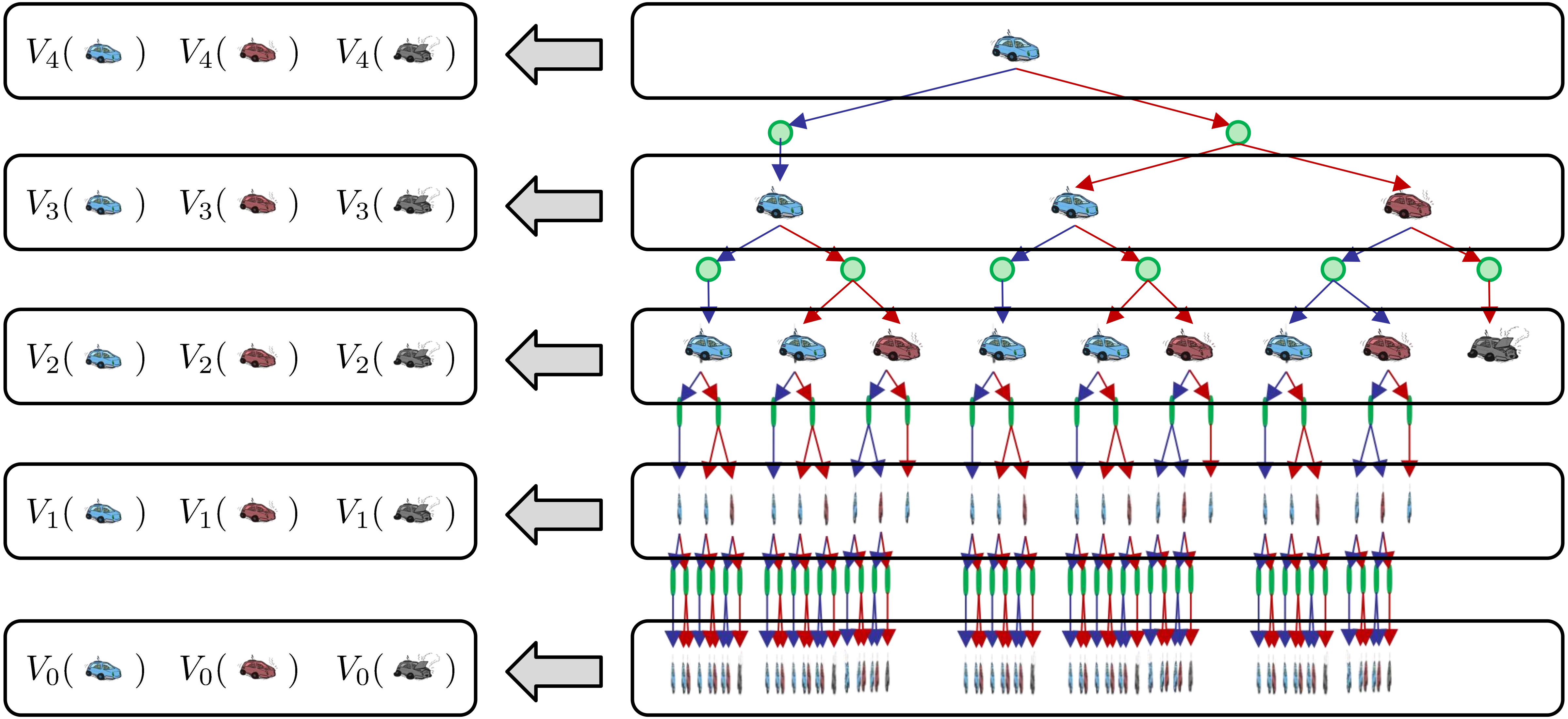
Noise = 0.2
Discount = 0.9
Living reward = 0

k=100

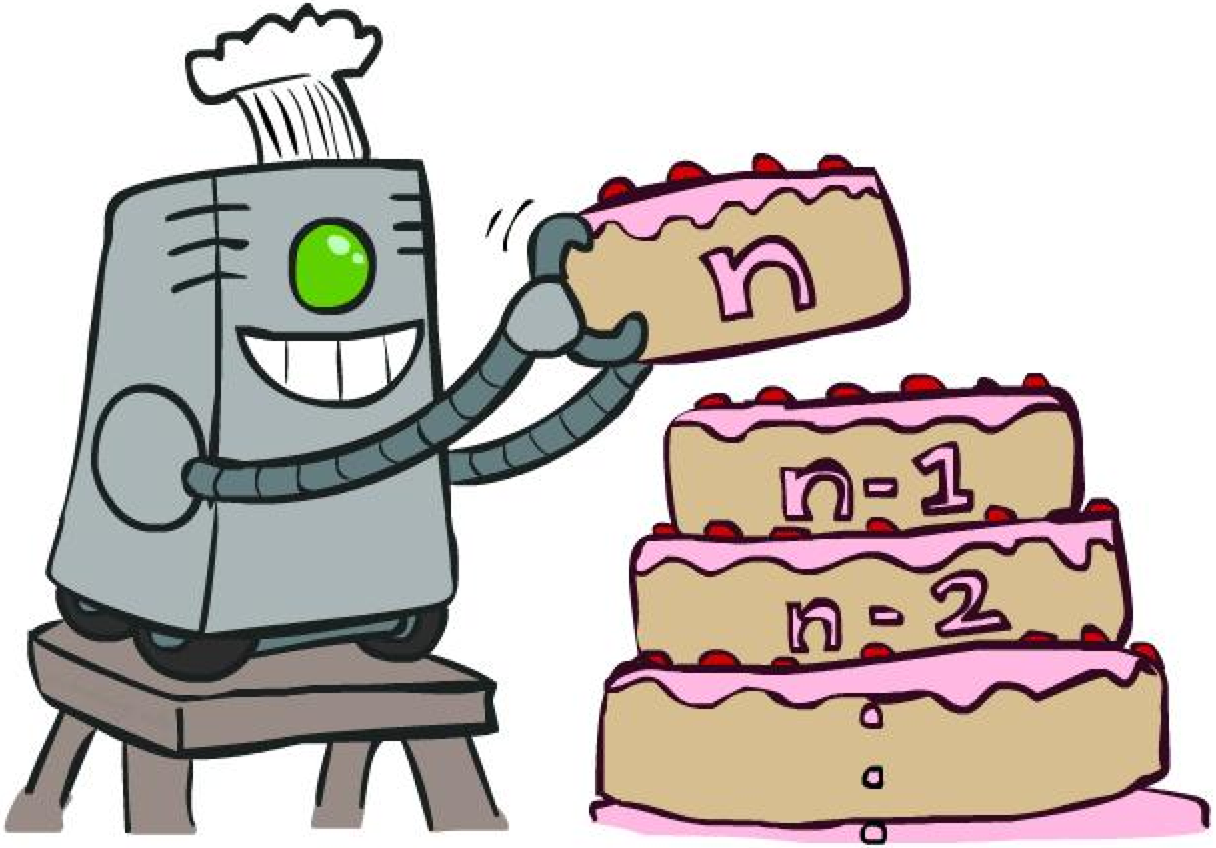


Noise = 0.2
Discount = 0.9
Living reward = 0

Computing Time-Limited Values



Value Iteration

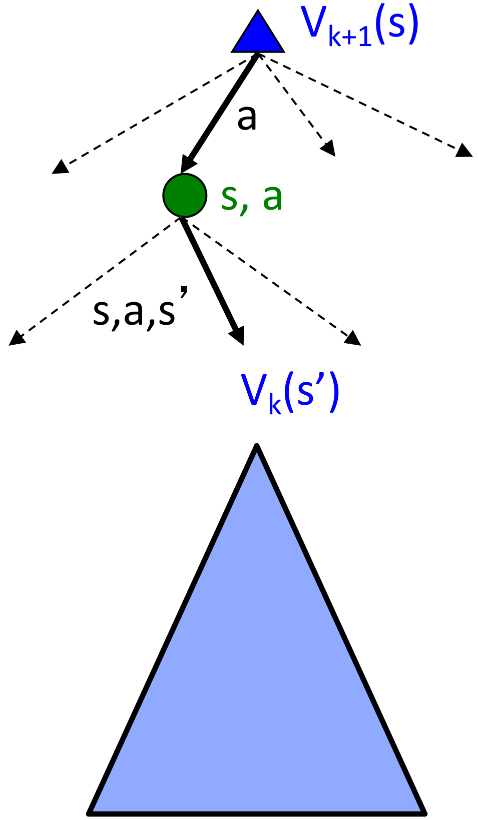


Value Iteration

- 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:

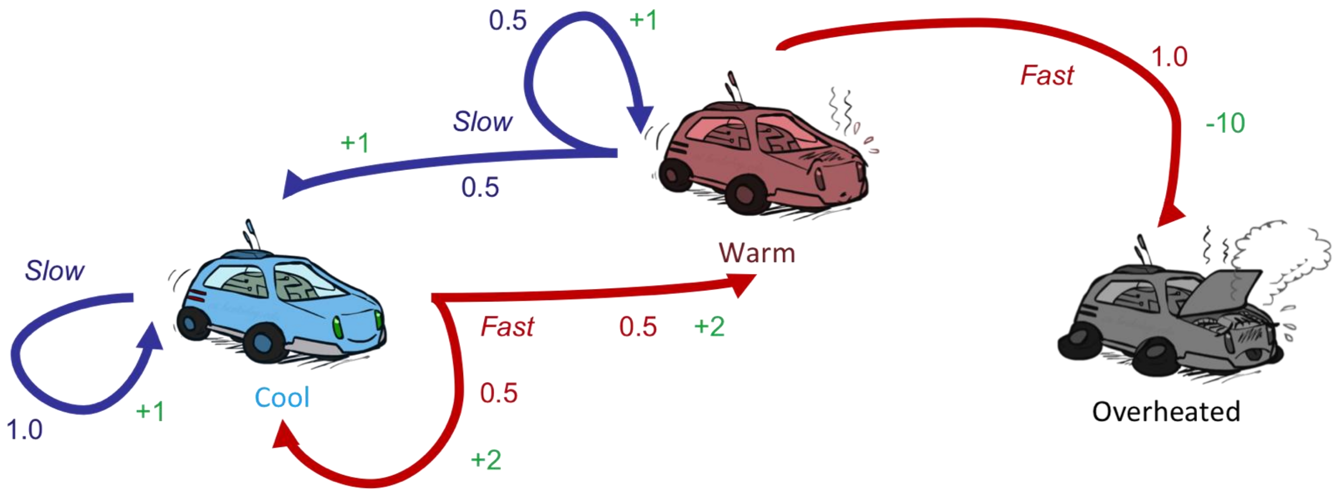
$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V_k(s')\right]$$

- Repeat until convergence
- Complexity of each iteration: $O(S^2A)$
- 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

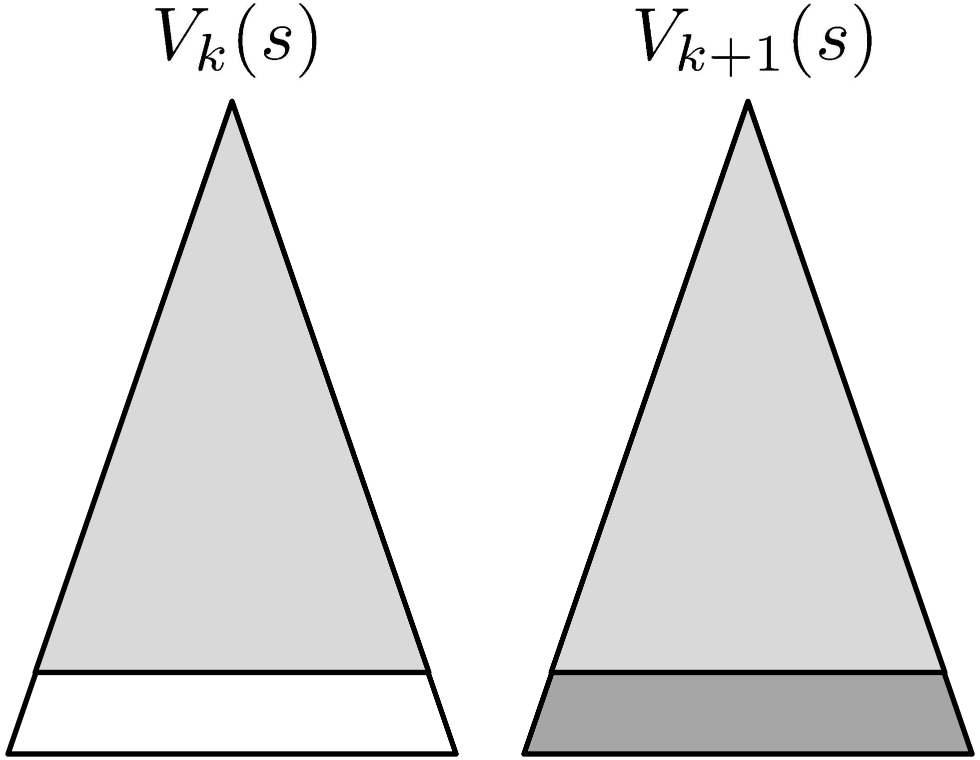


Assume no discount!

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

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 γ^k max|R| different
  - So as k increases, the values converge



Next Time: Policy-Based Methods

Non-Deterministic Search