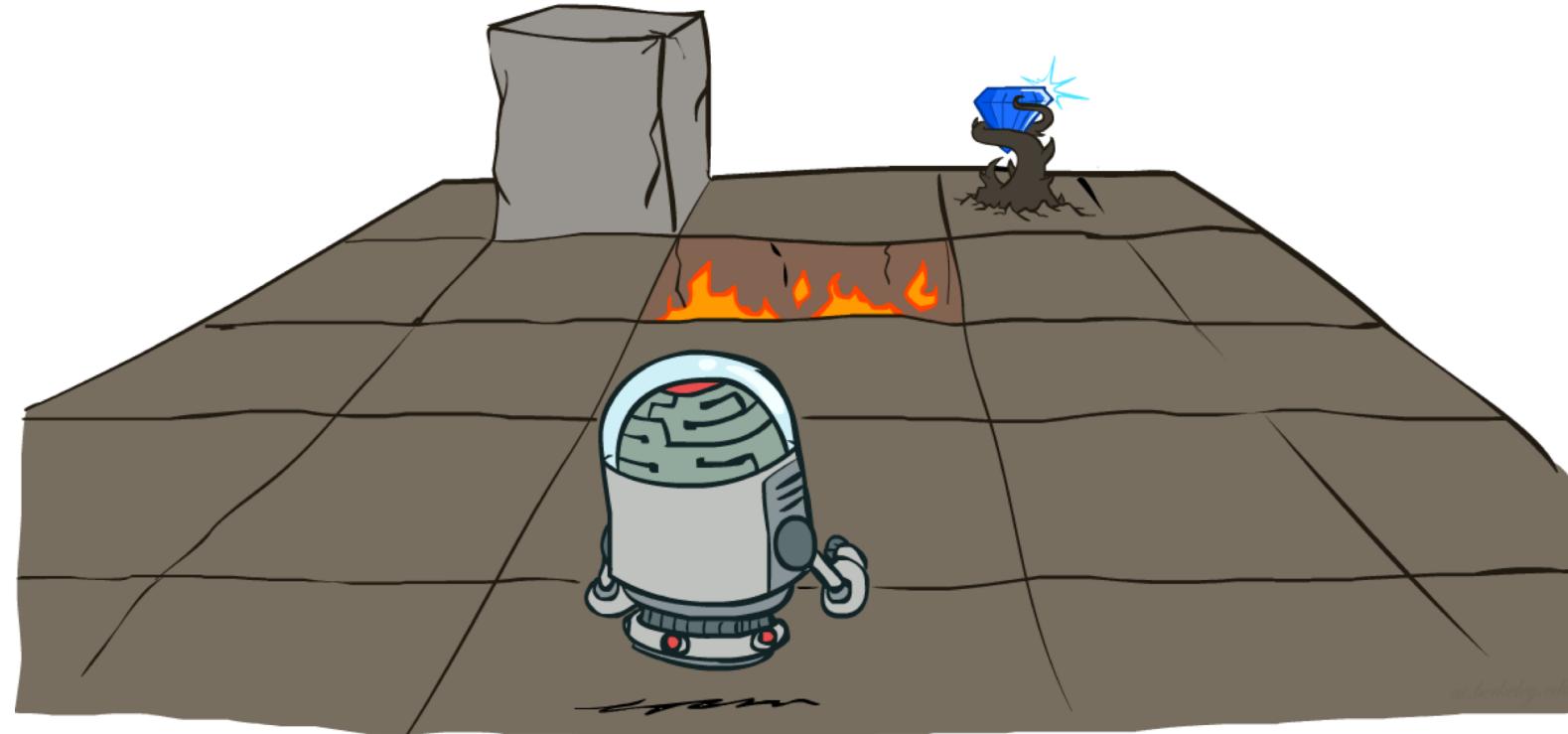


# CS 188: Artificial Intelligence

## Markov Decision Processes

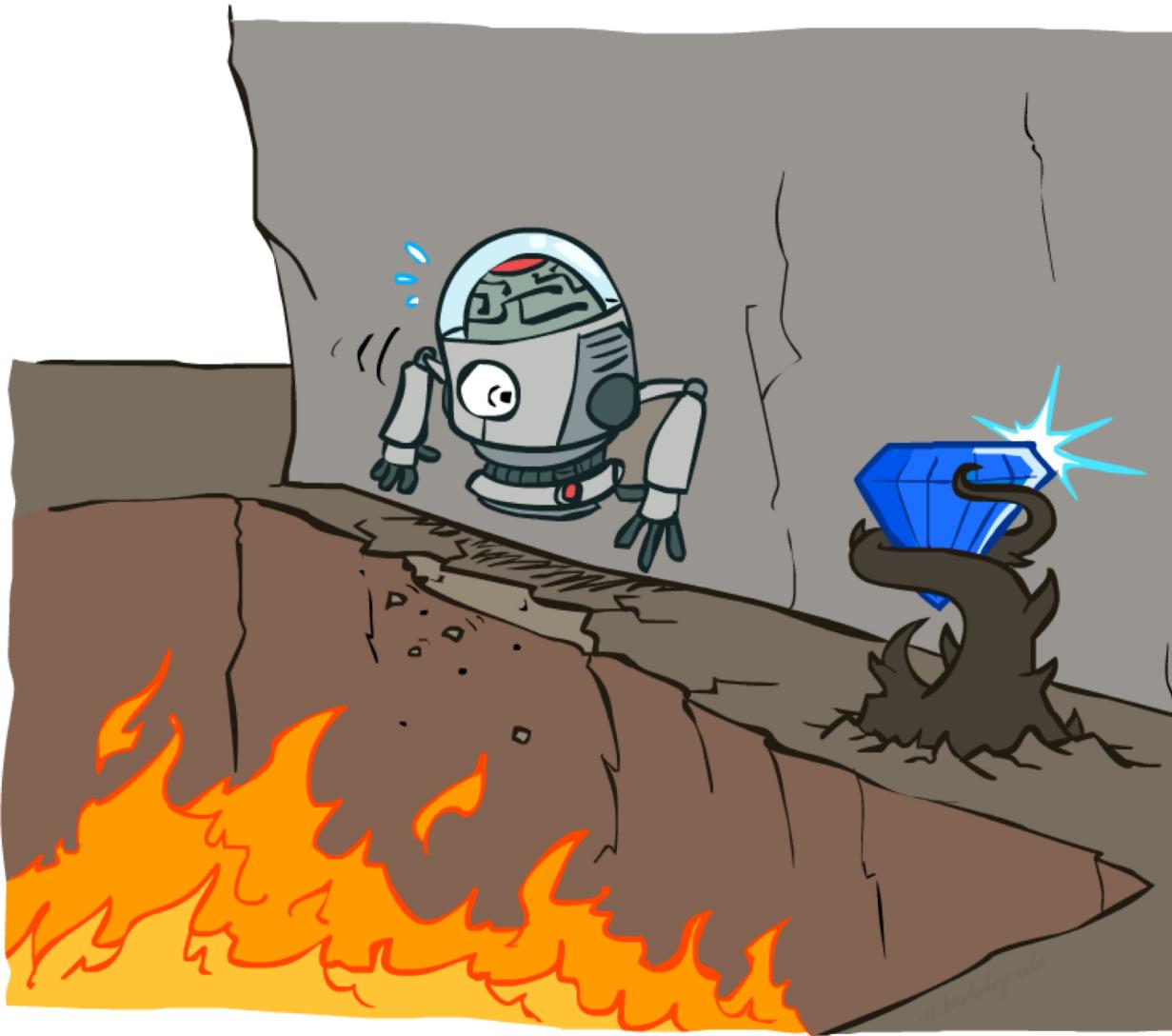


Instructors: Dan Klein and Pieter Abbeel

University of California, Berkeley

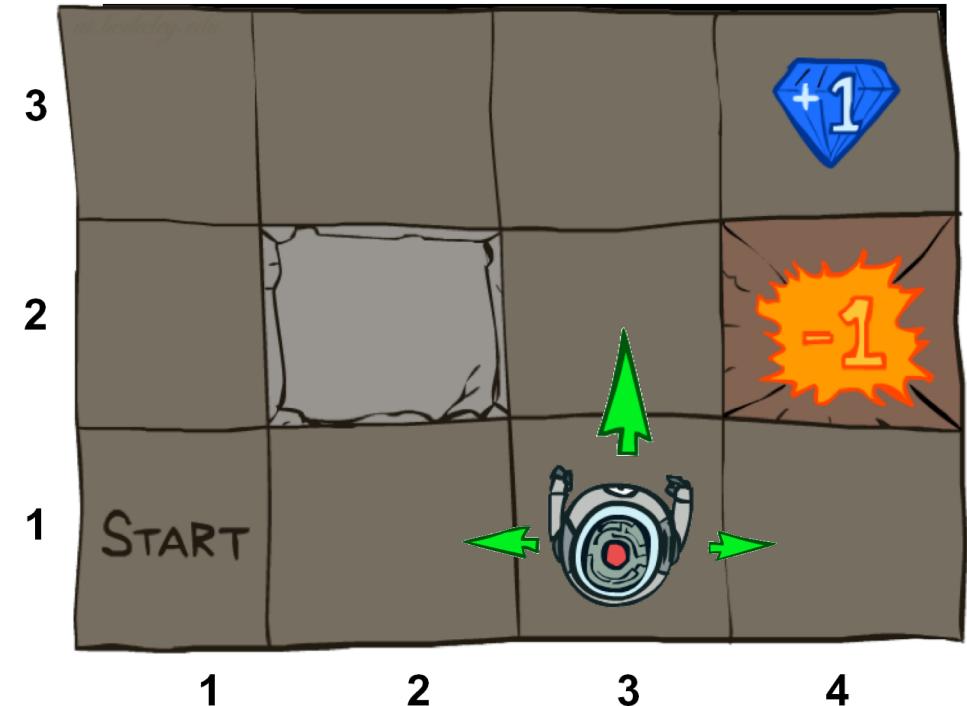
# Non-Deterministic Search

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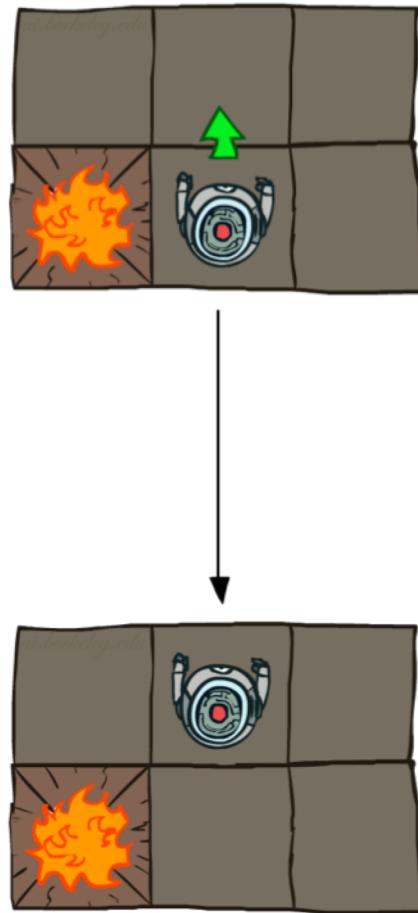
# Example: Grid World

- 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

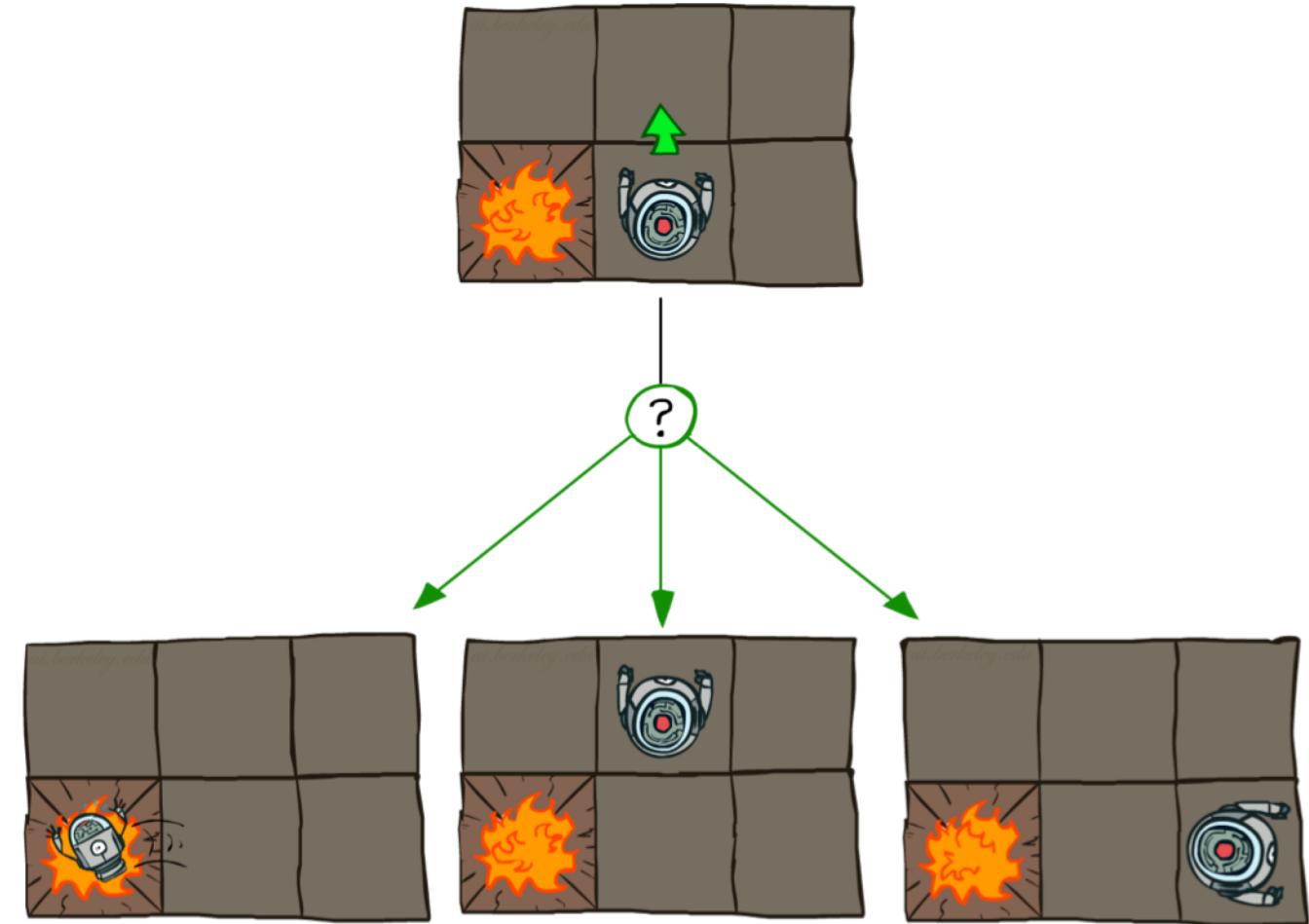


# Grid World Actions

Deterministic Grid World

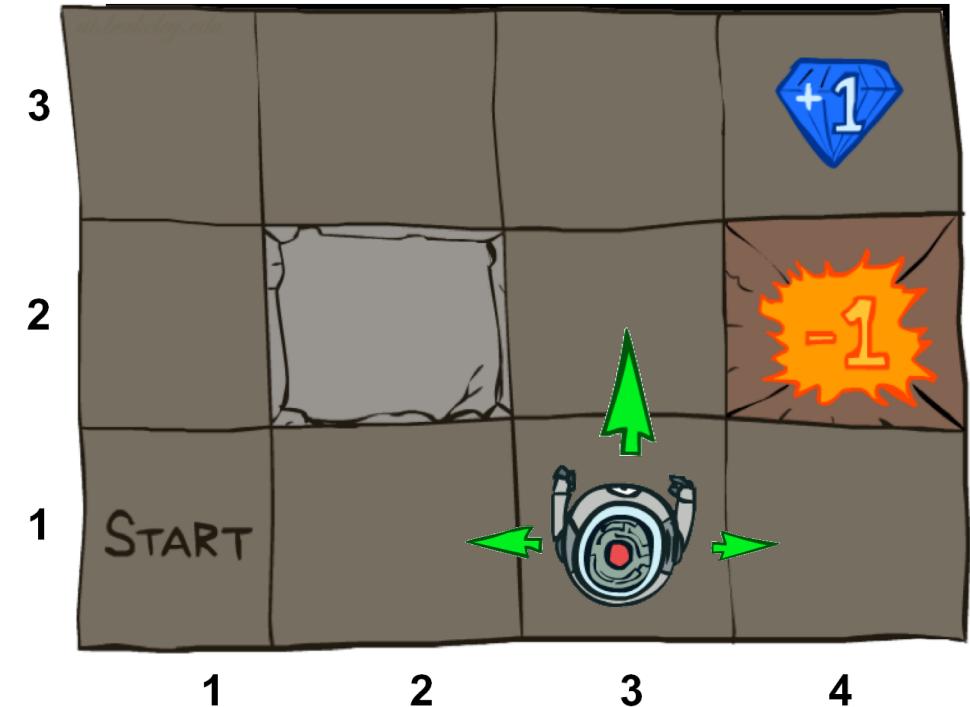


Stochastic Grid World



# 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



# Video of Demo Gridworld Manual Intro

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# 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

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

=

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

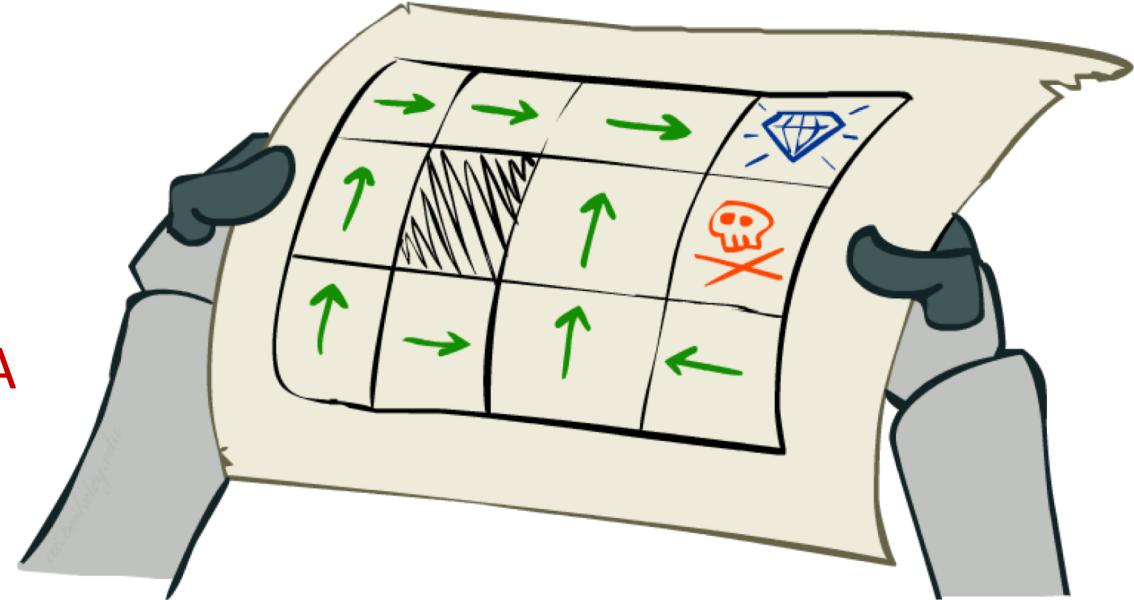


Andrey Markov  
(1856-1922)

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

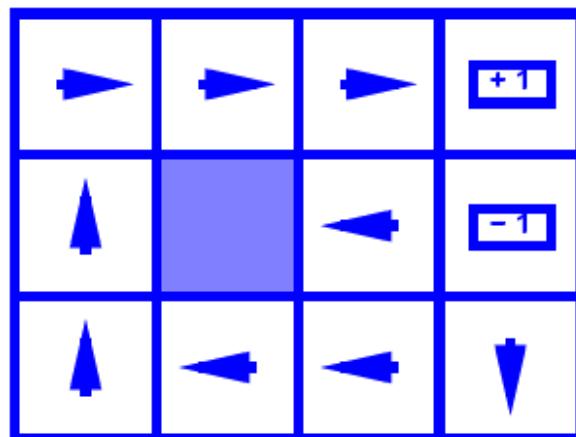
# Policies

- 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  $\pi$  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

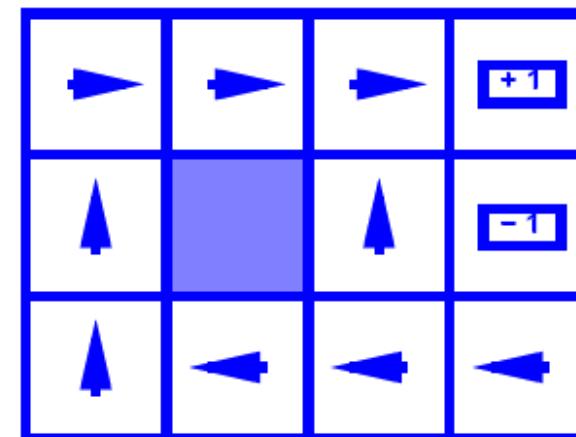


Optimal policy when  $R(s, a, s') = -0.03$   
for all non-terminals  $s$

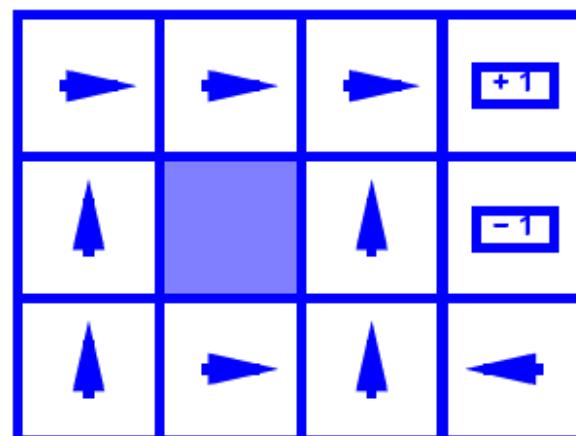
# Optimal Policies



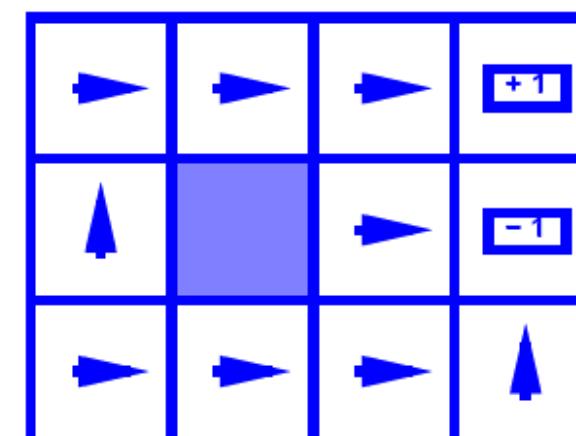
$$R(s) = -0.01$$



$$R(s) = -0.03$$



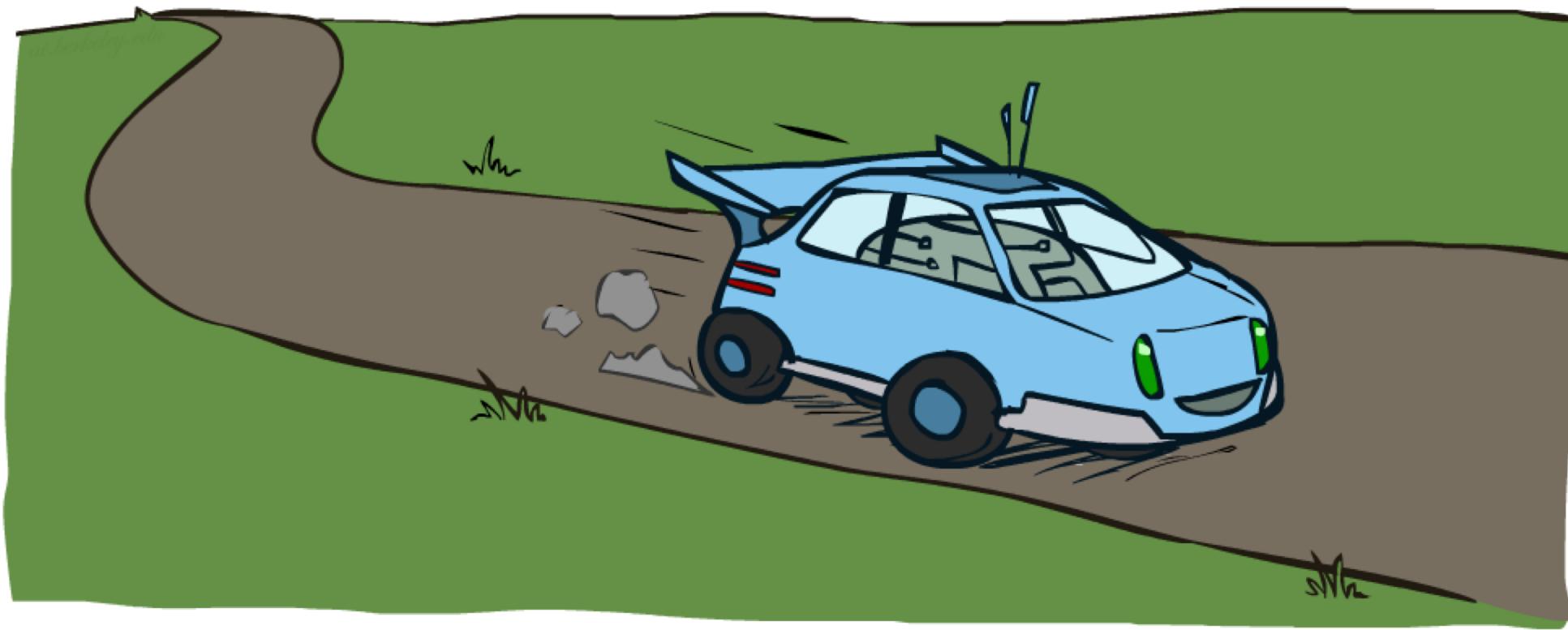
$$R(s) = -0.4$$



$$R(s) = -2.0$$

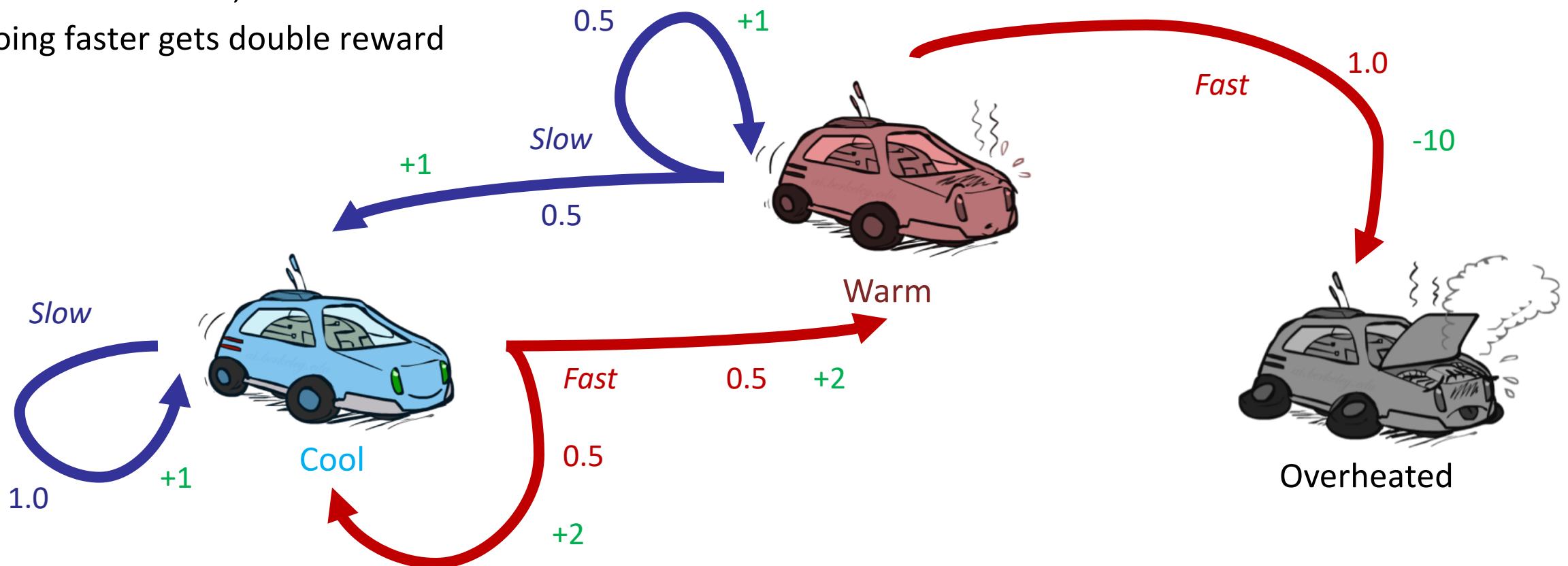
# Example: Racing

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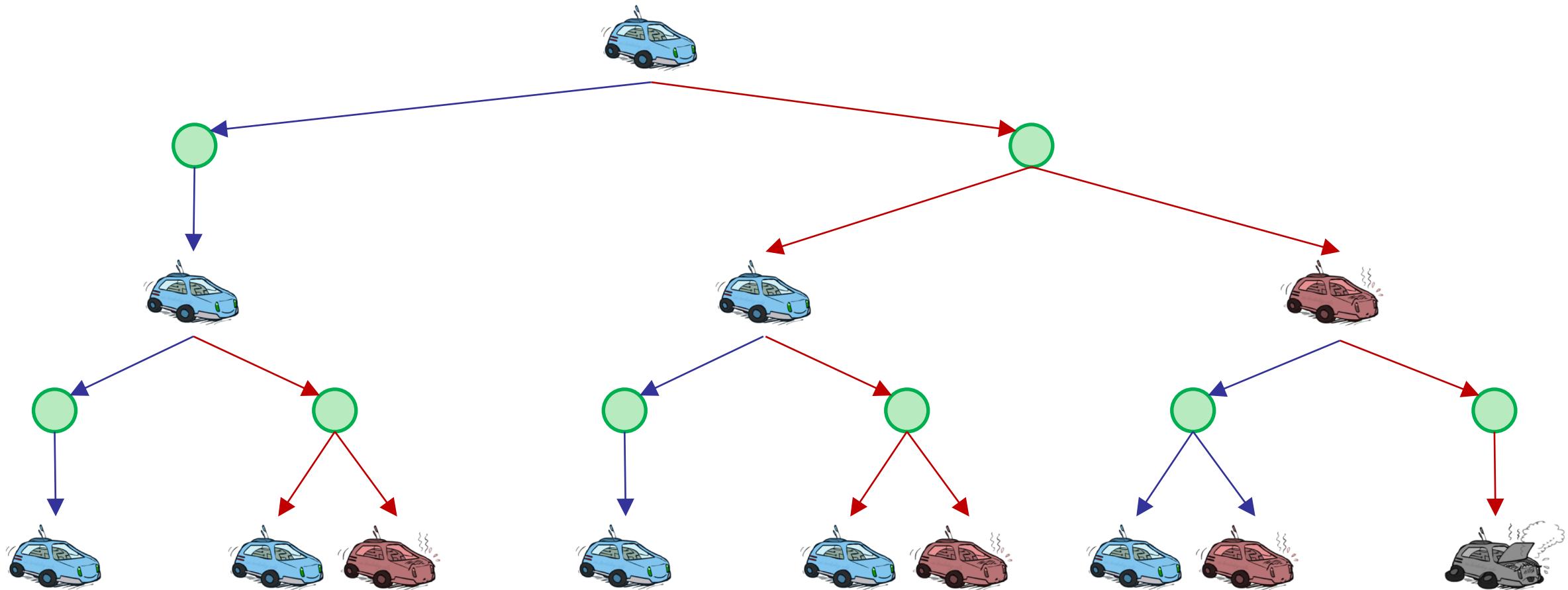


# Example: Racing

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

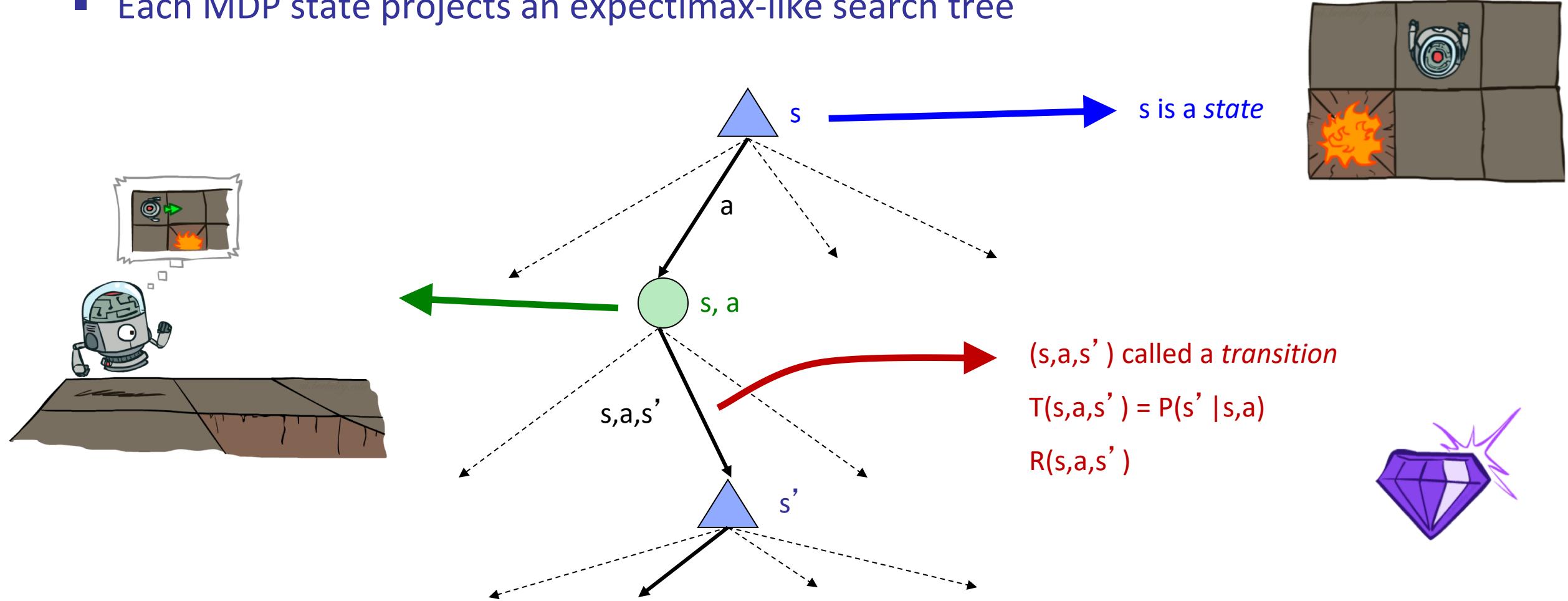


# Racing Search Tree



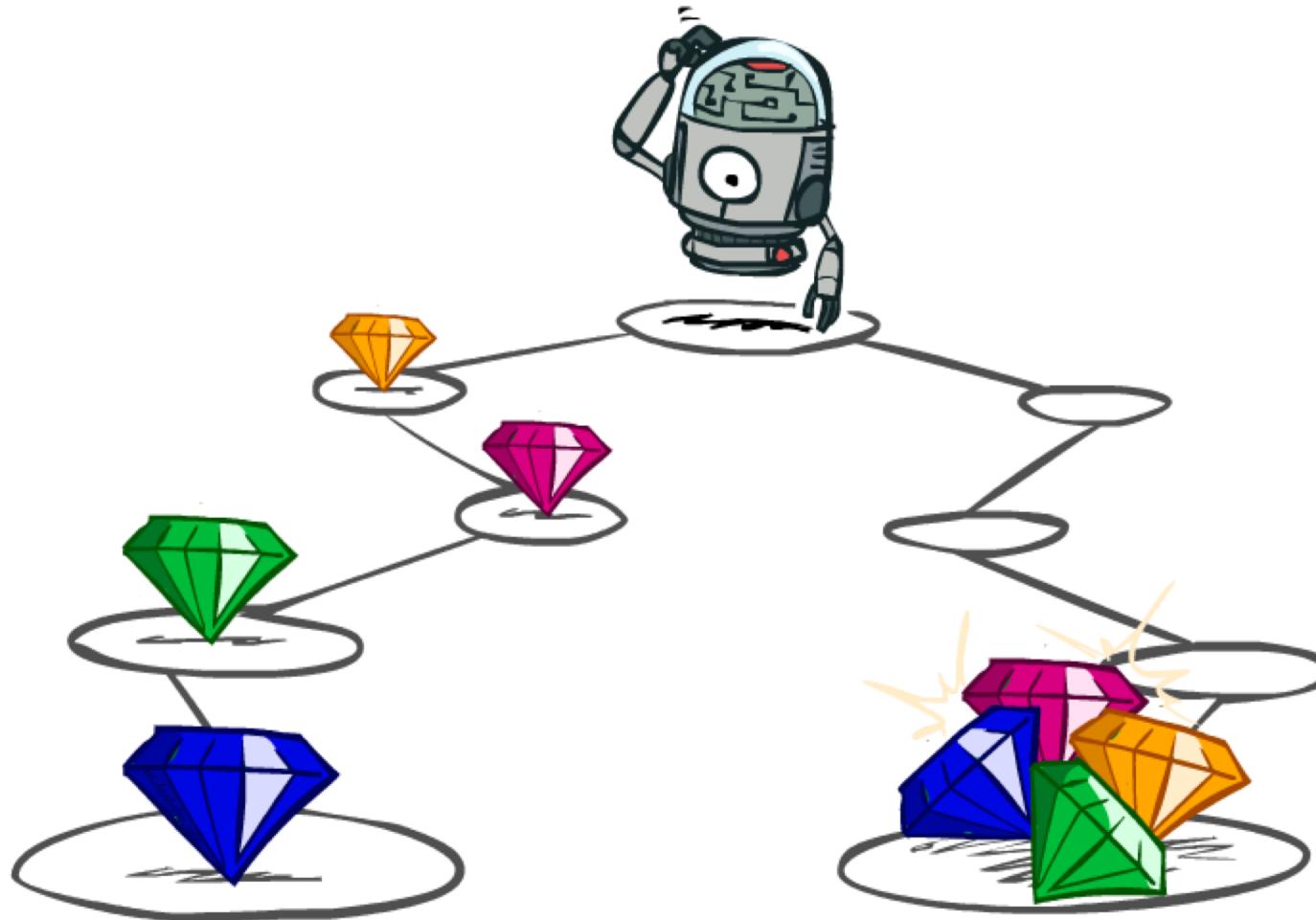
# MDP Search Trees

- Each MDP state projects an expectimax-like search tree



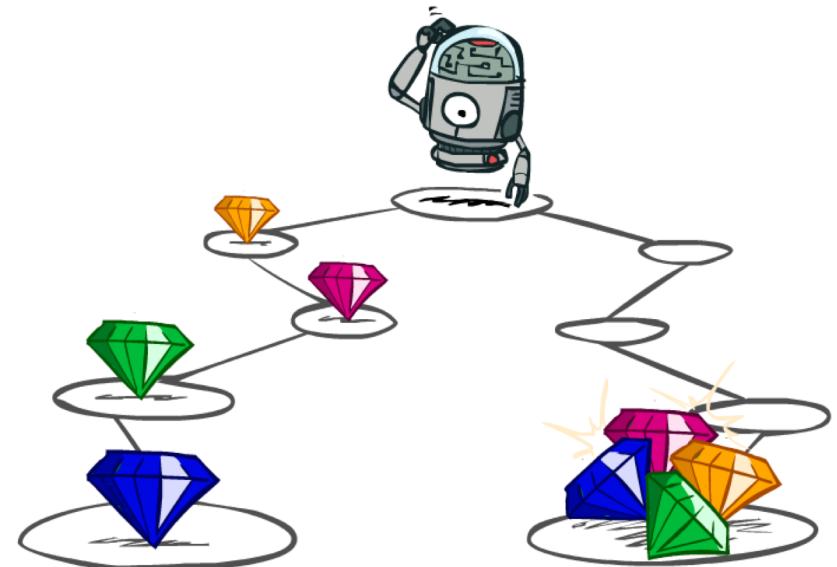
# Utilities of Sequences

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# 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



$\gamma$

Worth Next Step



$\gamma^2$

Worth In Two Steps

# Discounting

- How to discount?

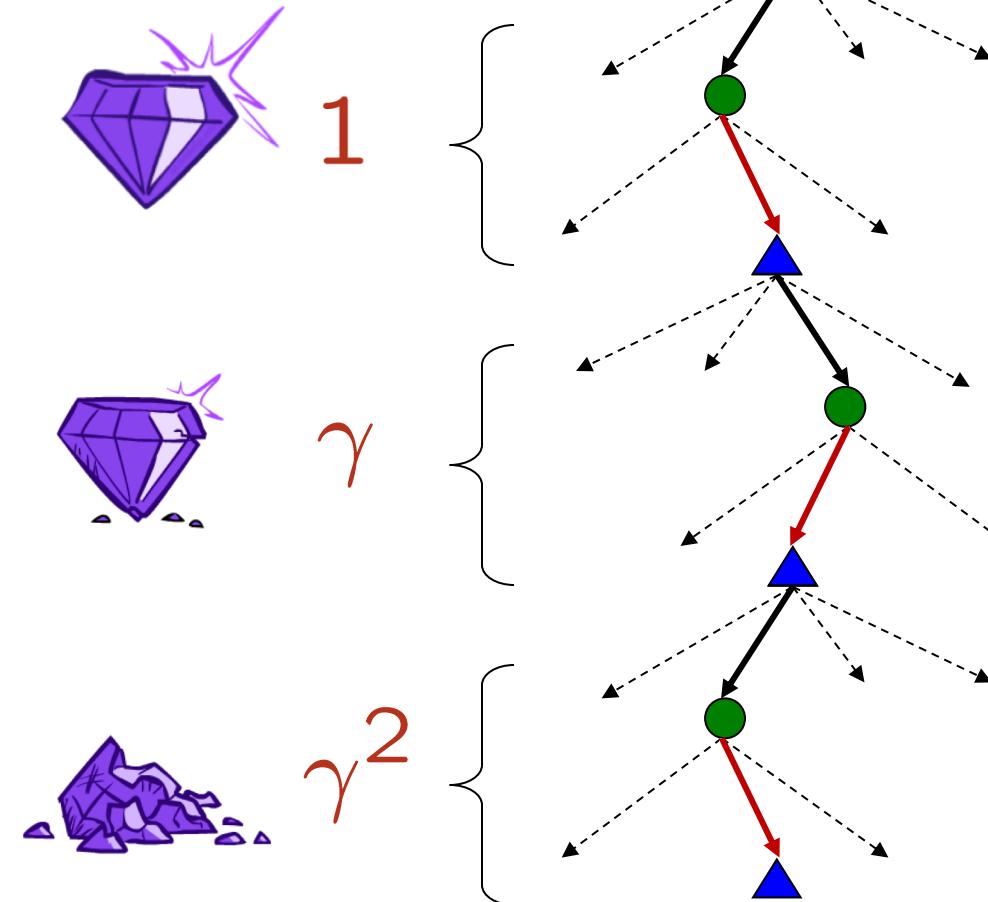
- Each time we descend a level, we multiply in the discount once

- Why discount?

- Sooner rewards probably do have higher utility than later rewards
- Also helps our algorithms converge

- Example: discount of 0.5

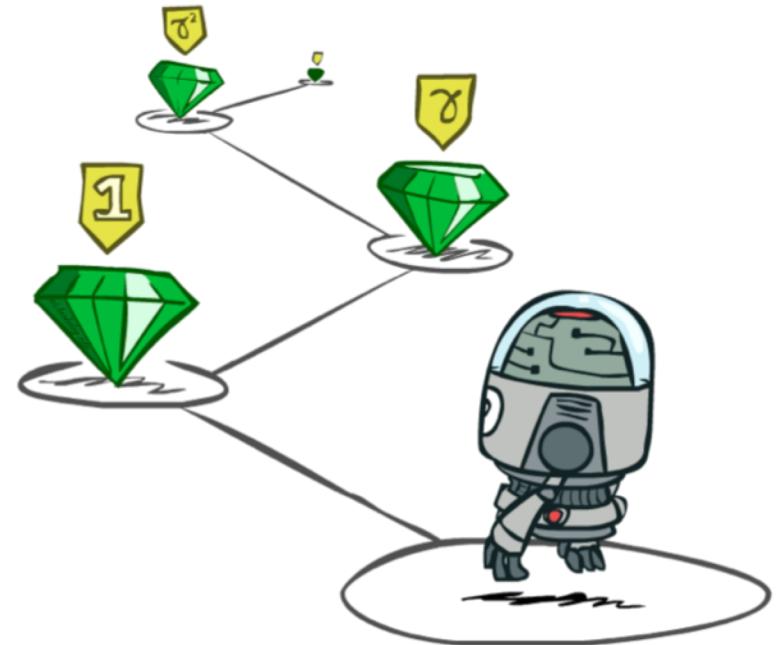
- $U([1,2,3]) = 1*1 + 0.5*2 + 0.25*3$
- $U([1,2,3]) < U([3,2,1])$



# Stationary Preferences

- Theorem: if we assume stationary preferences:

$$\begin{aligned}[a_1, a_2, \dots] &\succ [b_1, b_2, \dots] \\ \Updownarrow \\ [r, a_1, a_2, \dots] &\succ [r, b_1, b_2, \dots]\end{aligned}$$

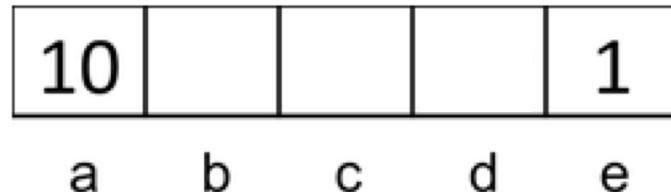


- Then: there are only two ways to define utilities

- Additive utility:  $U([r_0, r_1, r_2, \dots]) = r_0 + r_1 + r_2 + \dots$
- Discounted utility:  $U([r_0, r_1, r_2, \dots]) = r_0 + \gamma r_1 + \gamma^2 r_2 \dots$

# Quiz: Discounting

- Given:



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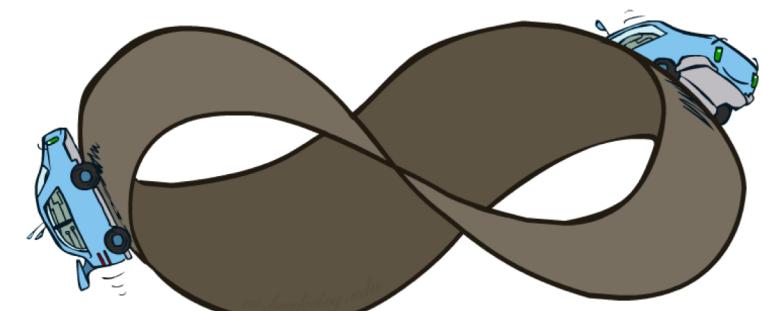
- Quiz 2: For  $\gamma = 0.1$ , what is the optimal policy?

10				1
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- Quiz 3: For which  $\gamma$  are West and East equally good when in state d?

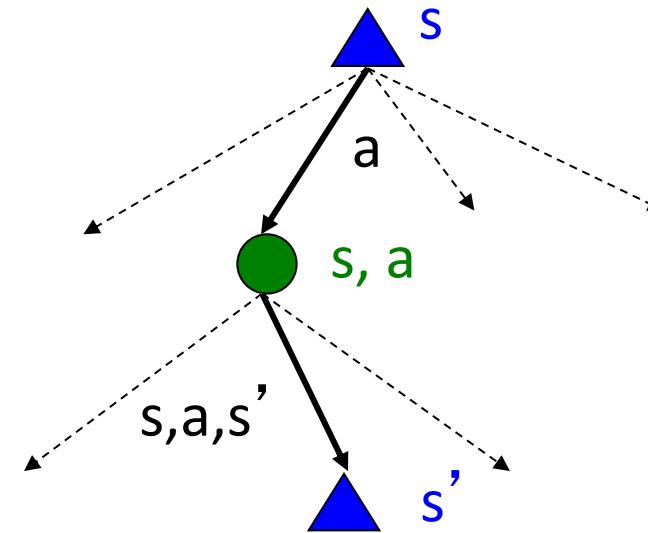
# Infinite Utilities?!

- 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 ( $\pi$  depends on time left)
  - Discounting: use  $0 < \gamma < 1$ 
$$U([r_0, \dots r_\infty]) = \sum_{t=0}^{\infty} \gamma^t r_t \leq R_{\max}/(1 - \gamma)$$
    - Smaller  $\gamma$  means smaller “horizon” – shorter term focus
    - Absorbing state: guarantee that for every policy, a terminal state will eventually be reached (like “overheated” for racing)



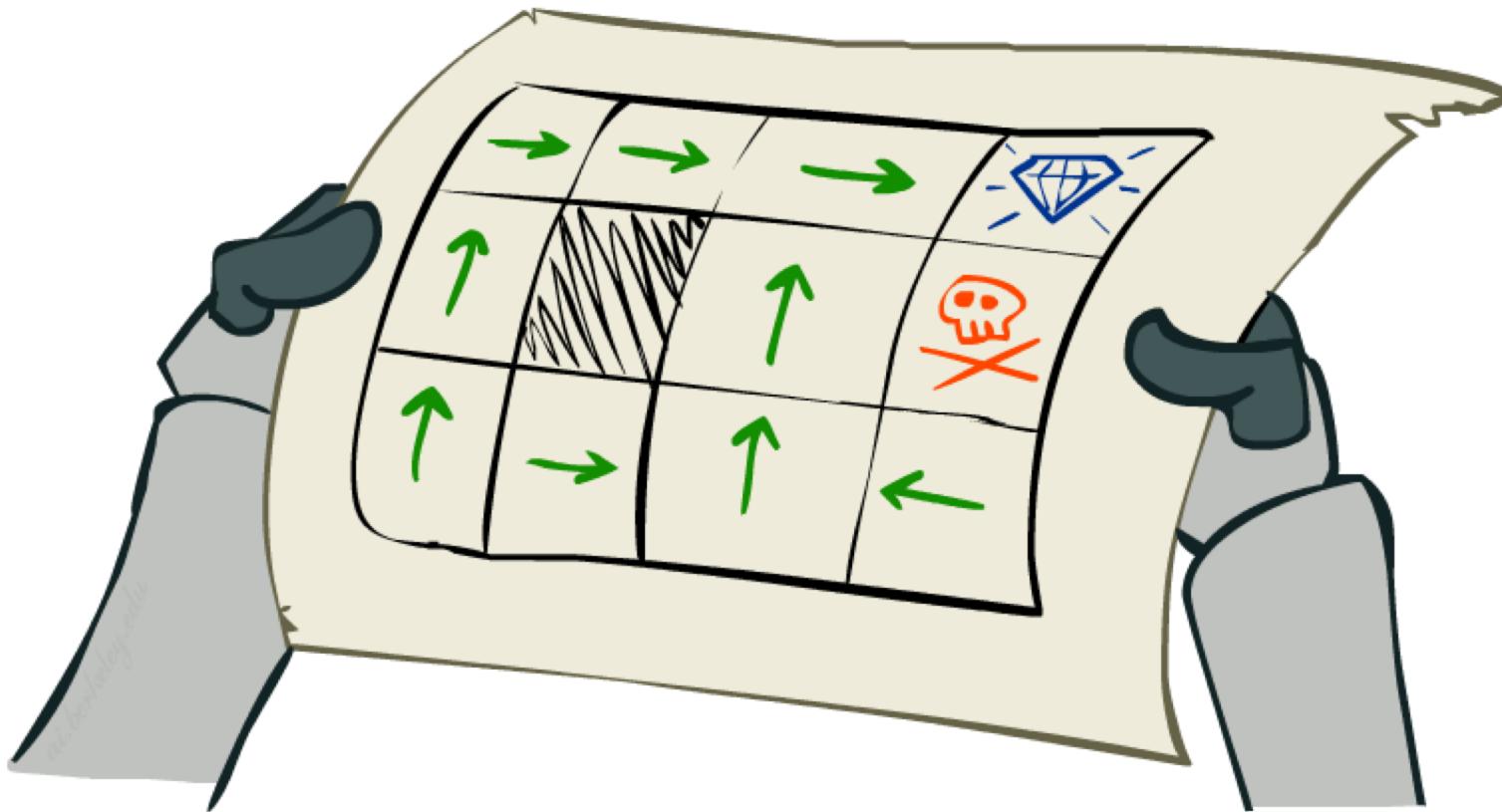
# Recap: Defining MDPs

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



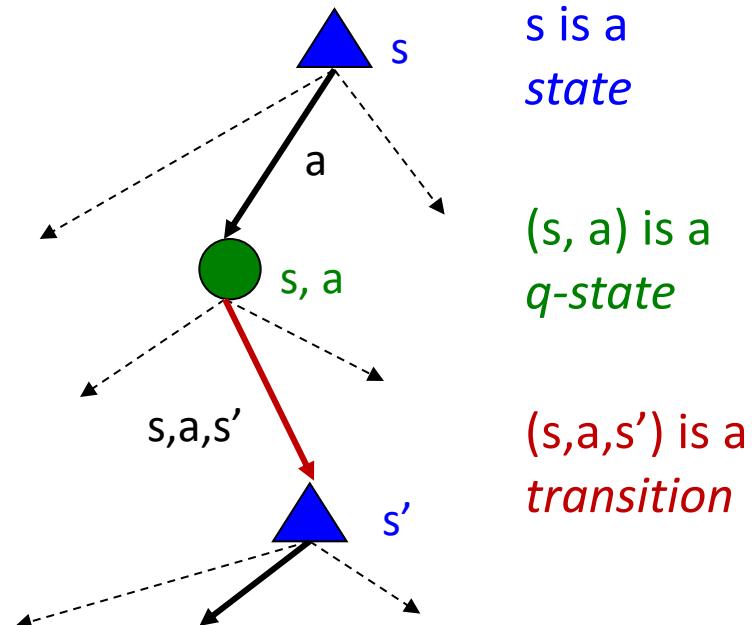
# Solving MDPs

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# Optimal Quantities

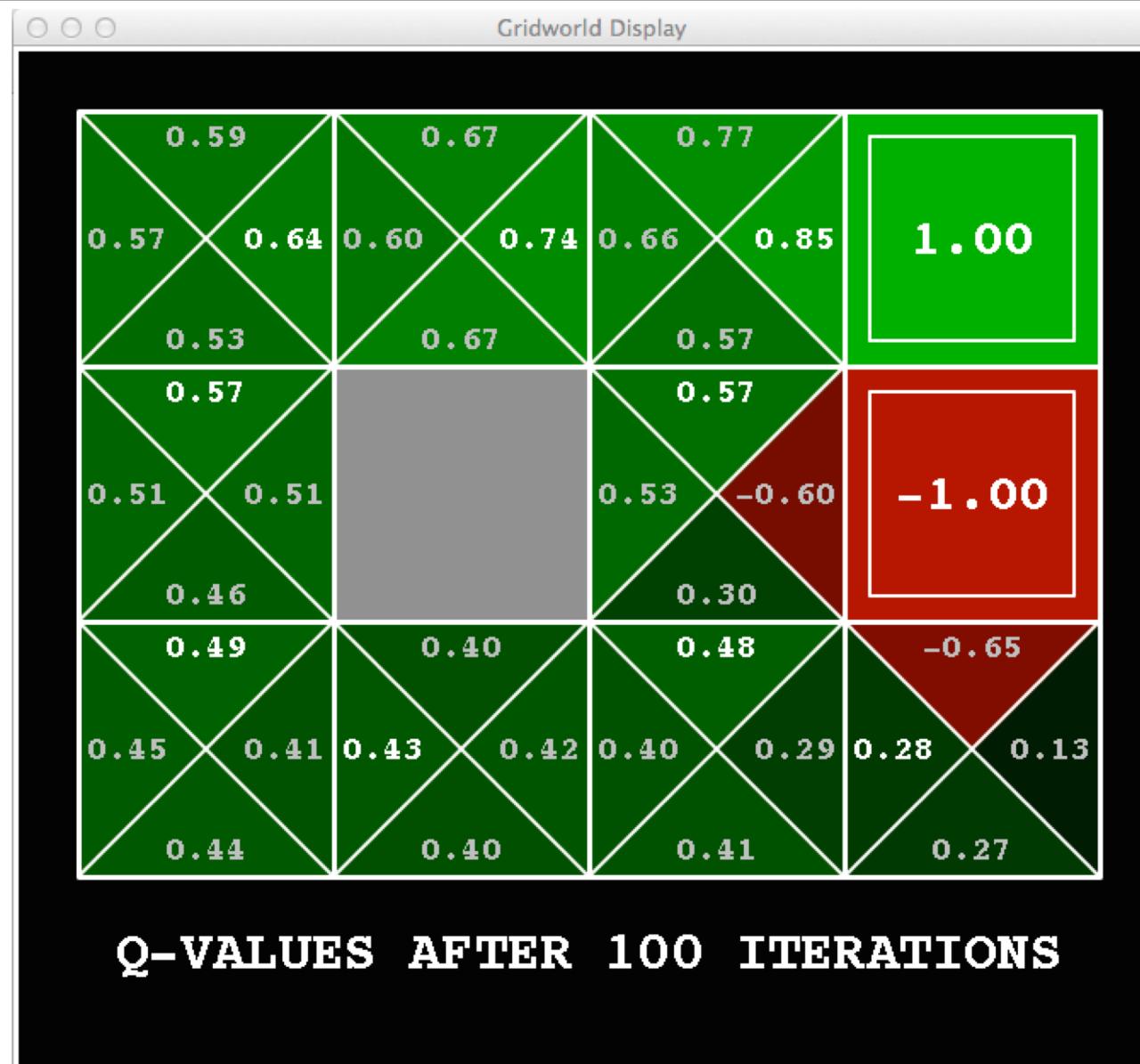
- The value (utility) of a state  $s$ :  
 $V^*(s)$  = expected utility starting in  $s$  and acting optimally
- The value (utility) of a q-state  $(s,a)$ :  
 $Q^*(s,a)$  = expected utility starting out having taken action  $a$  from state  $s$  and (thereafter) acting optimally
- The optimal policy:  
 $\pi^*(s)$  = optimal action from state  $s$



# Snapshot of Demo – Gridworld V Values



# Snapshot of Demo – Gridworld Q Values



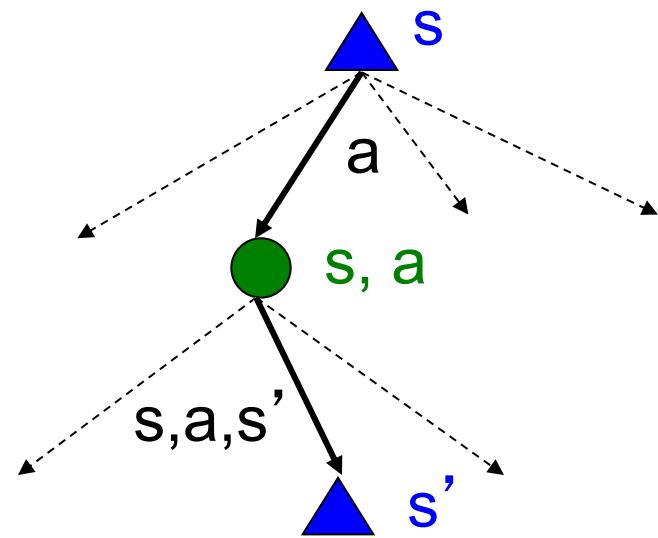
# Values of States

- 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:

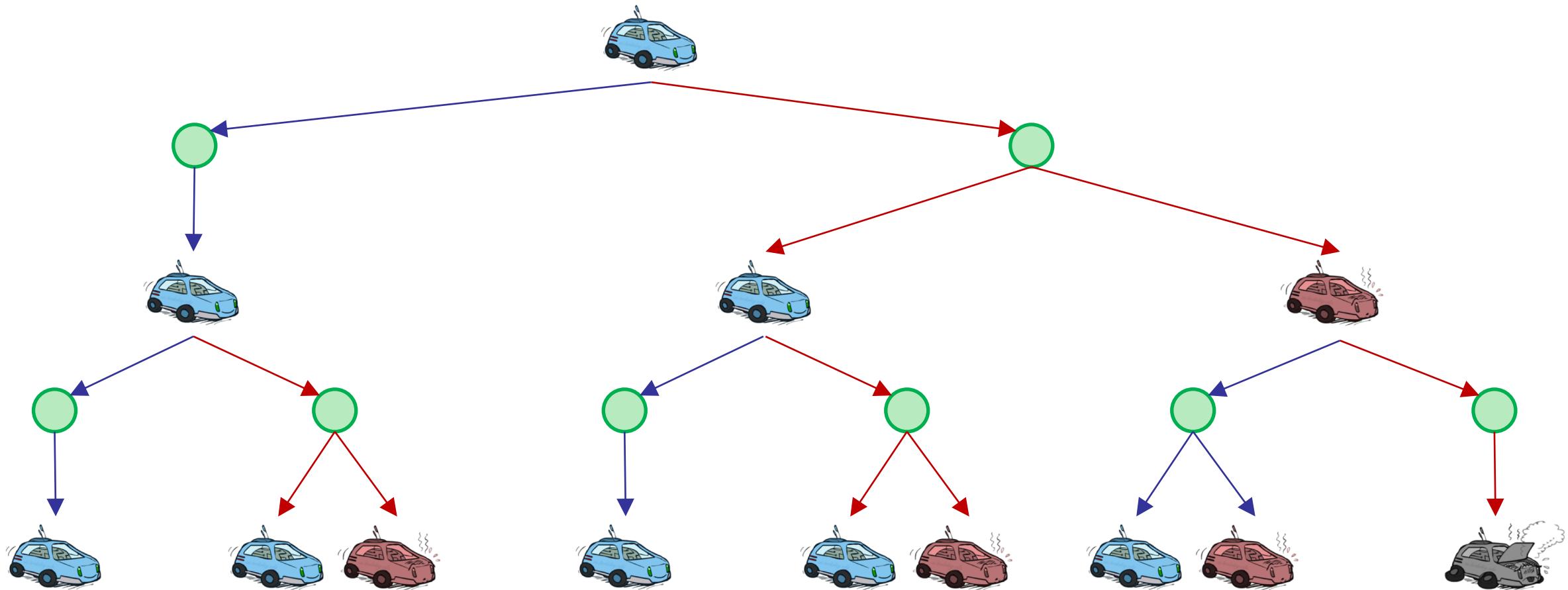
$$V^*(s) = \max_a Q^*(s, a)$$

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

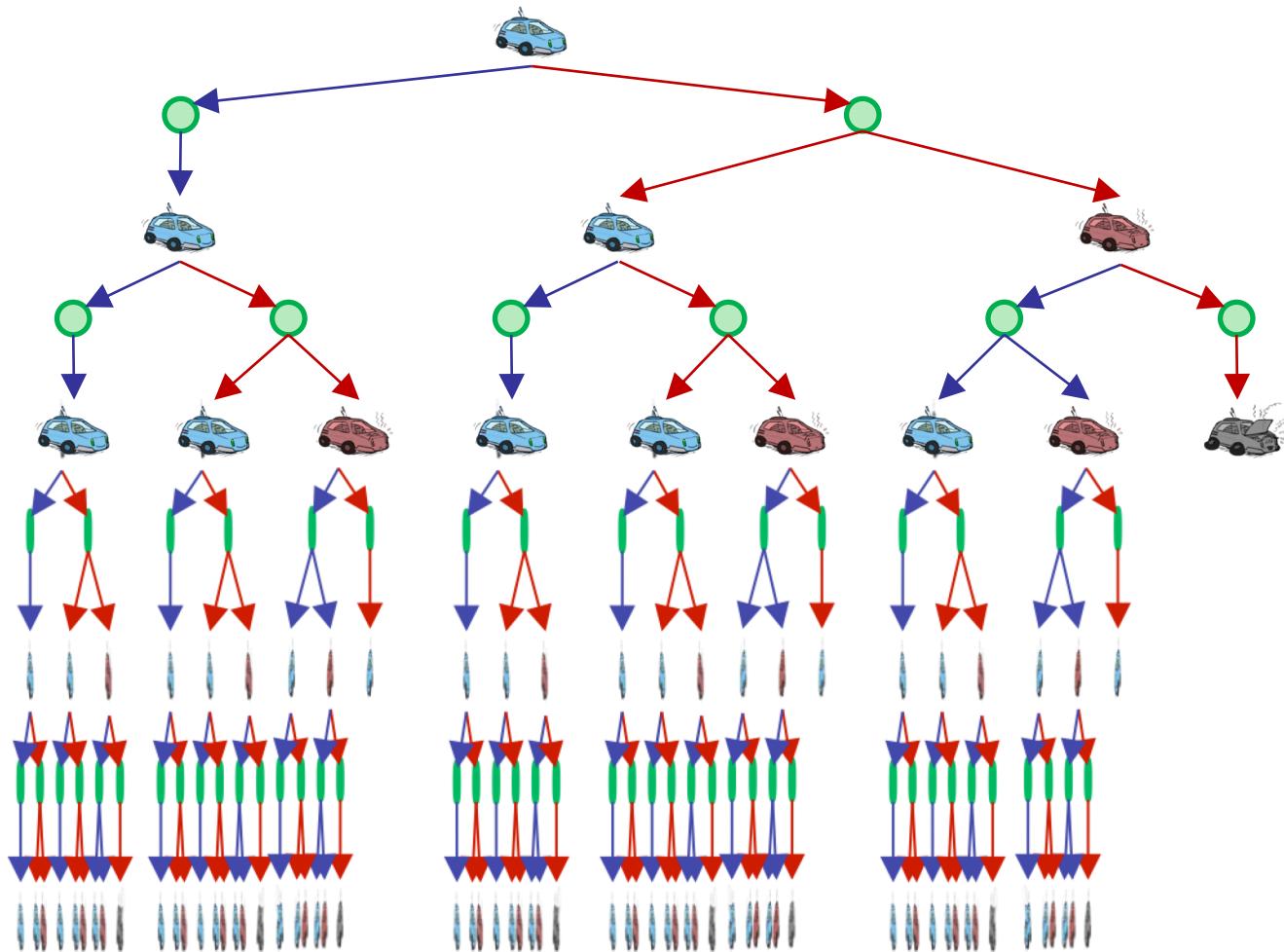
$$V^*(s) = \max_a \sum_{s'} T(s, a, s') [R(s, a, s') + \gamma V^*(s')]$$



# Racing Search Tree

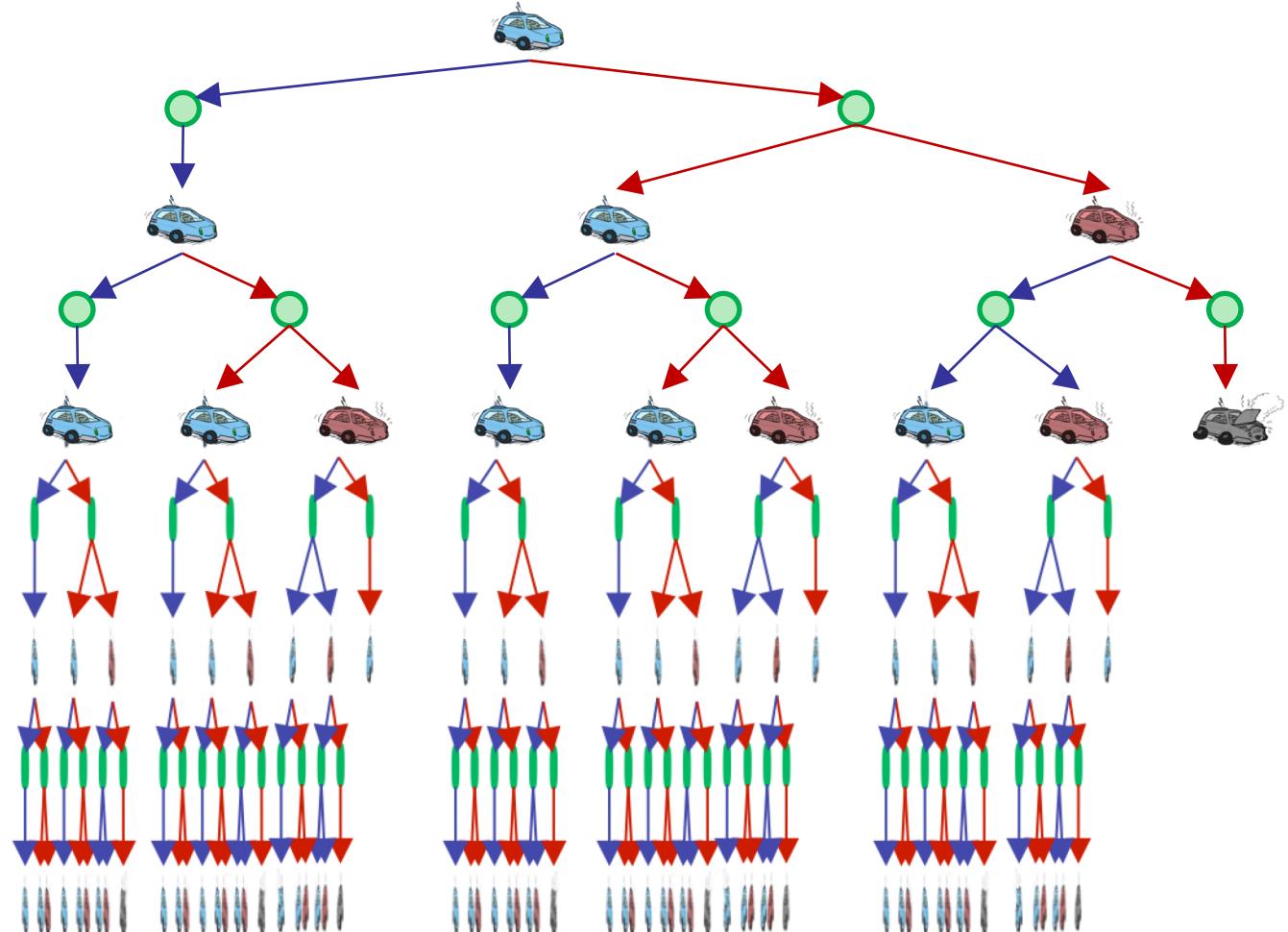


# Racing Search Tree



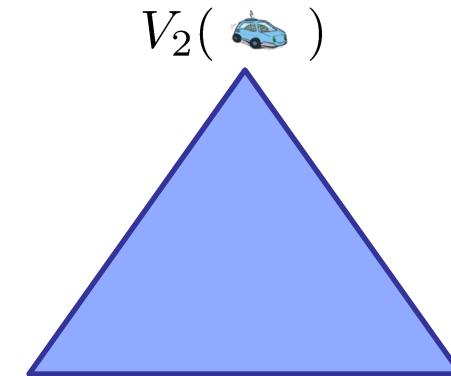
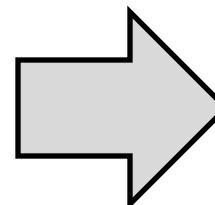
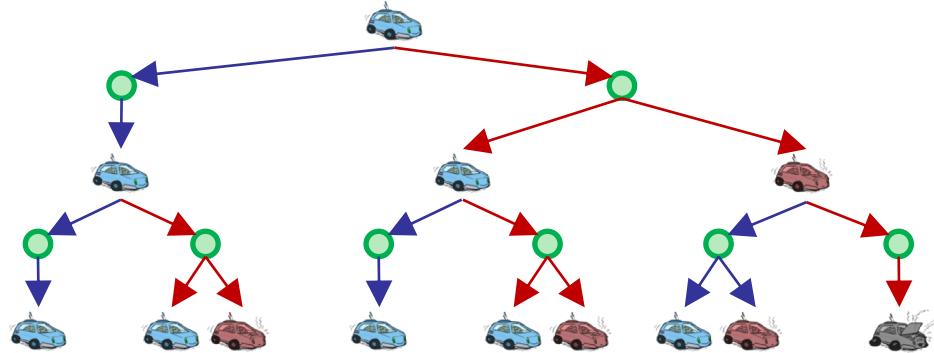
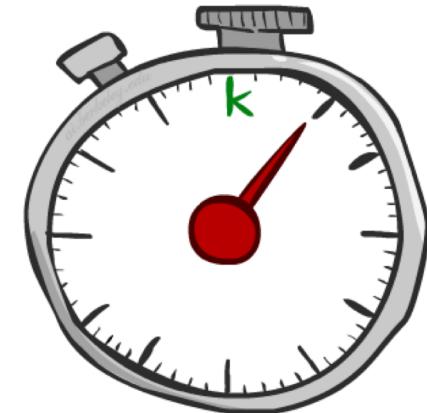
# Racing Search Tree

- 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  $\gamma < 1$

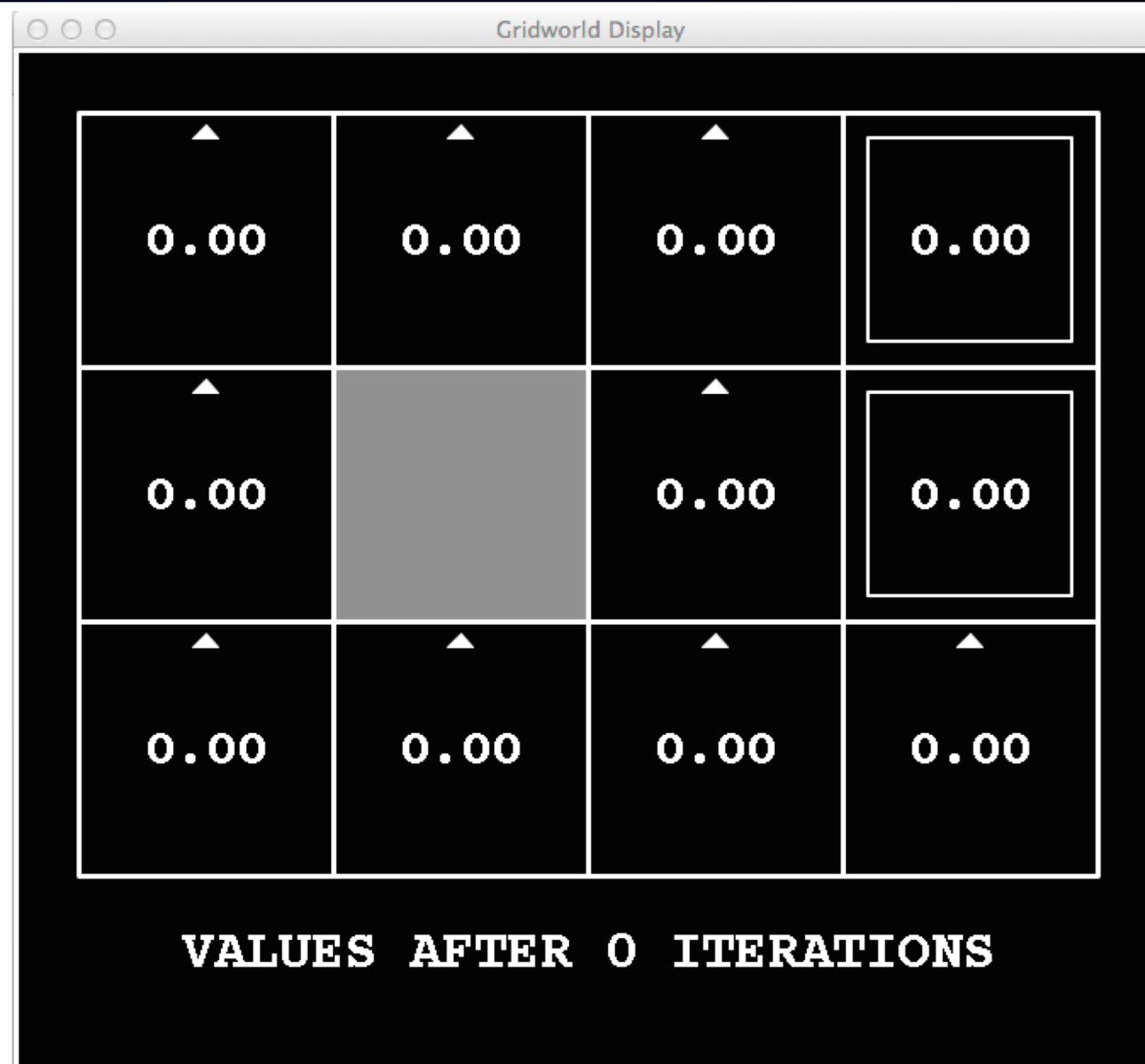


# Time-Limited Values

- 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  $s$



$k=0$



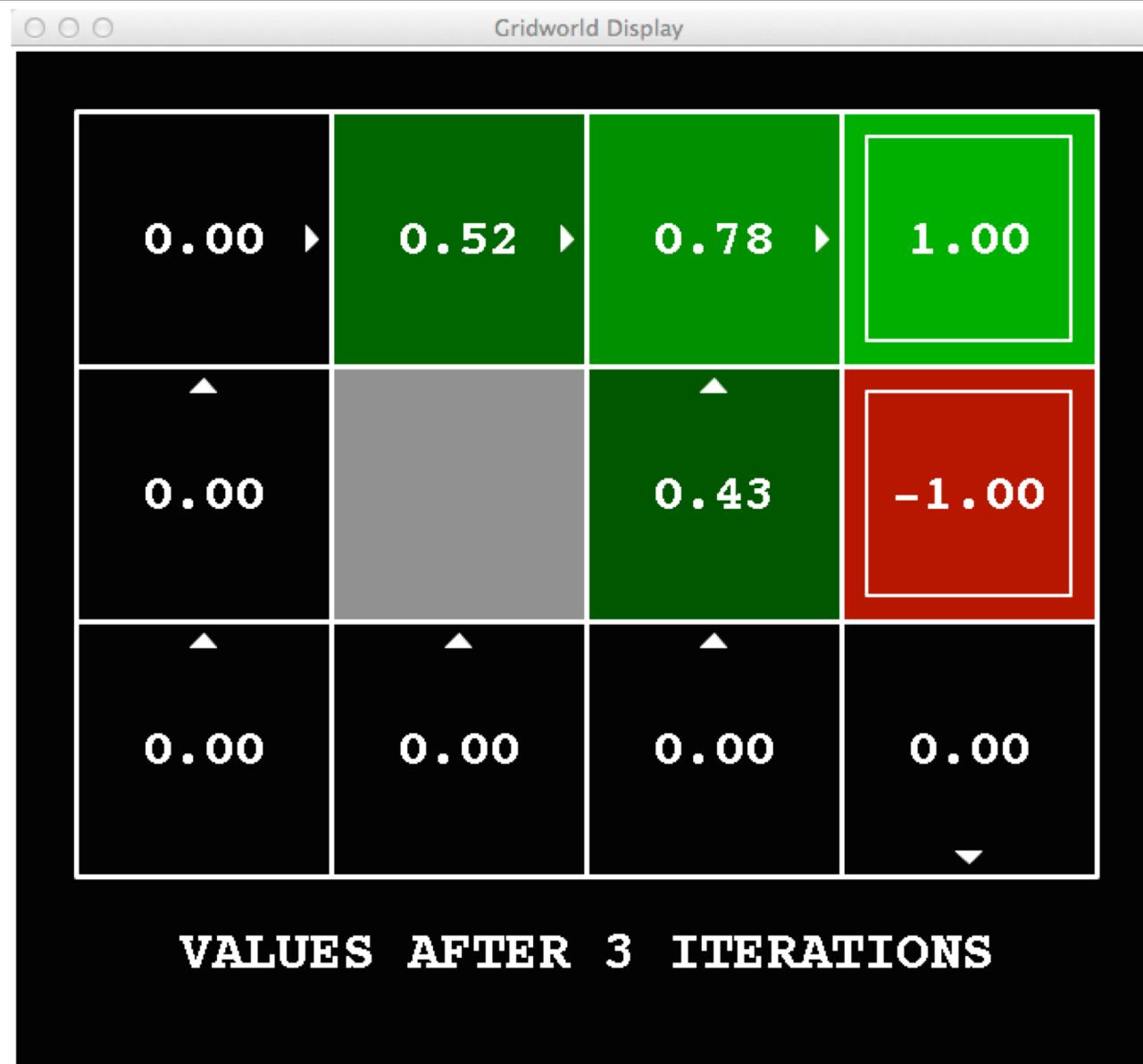
$k=1$



$k=2$



**k=3**



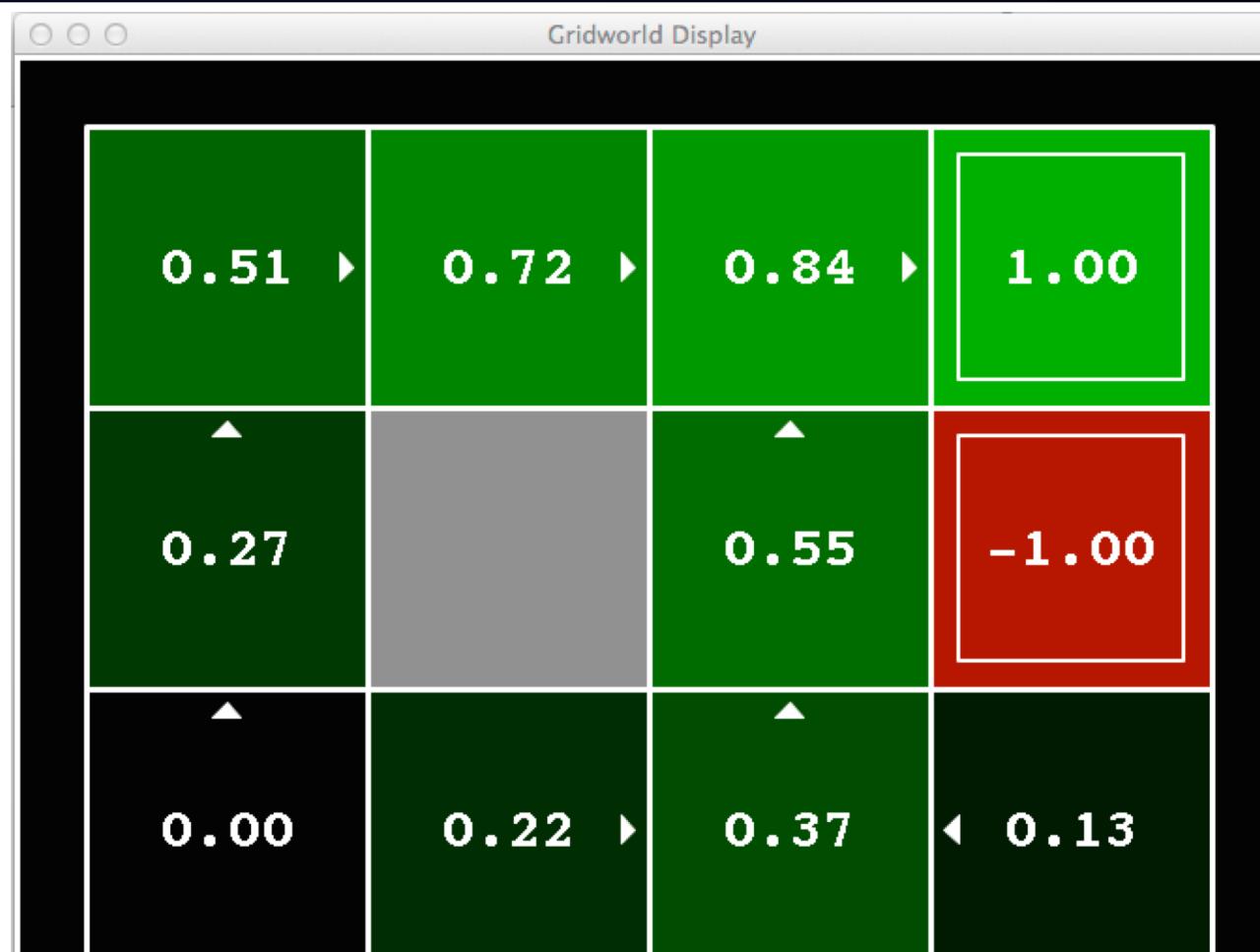
**k=4**



**VALUES AFTER 4 ITERATIONS**

Noise = 0.2  
Discount = 0.9  
Living reward = 0

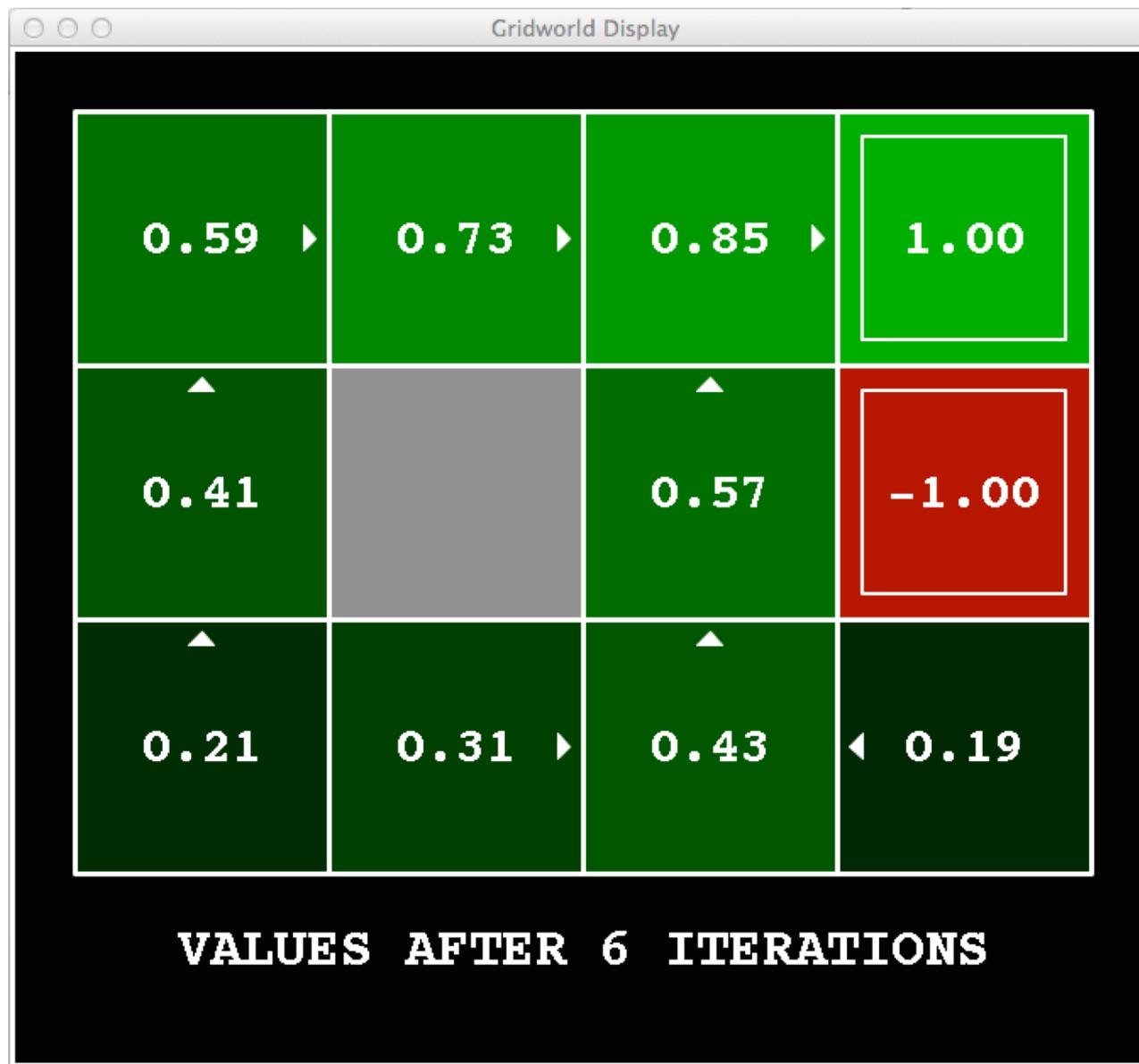
**k=5**



**VALUES AFTER 5 ITERATIONS**

Noise = 0.2  
Discount = 0.9  
Living reward = 0

k=6



**k=7**



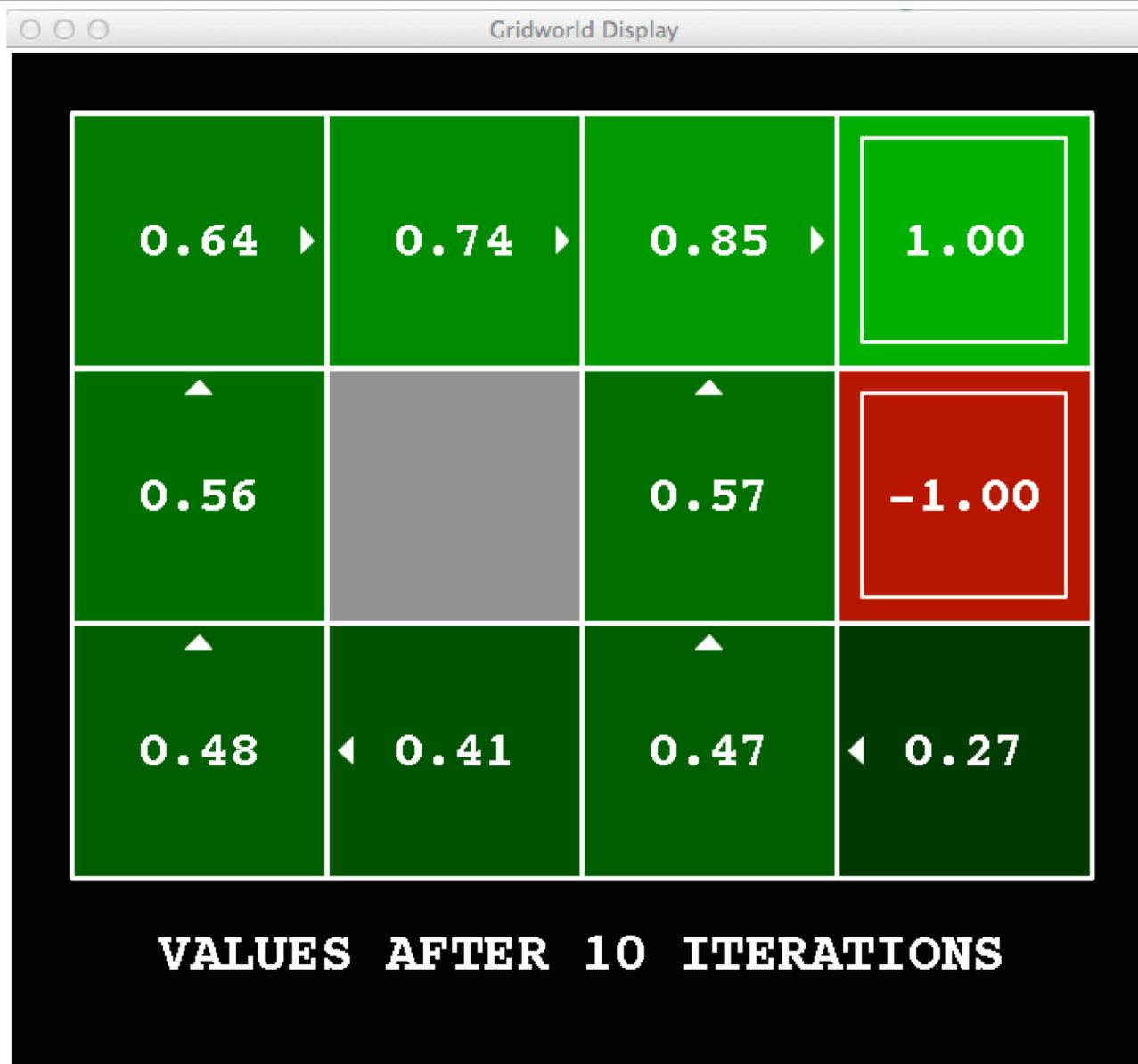
**k=8**



k=9



# k=10

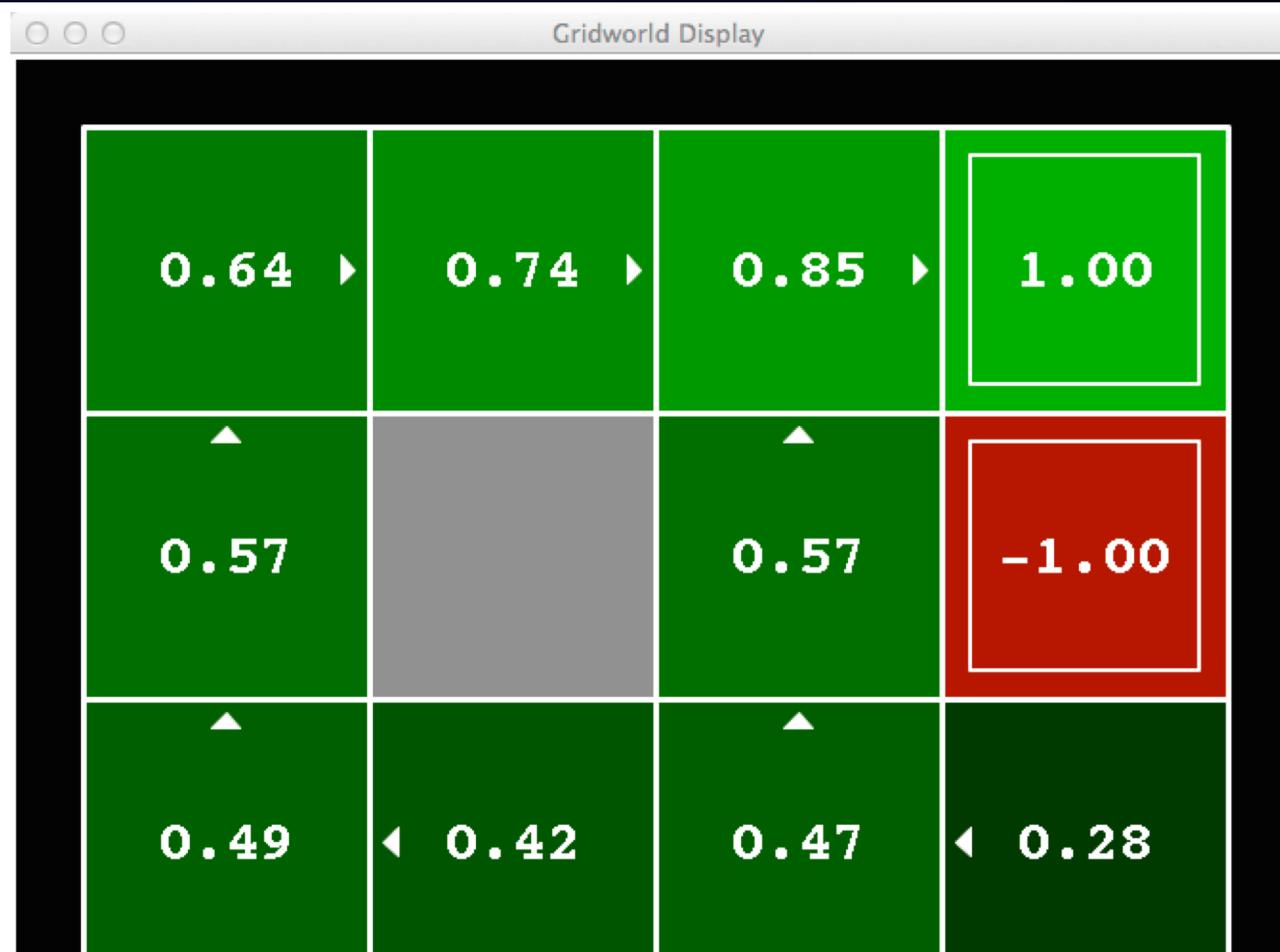


Noise = 0.2  
Discount = 0.9  
Living reward = 0

**k=11**



**k=12**



**VALUES AFTER 12 ITERATIONS**

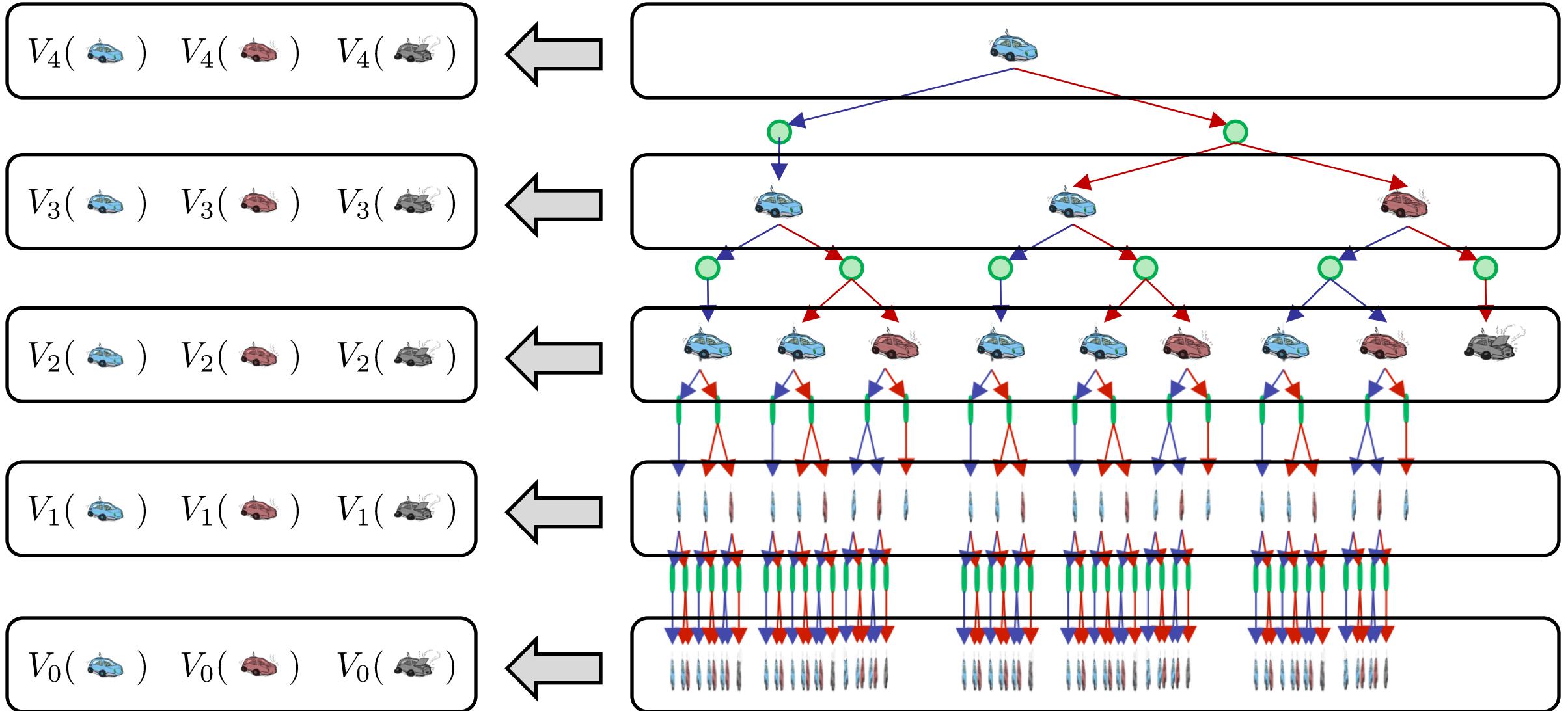
Noise = 0.2  
Discount = 0.9  
Living reward = 0

# k=100



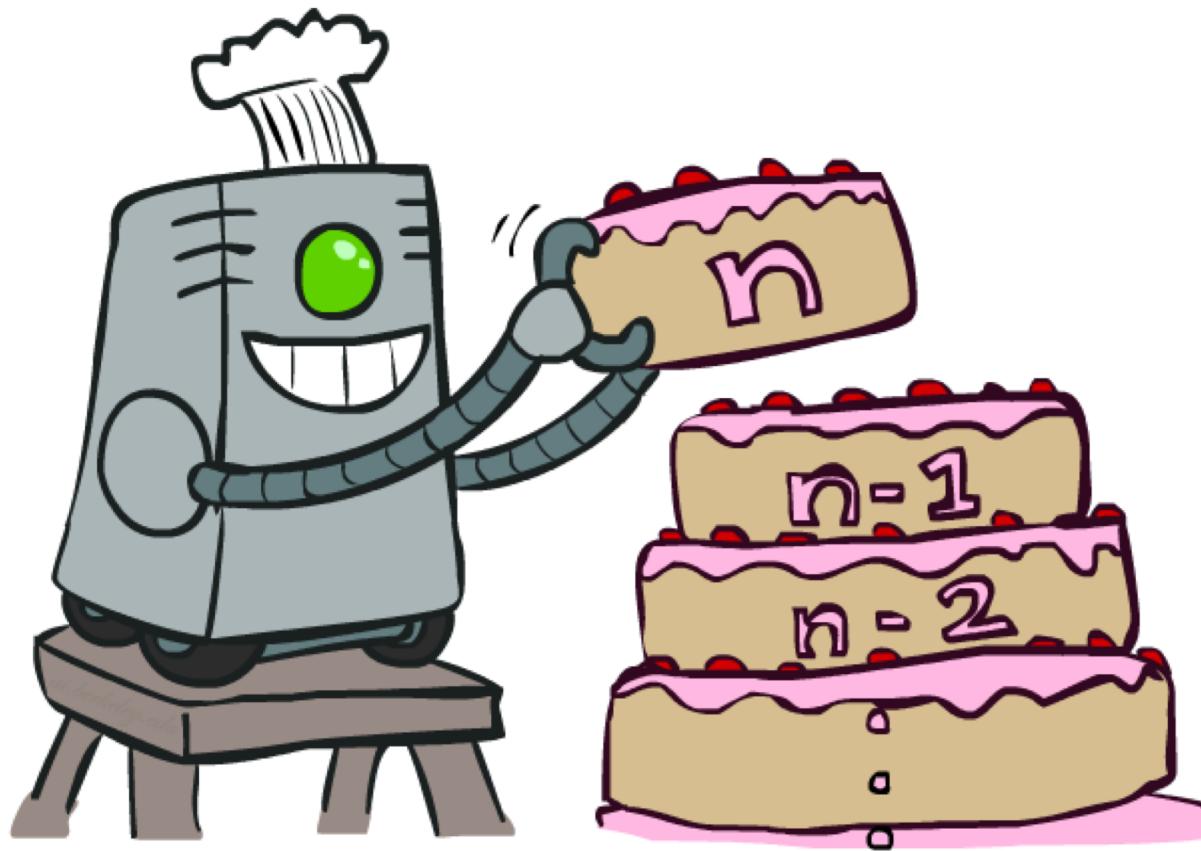
Noise = 0.2  
Discount = 0.9  
Living reward = 0

# Computing Time-Limited Values



# Value Iteration

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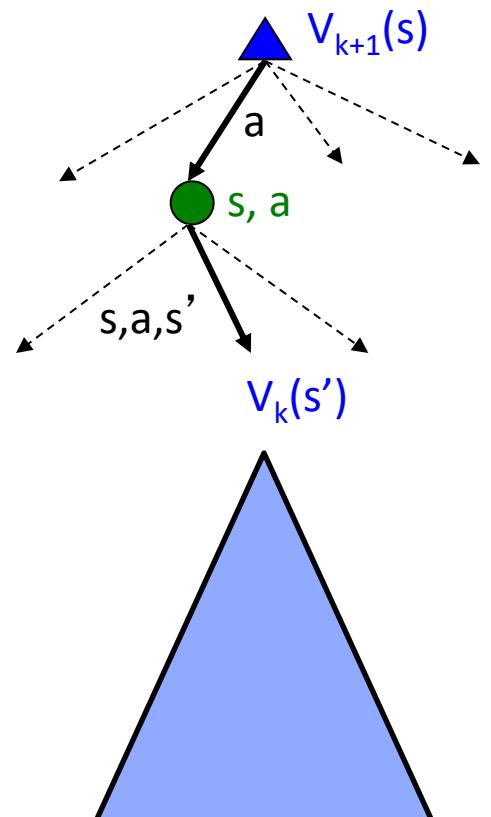


# Value Iteration

- 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:

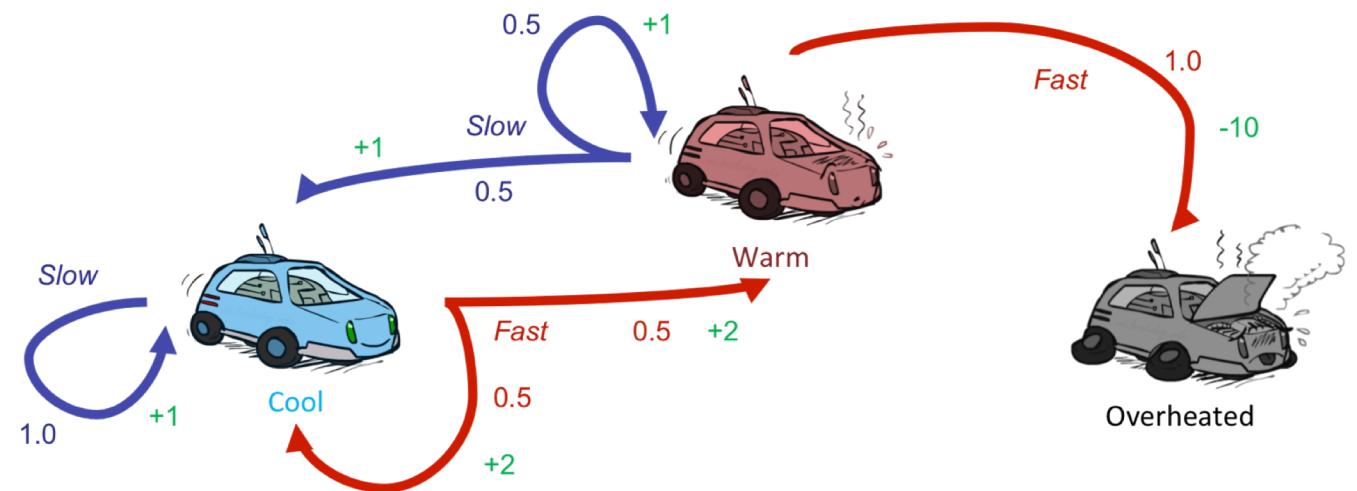
$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s, a, s') [R(s, a, s') + \gamma V_k(s')]$$

- 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

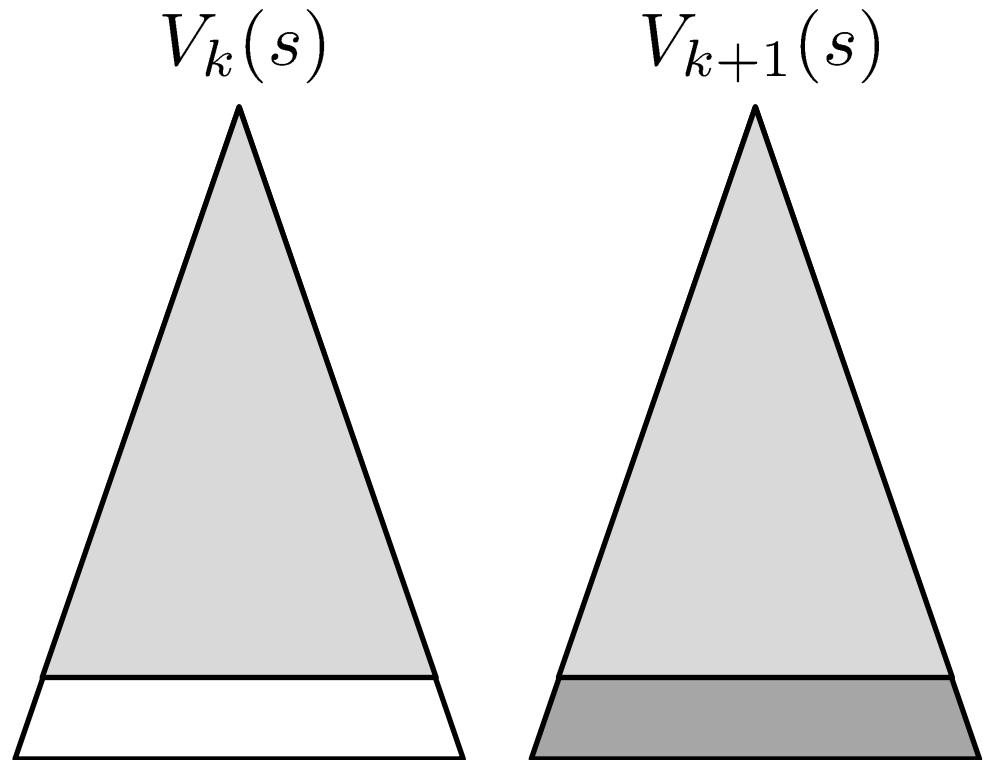


Assume no discount!

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

# 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  $R_{\text{MAX}}$
  - It is at worst  $R_{\text{MIN}}$
  - But everything is discounted by  $\gamma^k$  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



# Next Time: Policy-Based Methods

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