

# Artificial Intelligence: Basics & Applications

## Markov Decision Processes

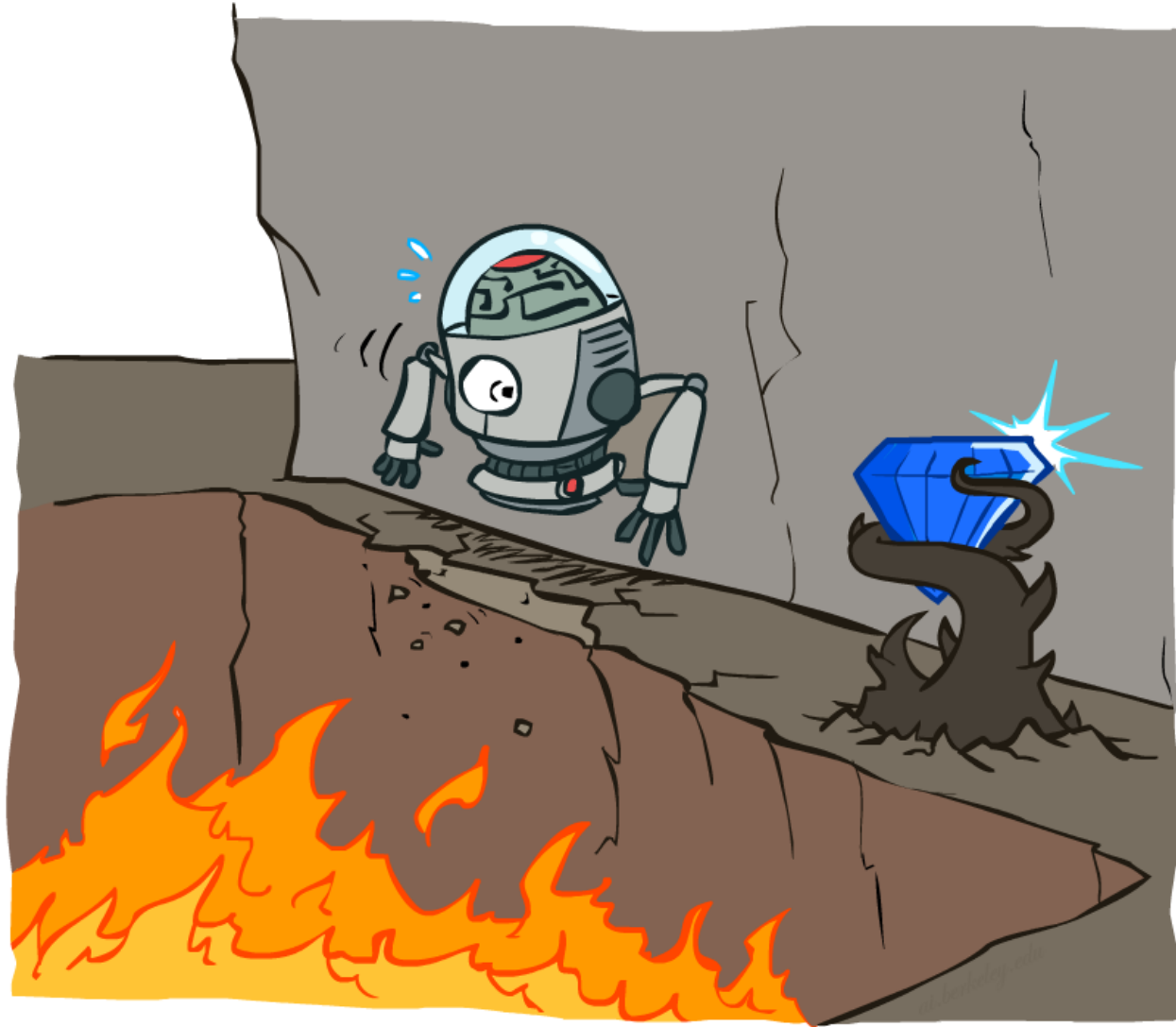


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Amirkabir University of Technology

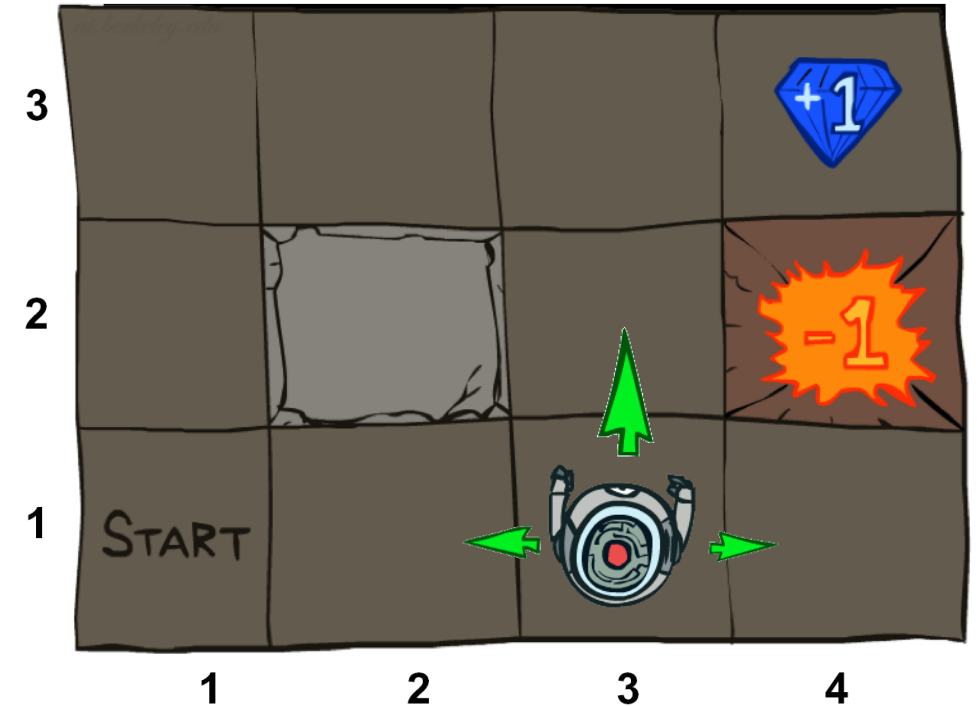
[slides adapted with permission from Dan Klein, Pieter Abbeel, Anca Dragan @ai.berkeley.edu]

# Non-Deterministic Search



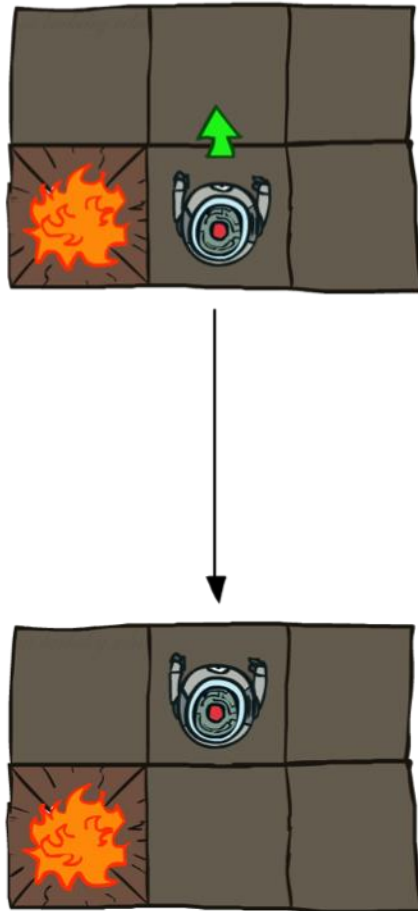
# Example: Grid World

- 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

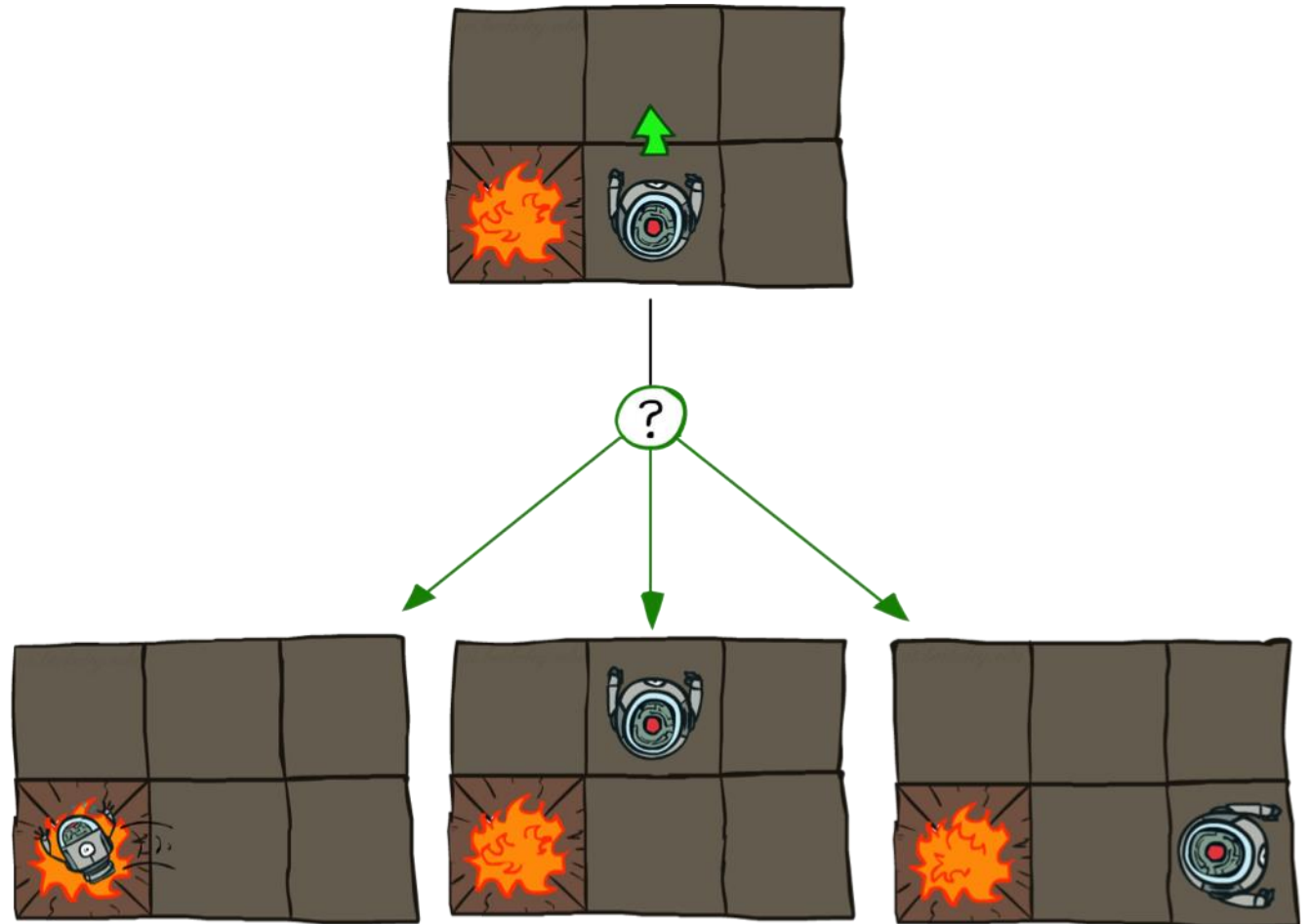


# Grid World Actions

Deterministic Grid World

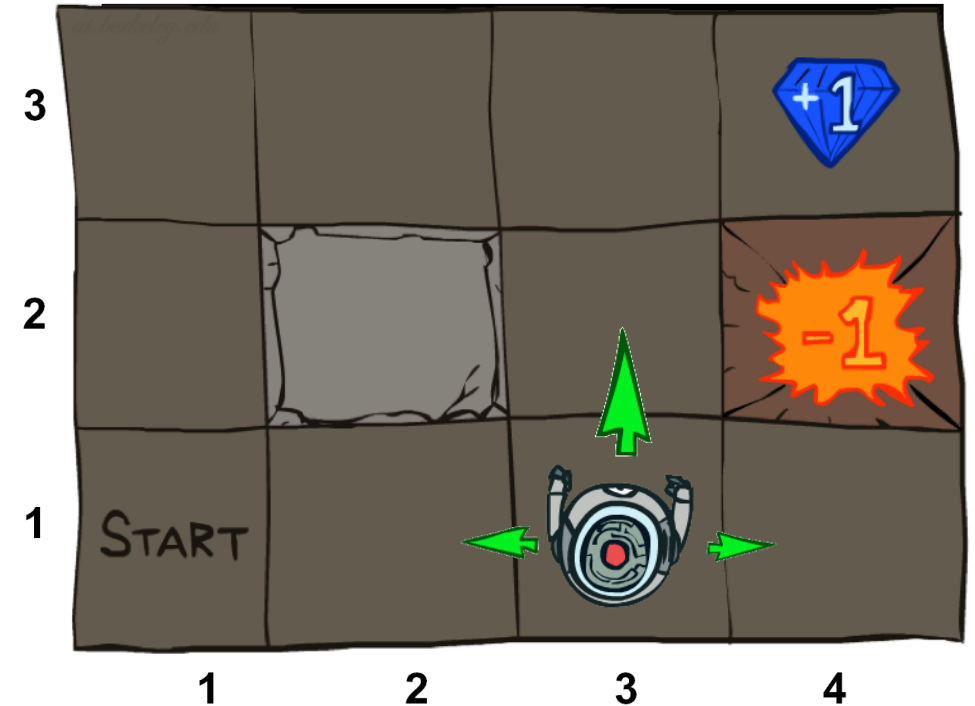


Stochastic Grid World



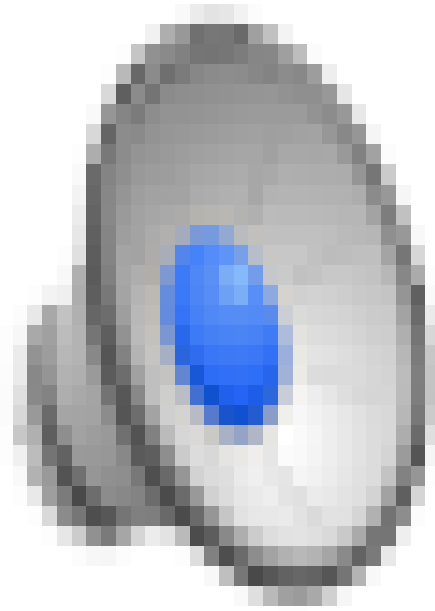
# Markov Decision Processes

- 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



# 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

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

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

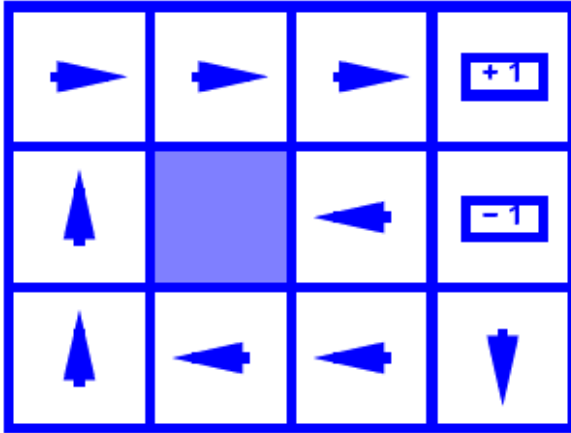


Andrey Markov  
(1856-1922)

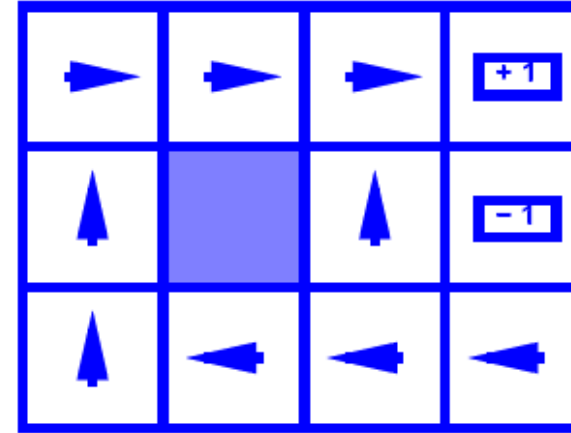




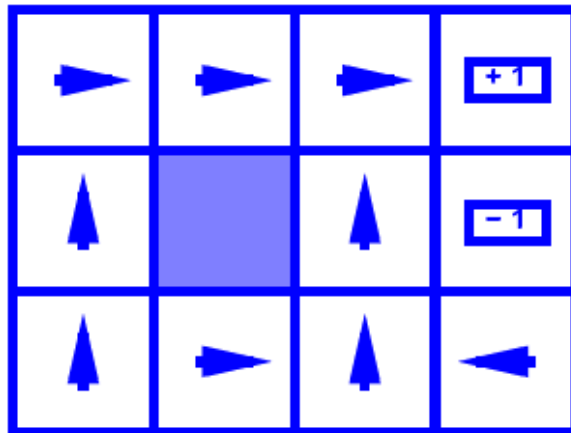
# Optimal Policies



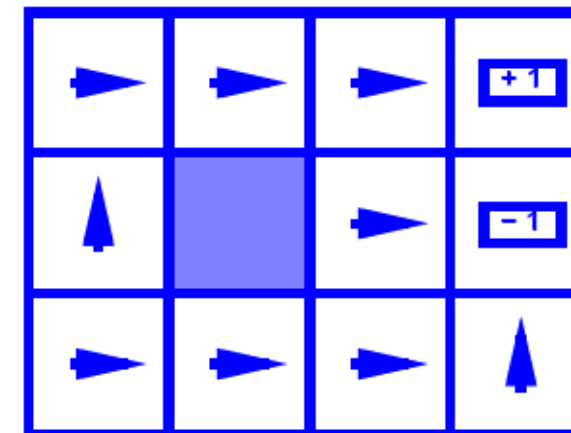
$R(s) = -0.01$



$R(s) = -0.03$



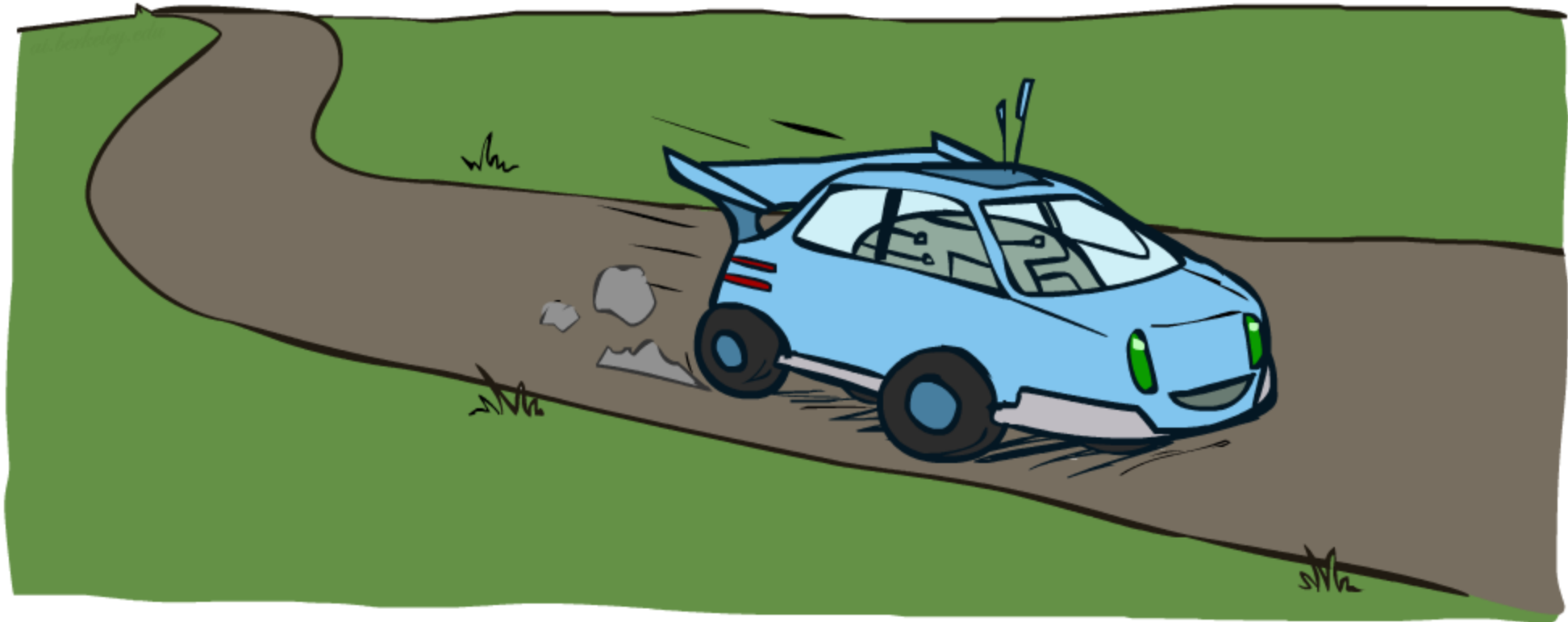
$R(s) = -0.4$



$R(s) = -2.0$

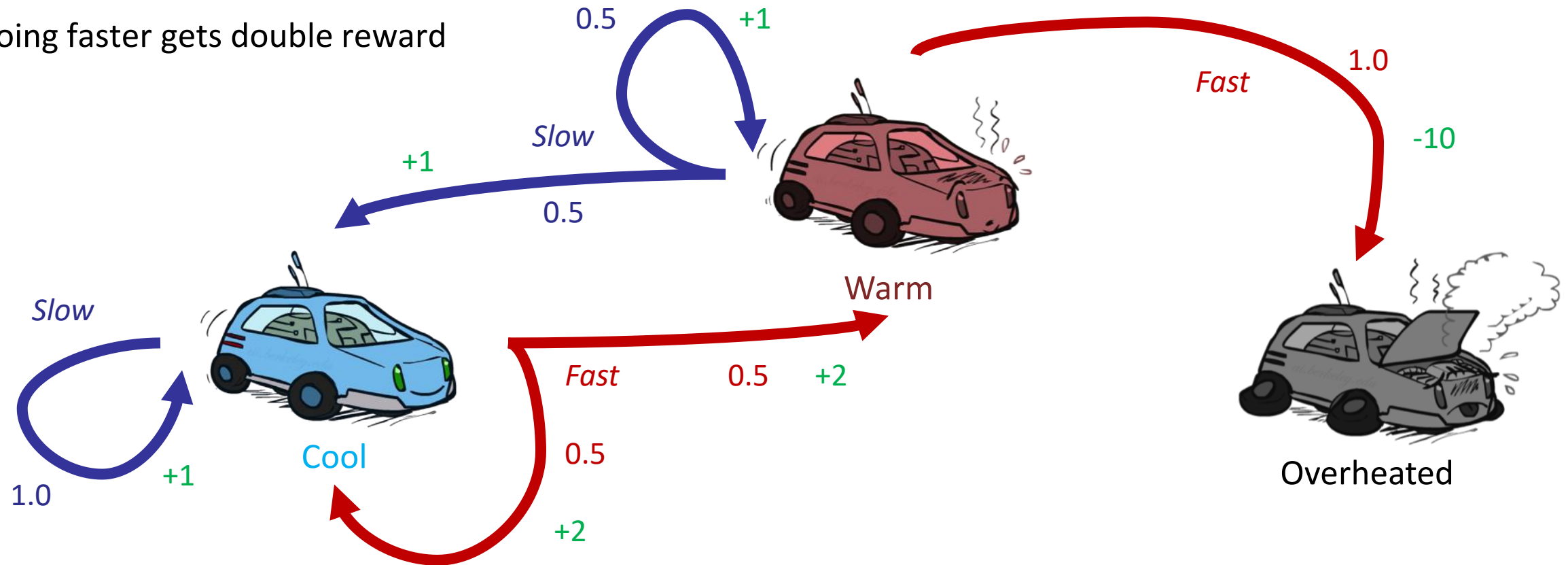
# Example: Racing

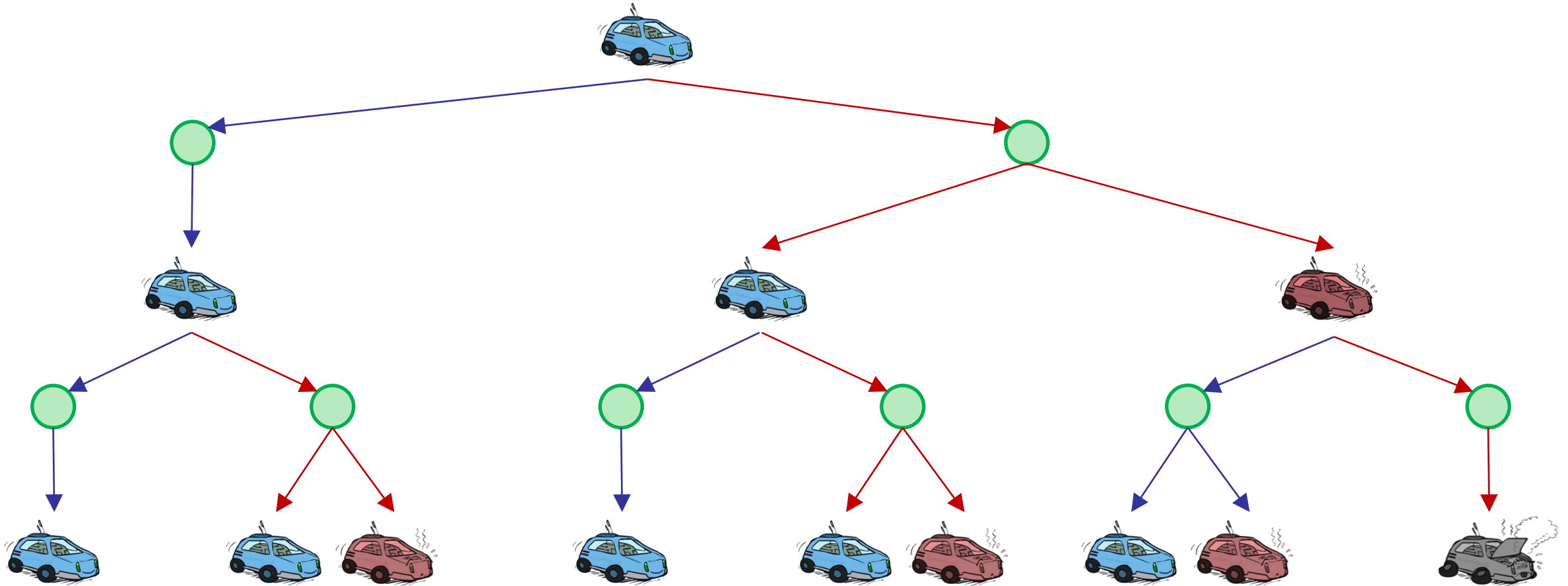
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# Example: Racing

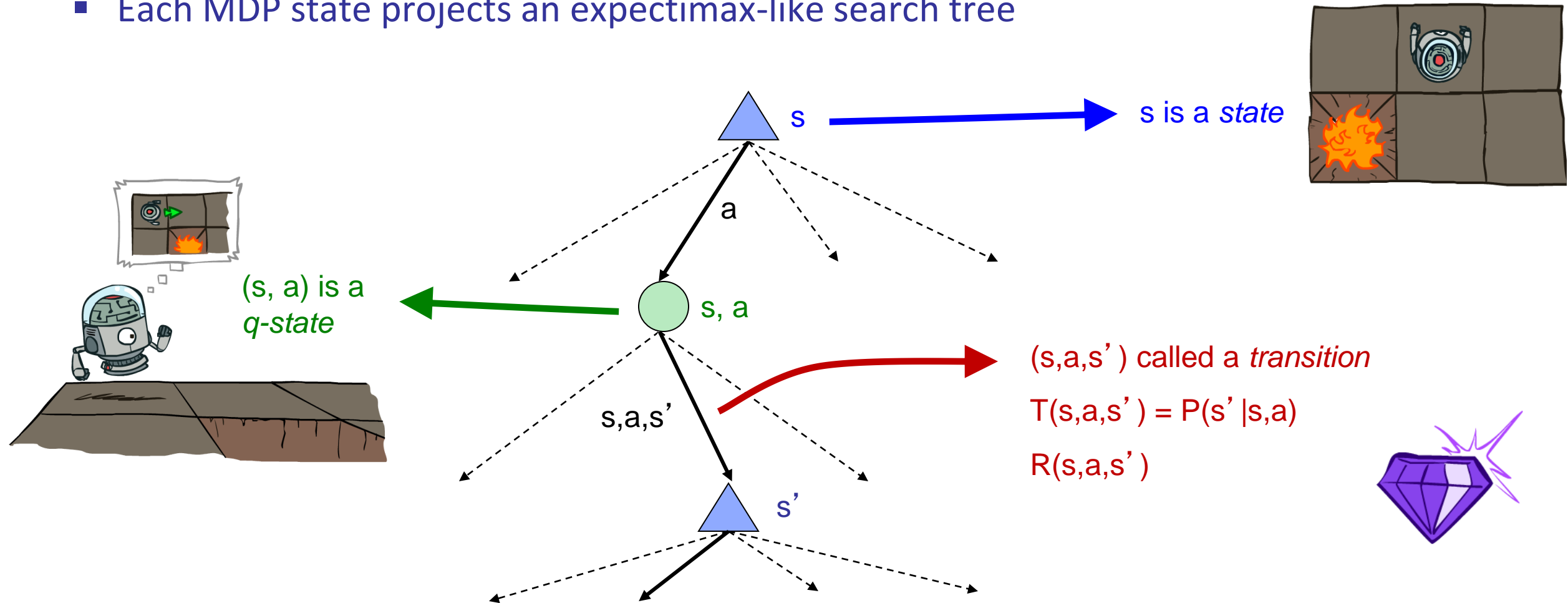
- A robot car wants to travel far, quickly
- Three states: **Cool**, **Warm**, Overheated
- Two actions: **Slow**, **Fast**
- Going faster gets double reward



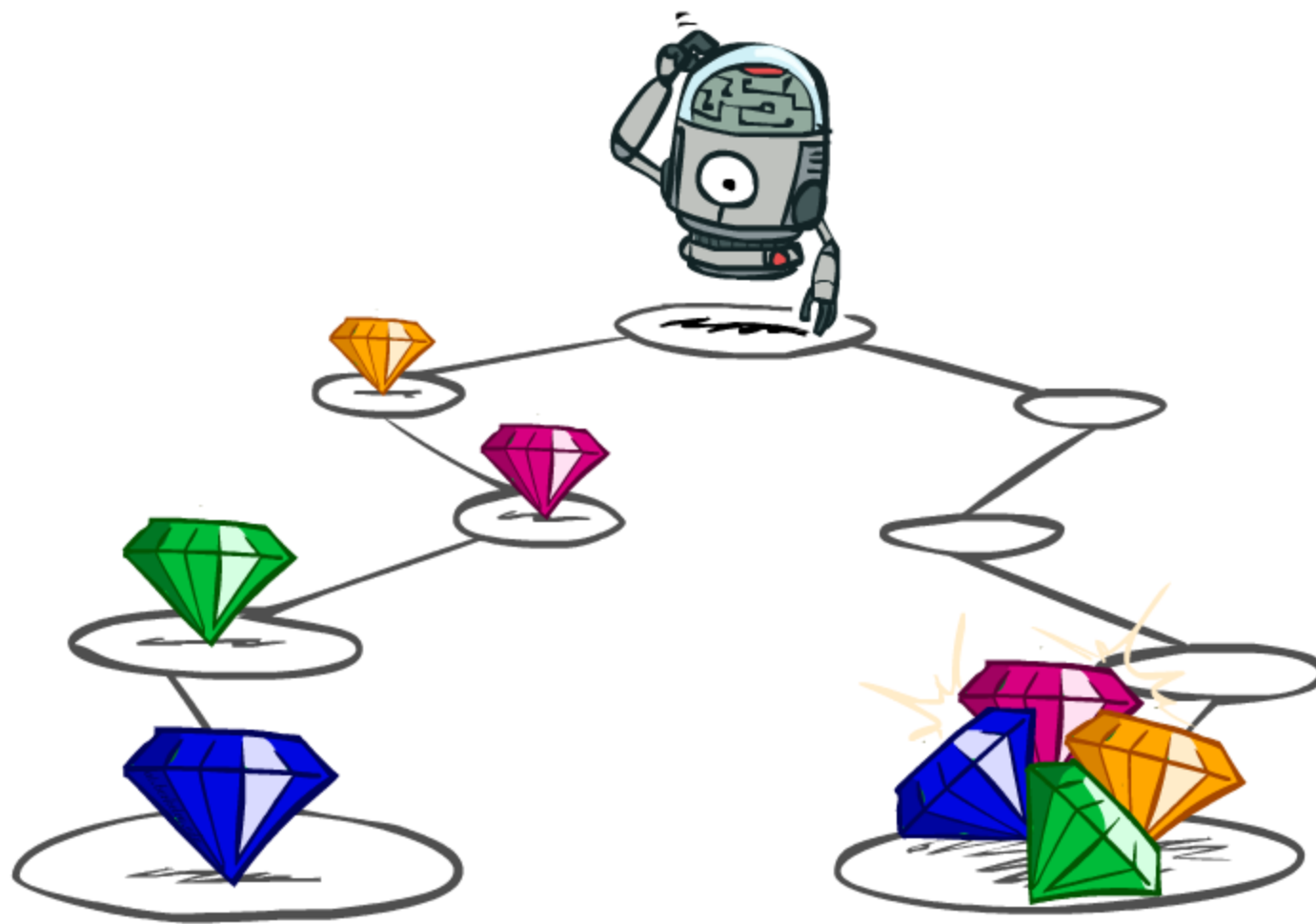


# MDP Search Trees

- Each MDP state projects an expectimax-like search tree

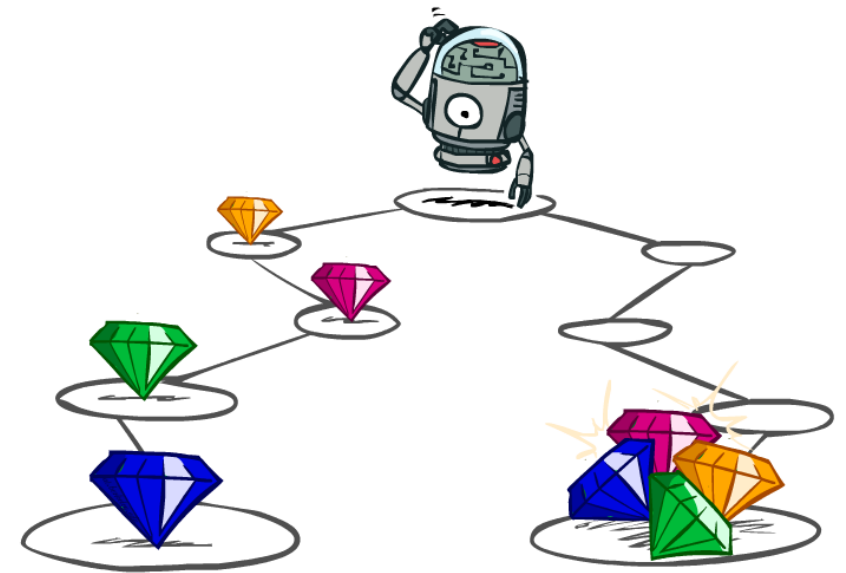


# Utilities of Sequences



# 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



$\gamma$

Worth Next Step



$\gamma^2$

Worth In Two Steps



# Discounting

- How to discount?

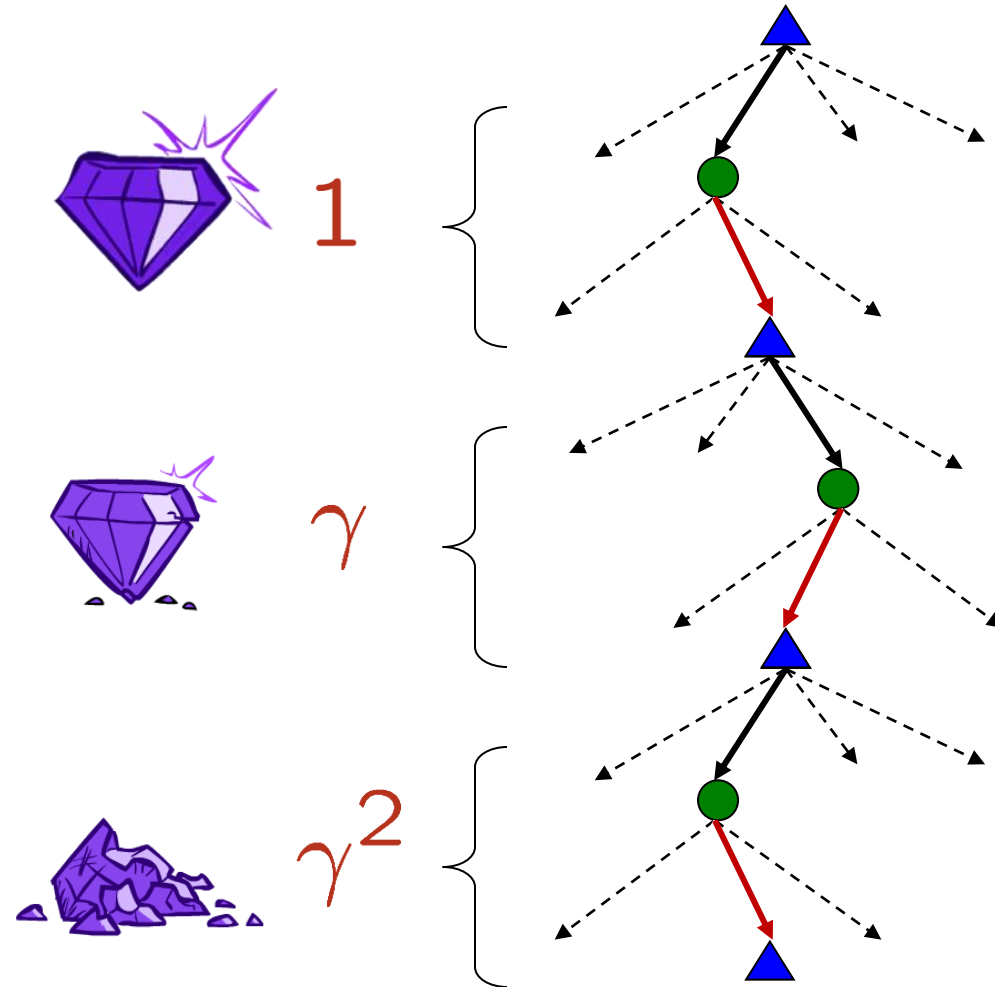
- Each time we descend a level, we multiply in the discount once

- Why discount?

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

- Example: discount of 0.5

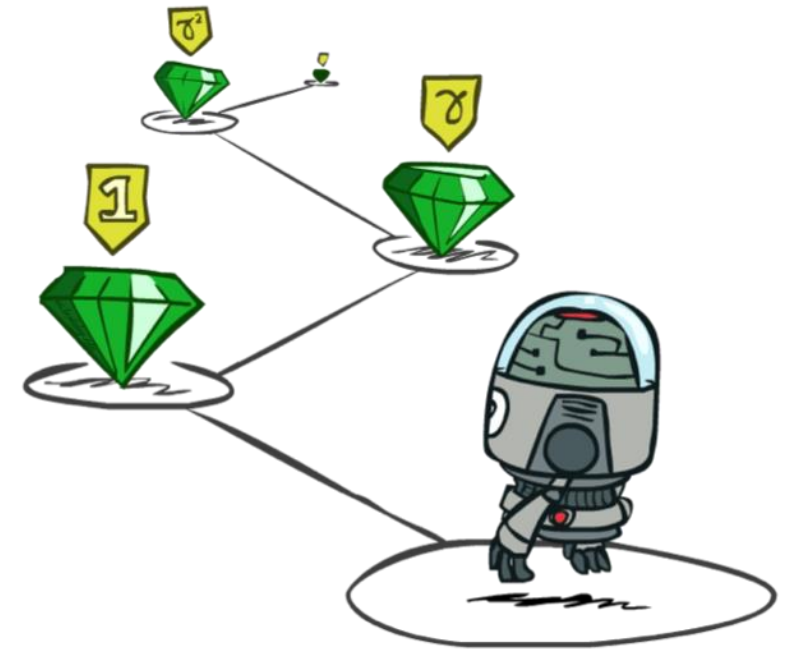
- $U([1,2,3]) = 1*1 + 0.5*2 + 0.25*3$
- $U([1,2,3]) < U([3,2,1])$



# 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:

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
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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?

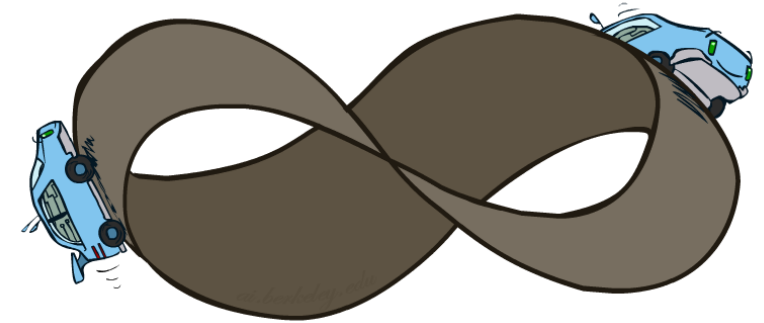
- Solutions:

- 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  $0 < \gamma < 1$

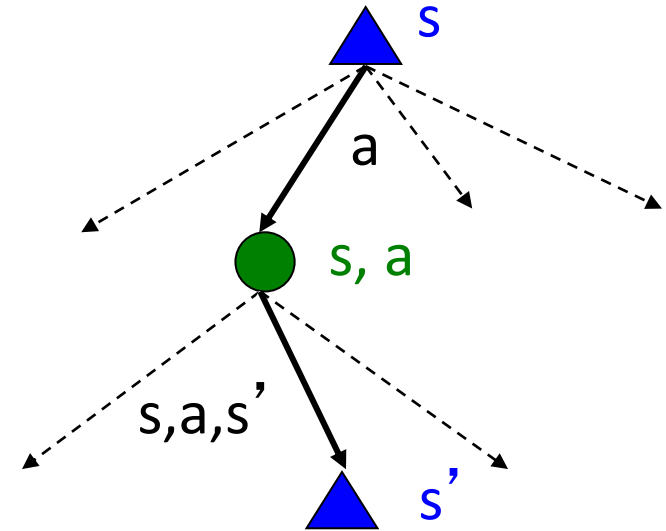
$$U([r_0, \dots, r_\infty]) = \sum_{t=0}^{\infty} \gamma^t r_t \leq R_{\max} / (1 - \gamma)$$

- 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)

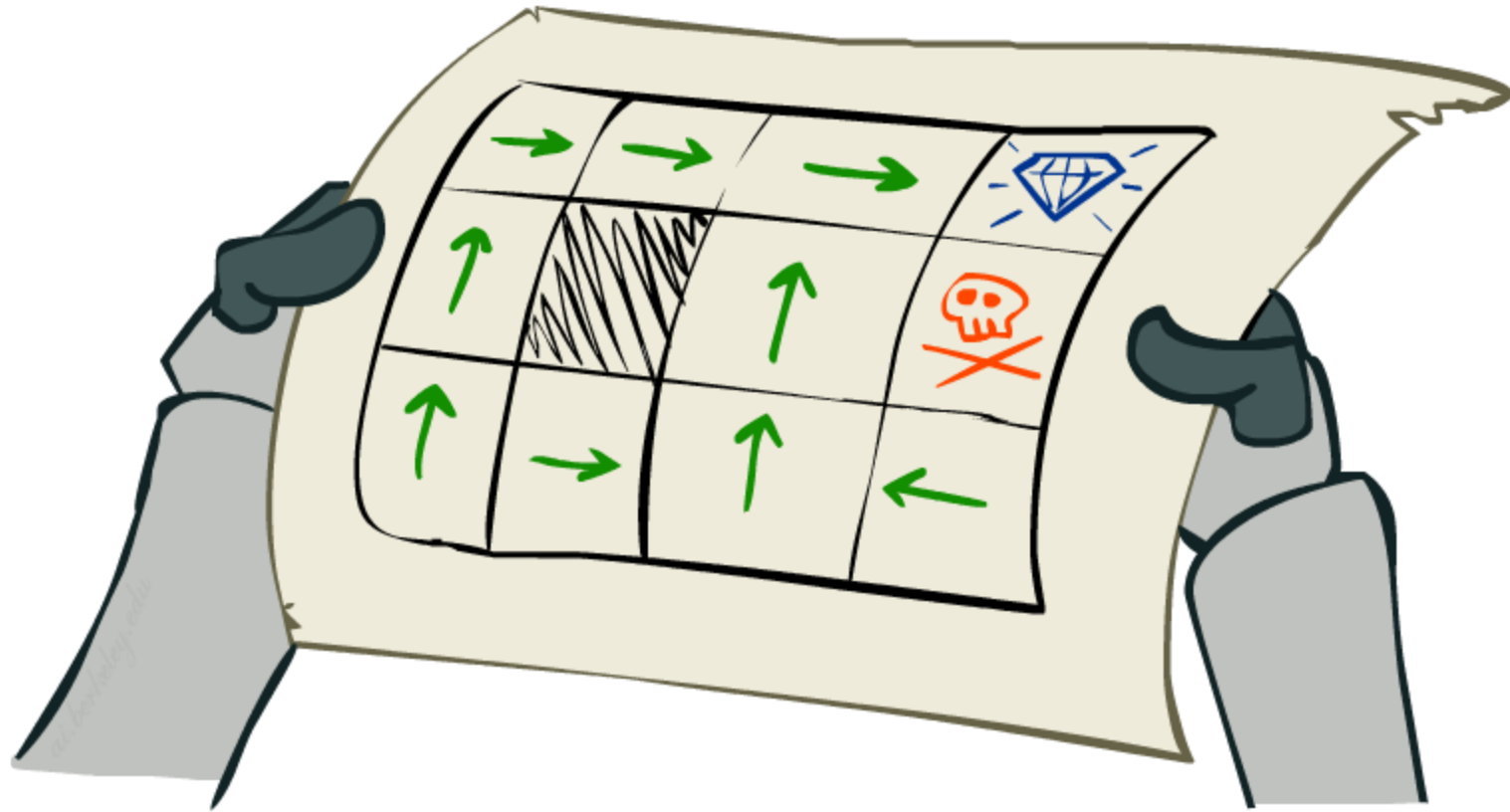


# Recap: Defining MDPs

- 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

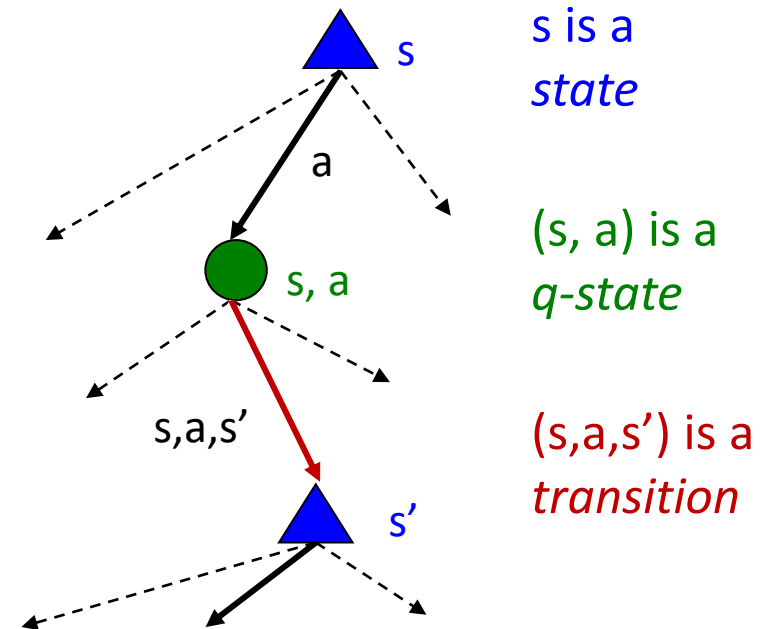


# Solving MDPs



# 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



Noise = 0.2  
Discount = 0.9  
Living reward = 0



# Snapshot of Demo – Gridworld Q Values



Noise = 0.2  
Discount = 0.9  
Living reward = 0

# Values of States

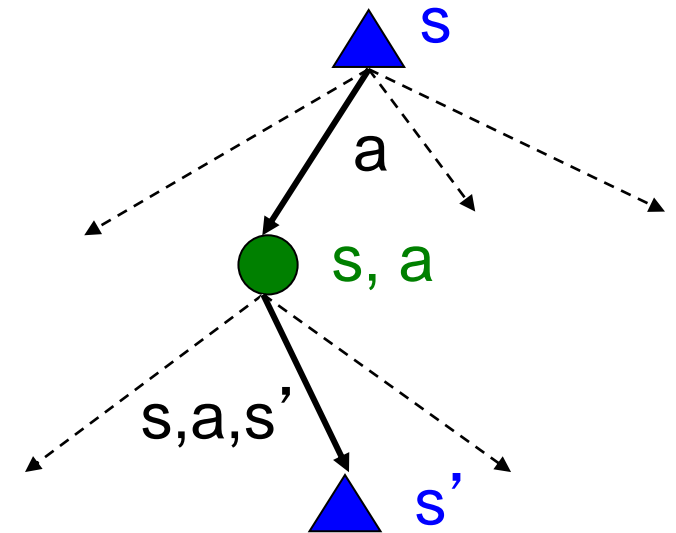
- Fundamental operation: compute the (expectimax) value of a state
  - Expected utility under optimal action
  - Average sum of (discounted) rewards
  - This is just what expectimax computed!

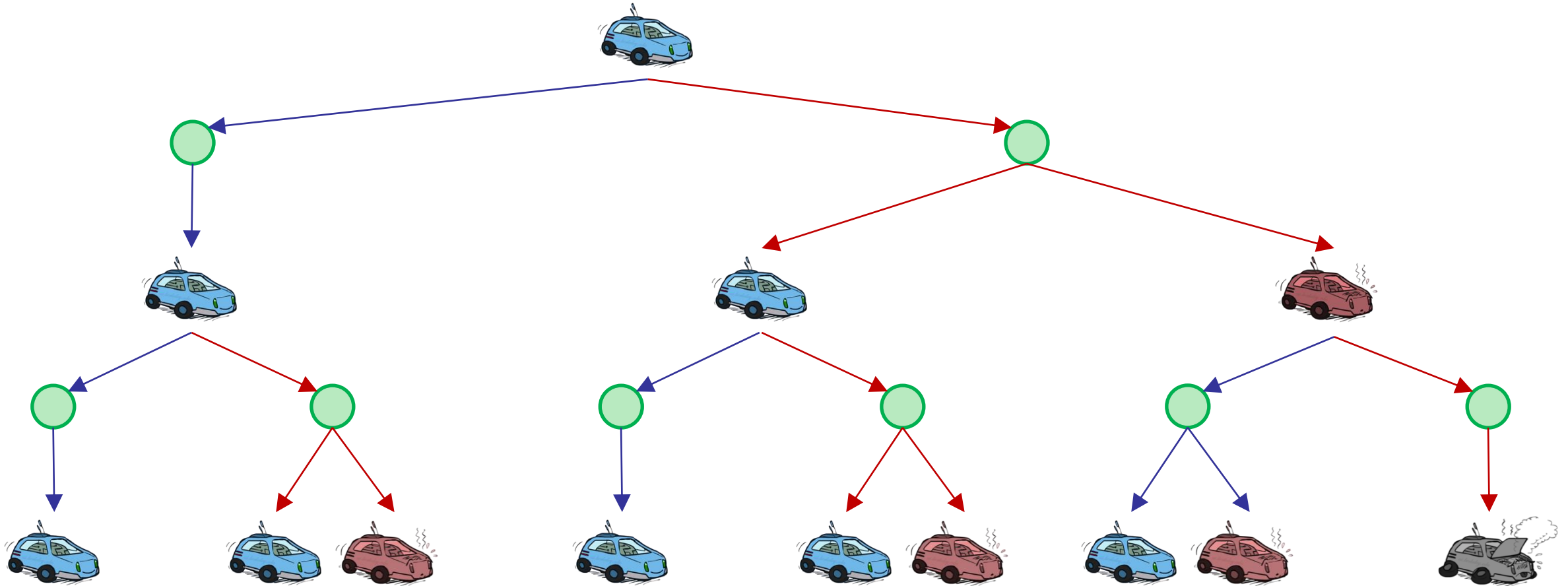
- Recursive definition of value:

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

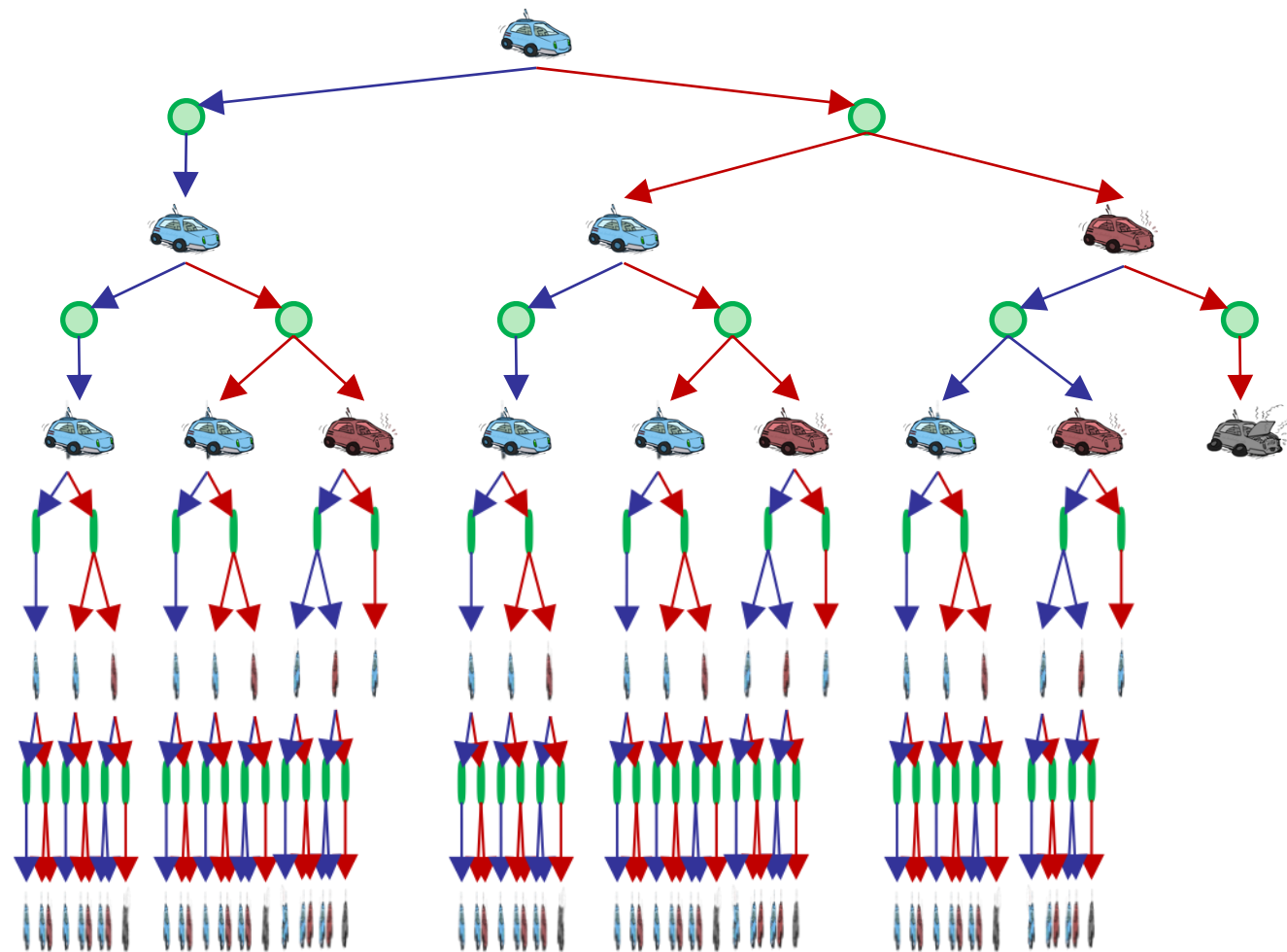
$$Q^*(s, a) = \sum_{s'} T(s, a, s') [R(s, a, s') + \gamma V^*(s')]$$

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



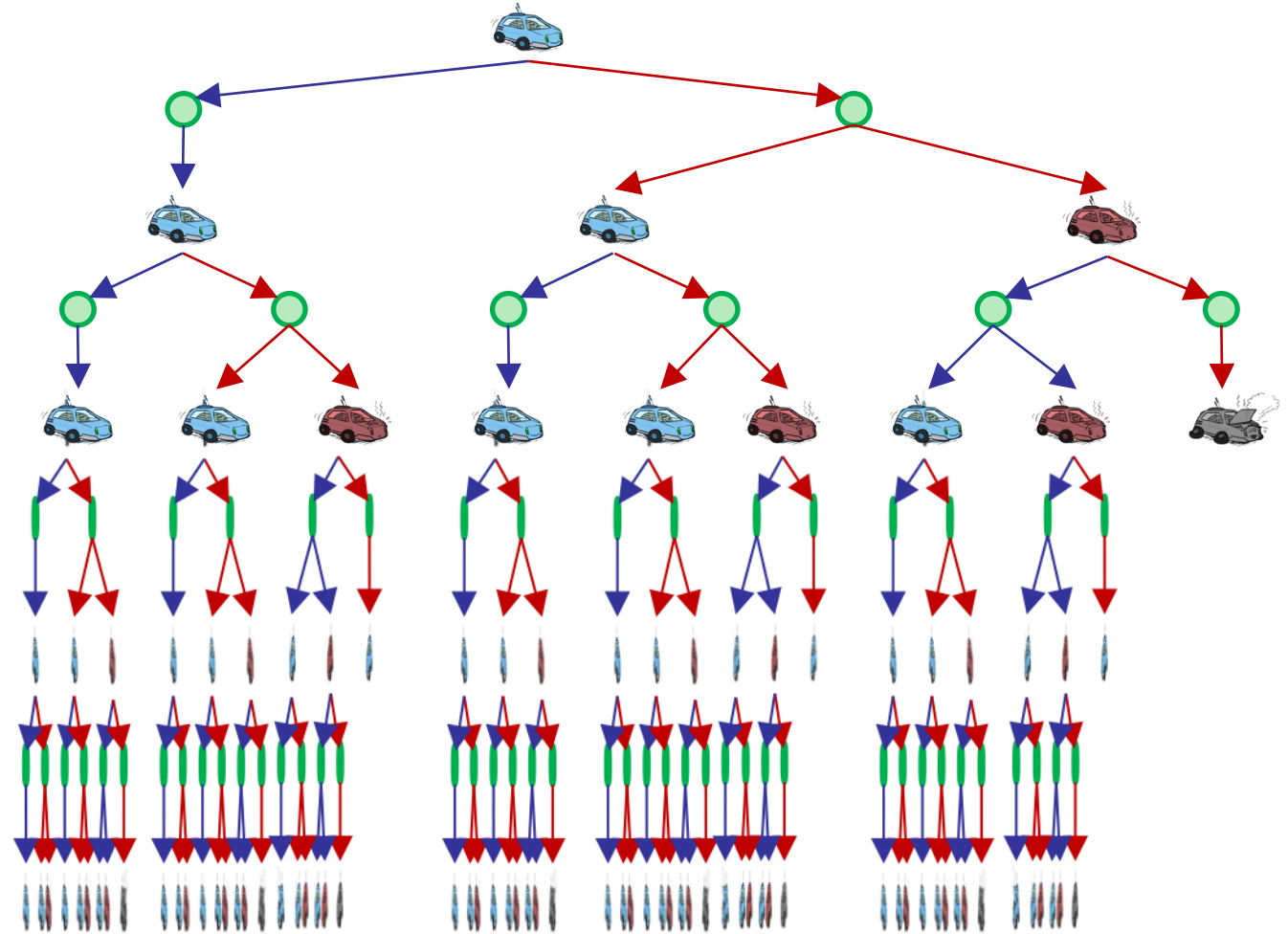


# Racing Search Tree



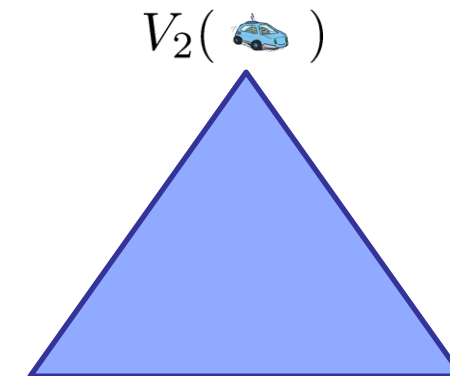
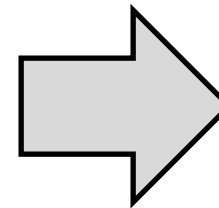
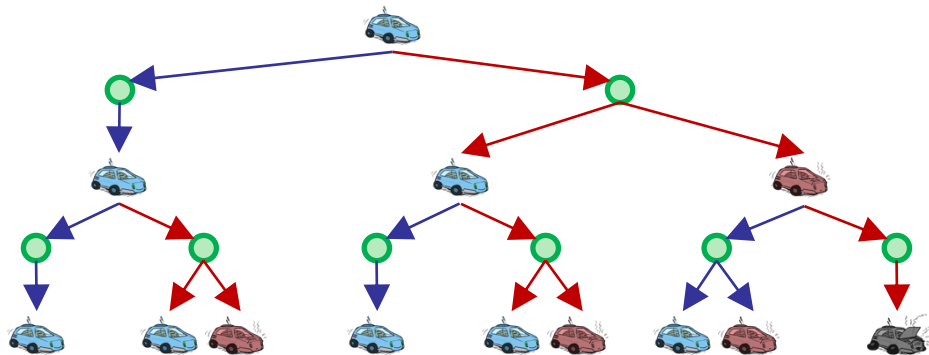
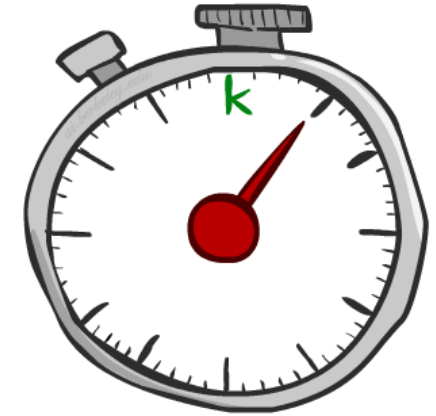
# Racing Search Tree

- 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  $\gamma < 1$

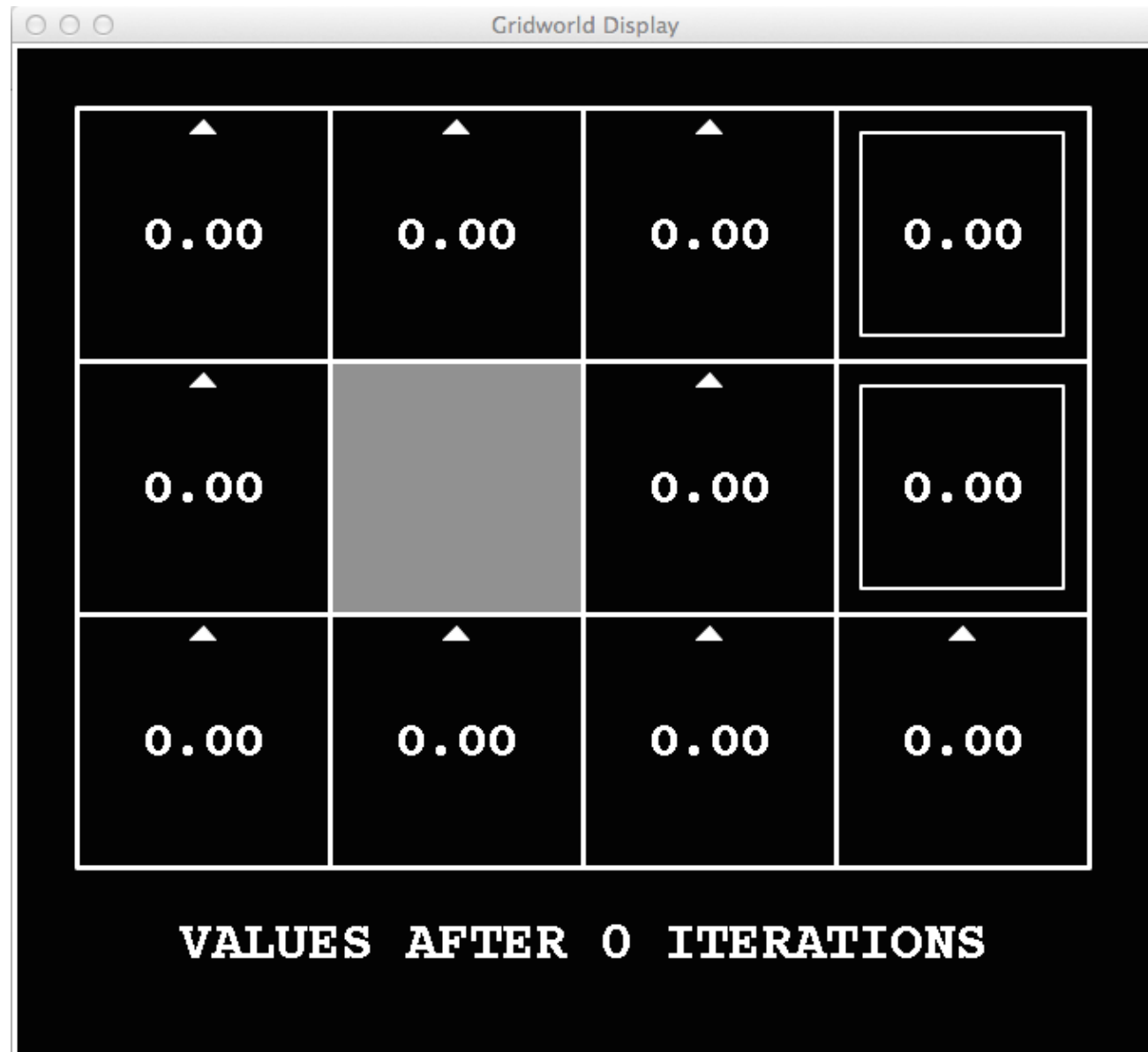


# Time-Limited Values

- 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  $s$

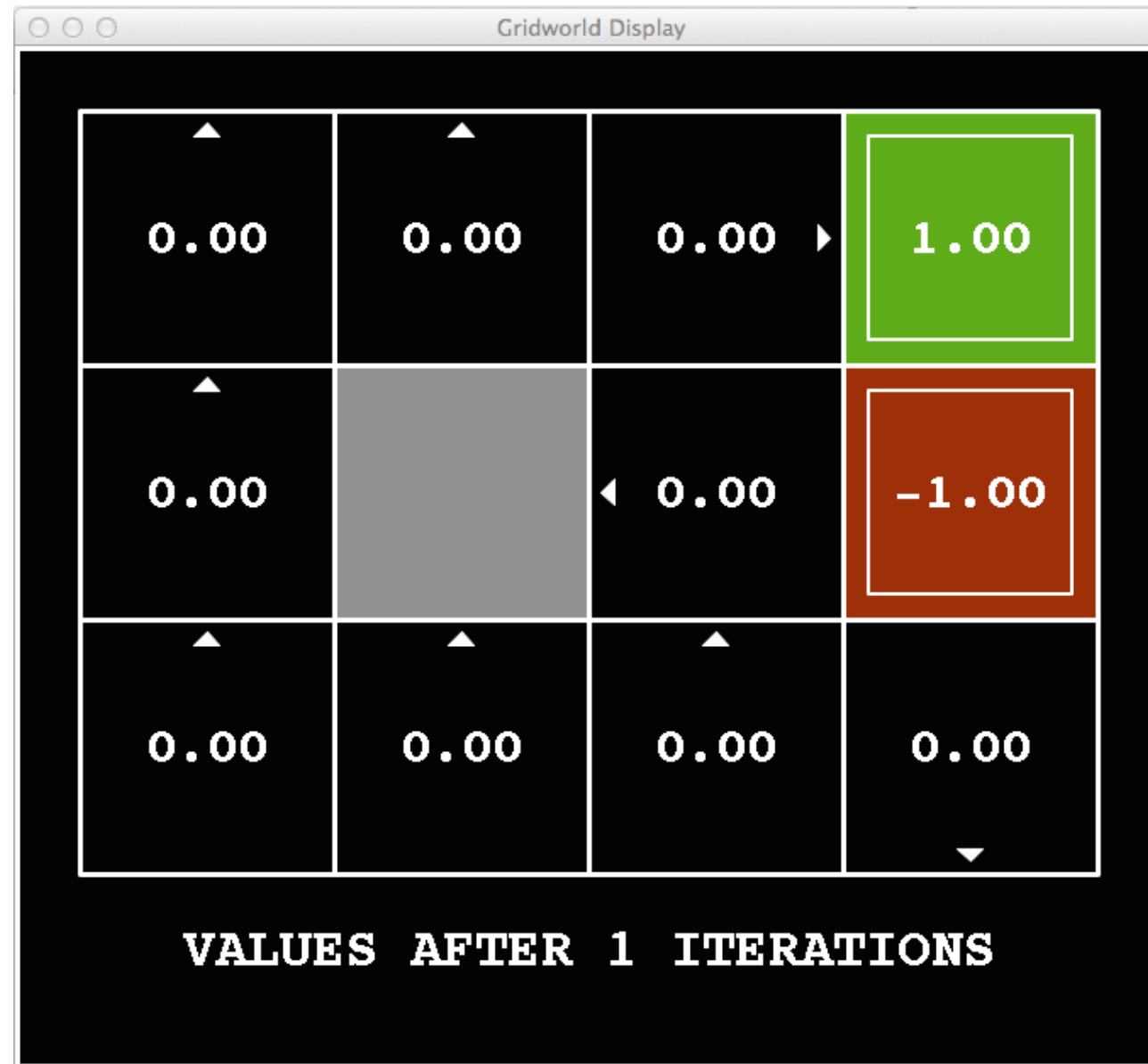


$k=0$



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



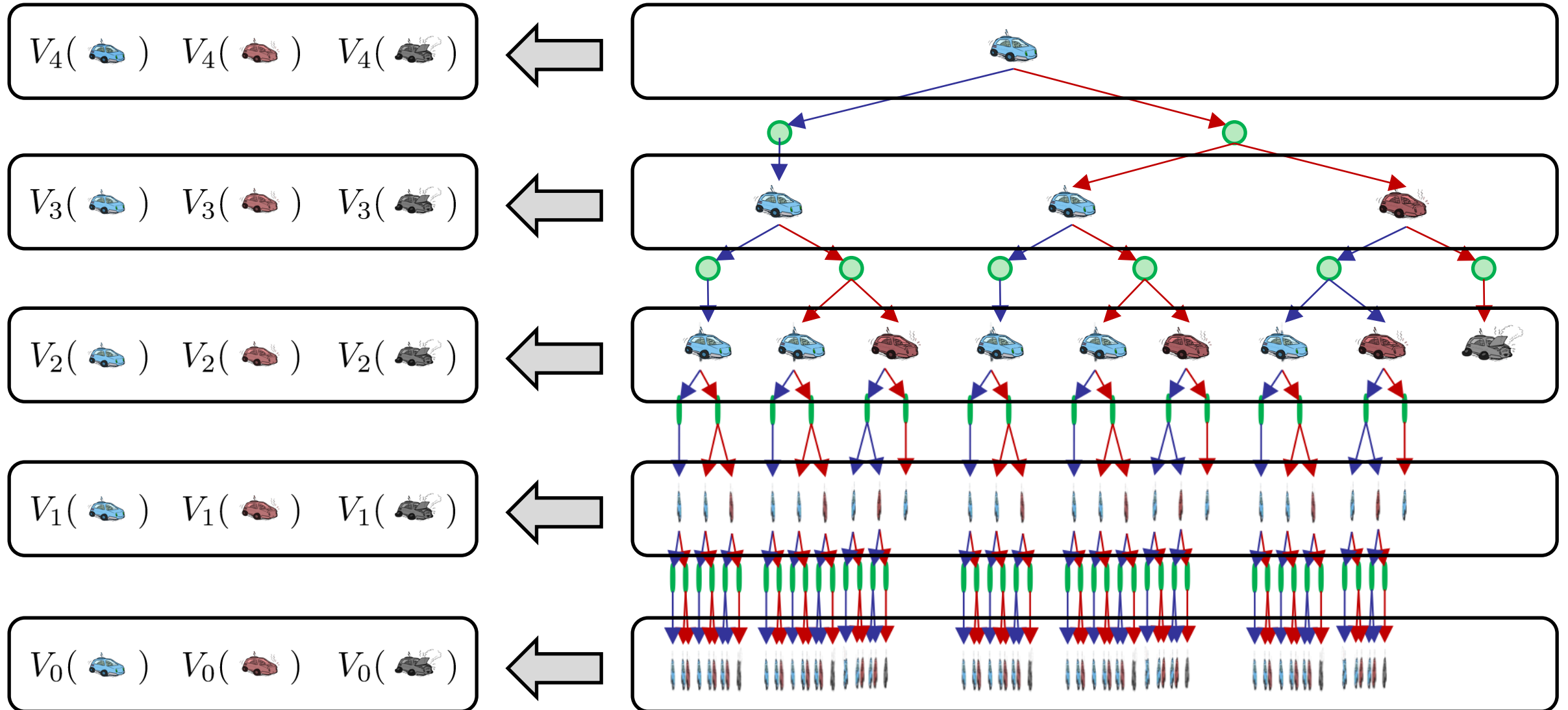
Noise = 0.2  
Discount = 0.9  
Living reward = 0

# k=100



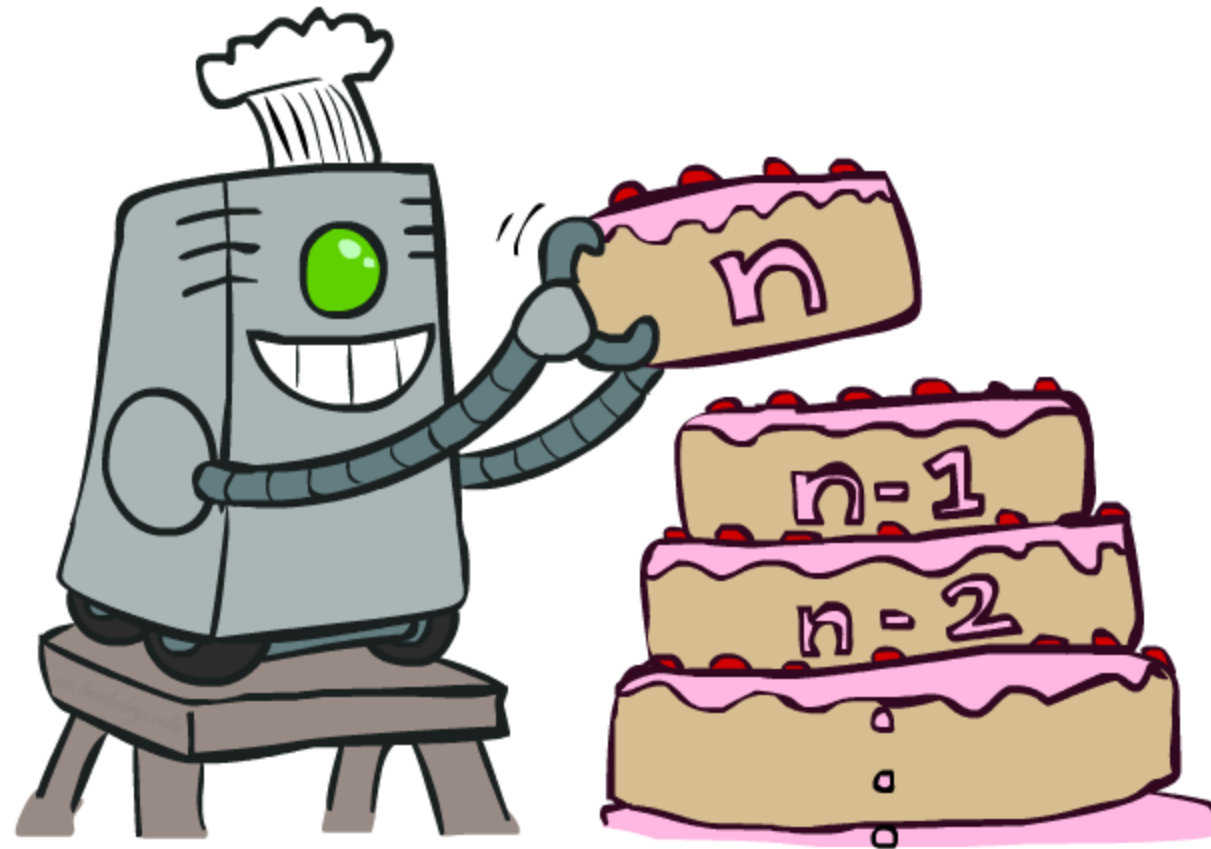
Noise = 0.2  
Discount = 0.9  
Living reward = 0

# Computing Time-Limited Values



# Value Iteration

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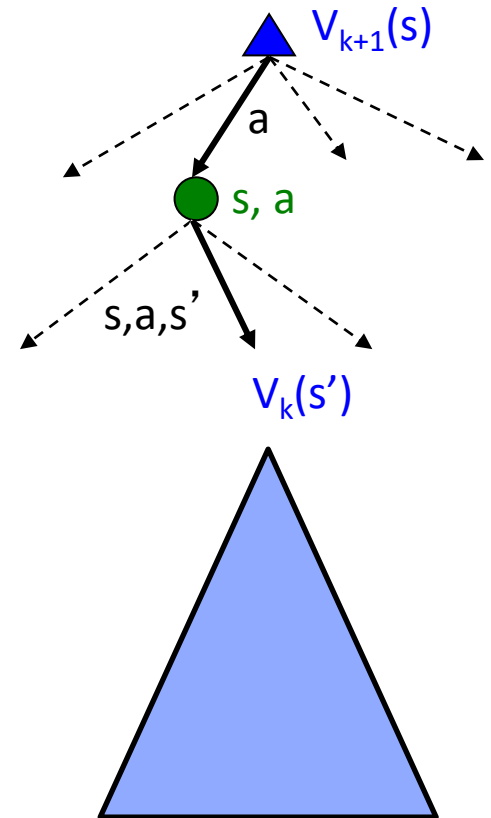


# Value Iteration




- 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:

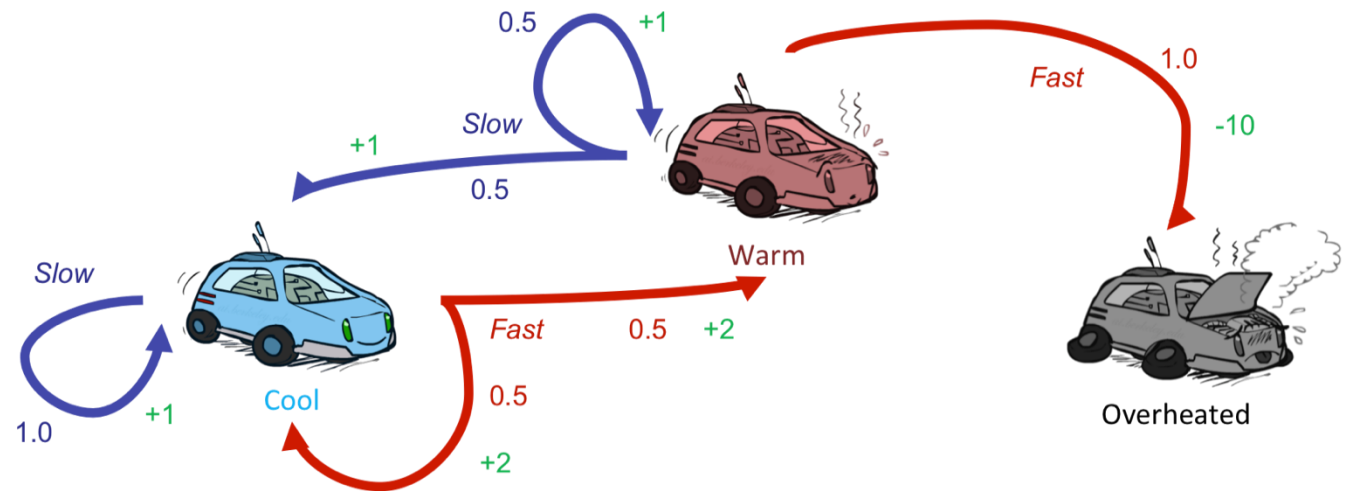
$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s, a, s') [R(s, a, s') + \gamma V_k(s')]$$

- 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



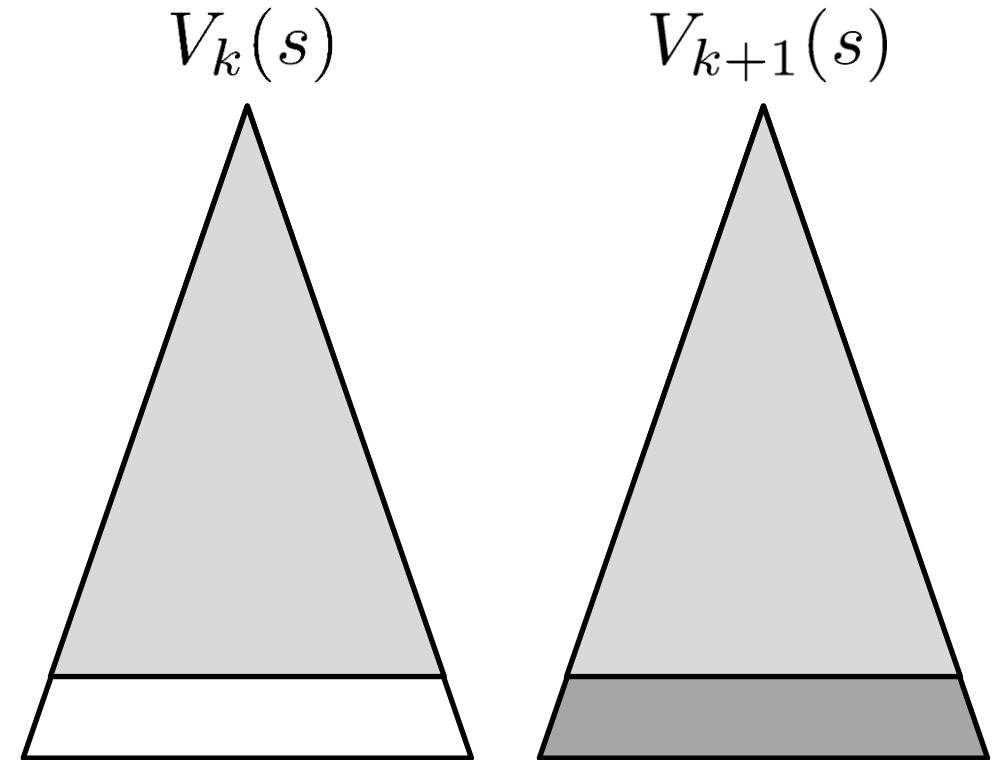
Assume no discount!

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



# 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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