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TODAY

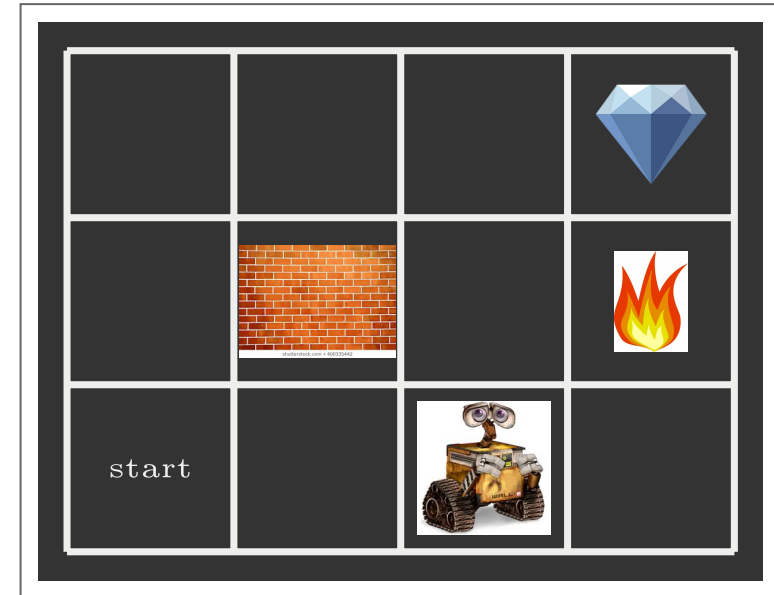
Markov Decision Processes (MDPs)

NON-DETERMINISTIC SEARCH

EXAMPLE: GRID WORLD

A maze like problem

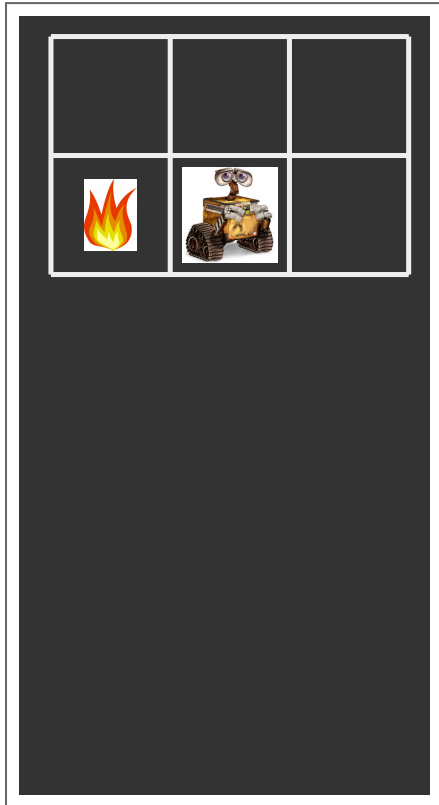
- The agent lives in a grid
- Walls block the agent's path
- Noisy movement: actions do not always go as planned
 - 80% of the time, the action North takes the agent North (if there is no wall there)
 - 10% of the time, North takes the agent West; 10% East
 - If there is a wall in the direction the agent 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)



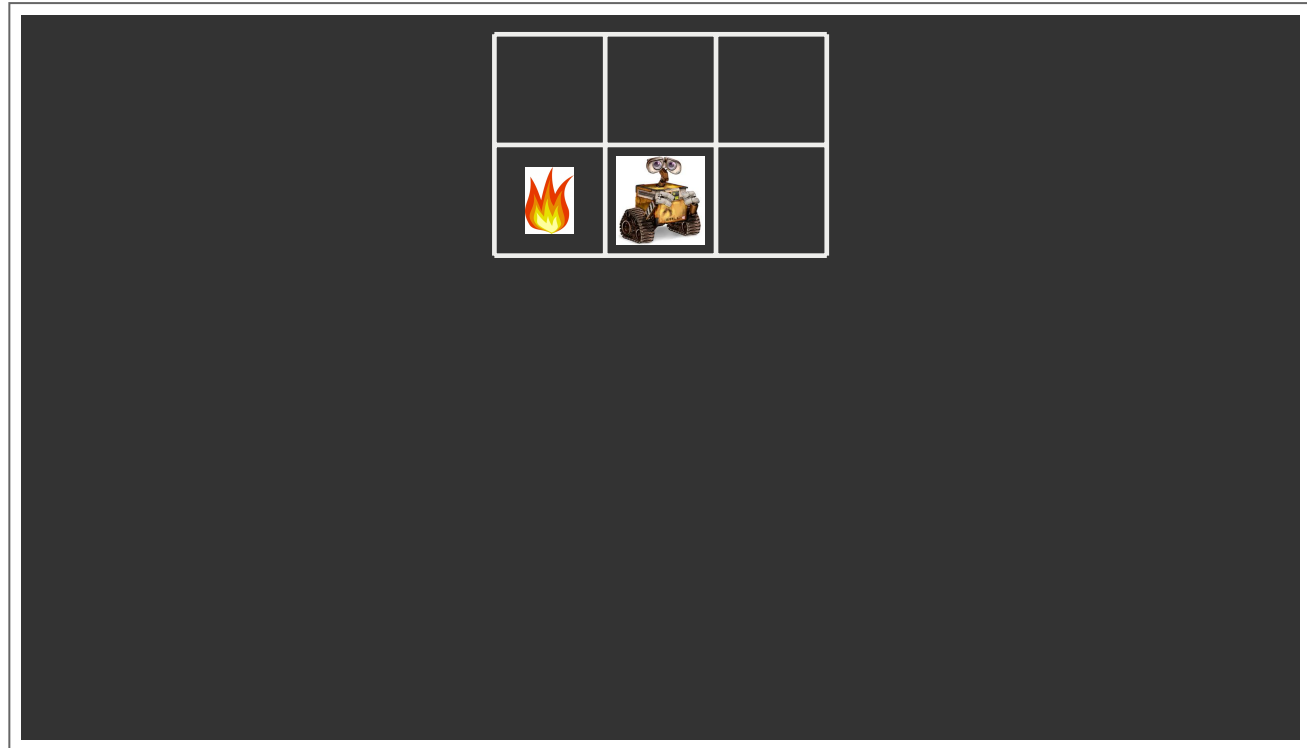
Goal: maximize sum of rewards

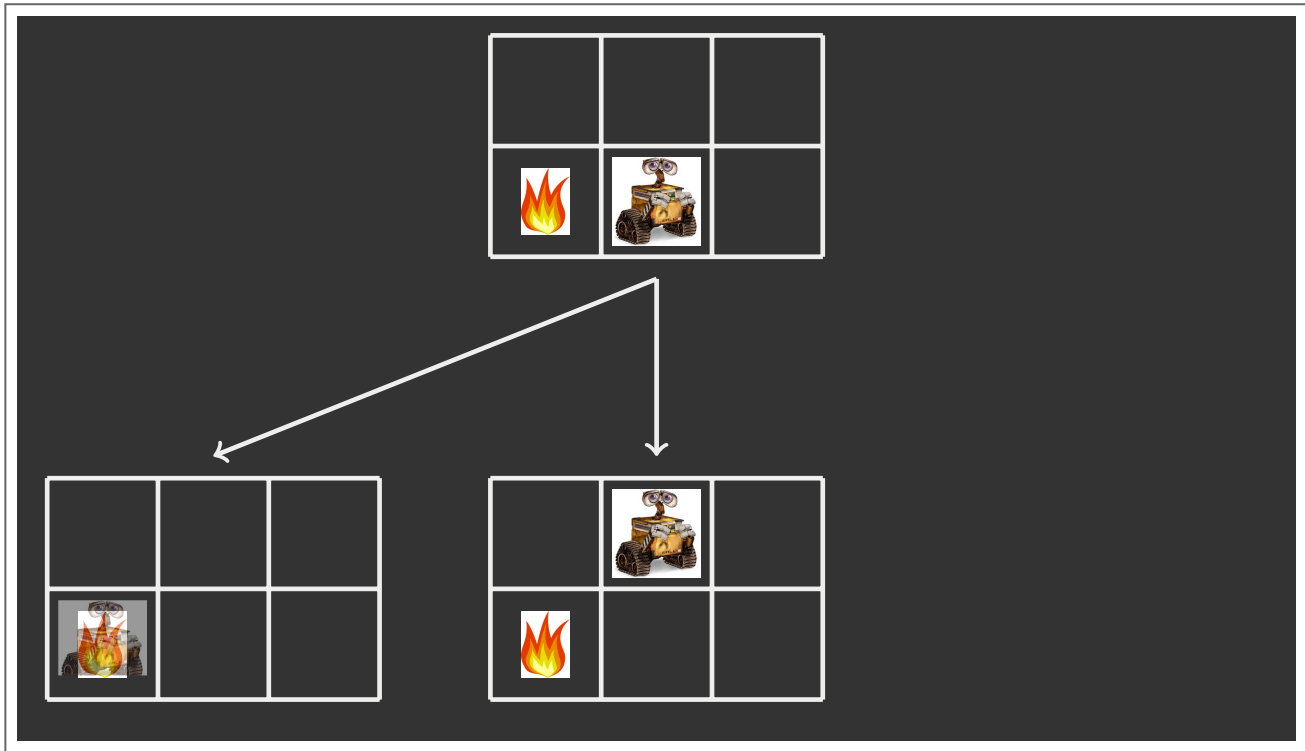
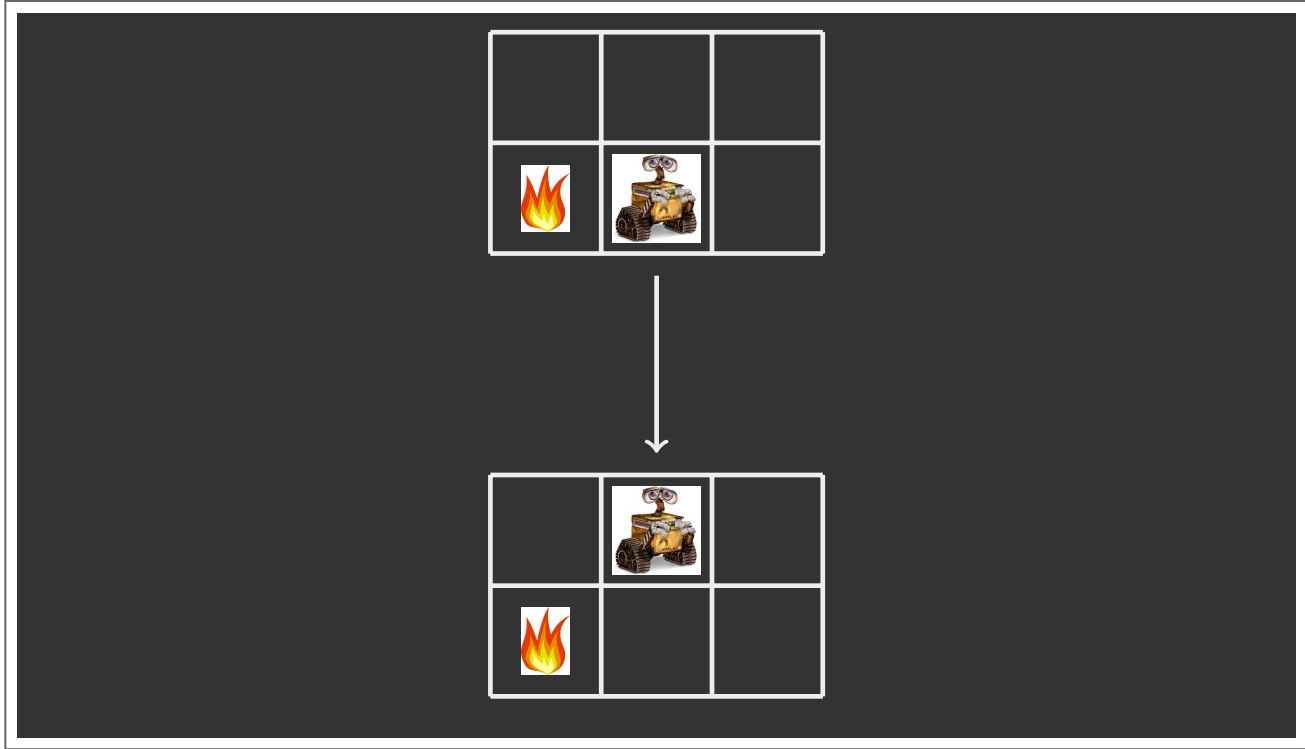
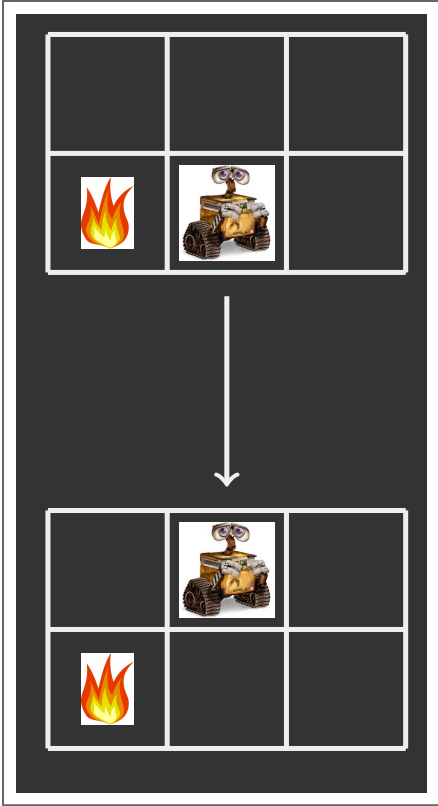
GRID WORLD ACTIONS

Deterministic Grid World

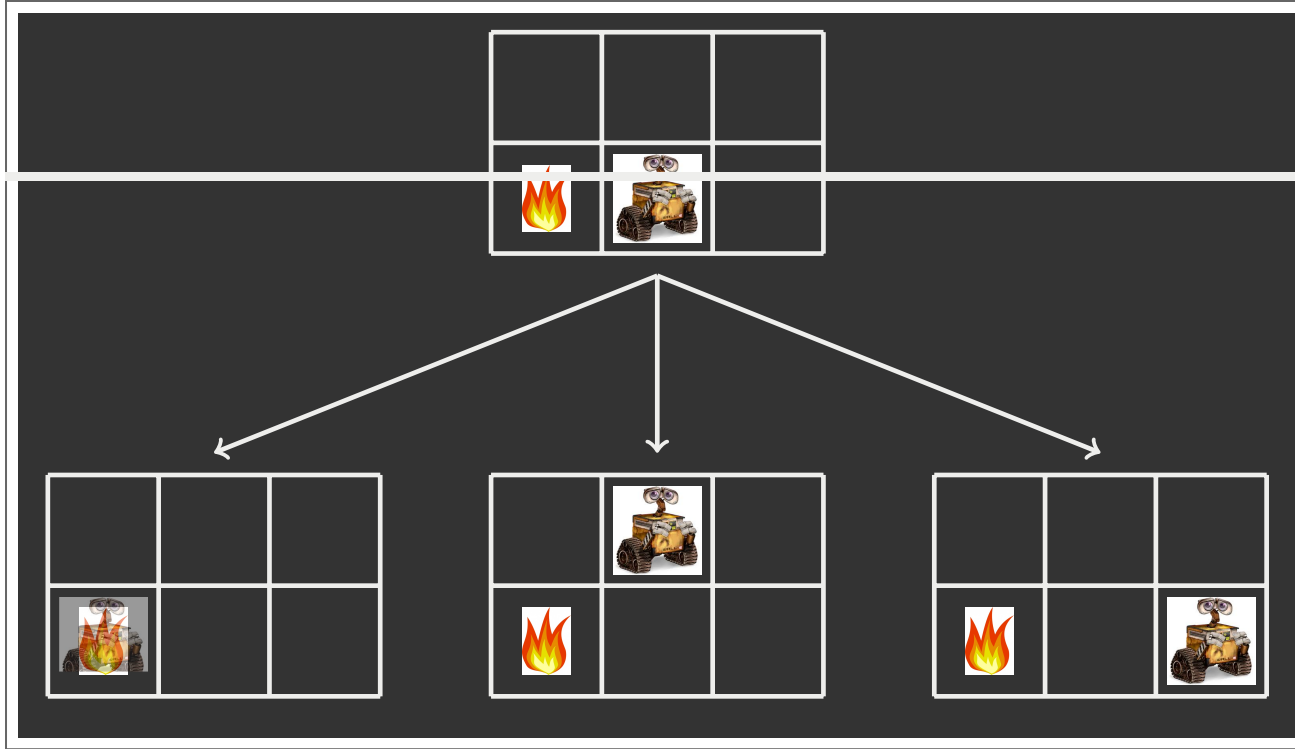


Stochastic Grid World



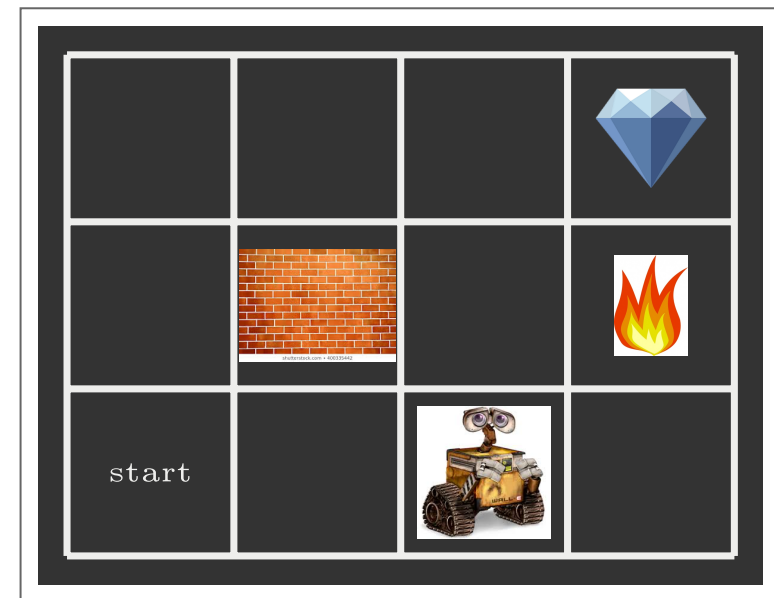


MARKOV DECISION PROCESSES



An MDP is defined by:

- A set of states $s \in \mathcal{S}$
- A set of actions $a \in \mathcal{A}$
- 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, s_0

- Maybe a terminal state

WHAT IS MARKOV ABOUT MDPS

MDPs are non-deterministic search problems

- One way to solve them is with expectimax search

- We will have a new tool soon

"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)

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 $\pi^* : \mathcal{S} \rightarrow \mathcal{A}$

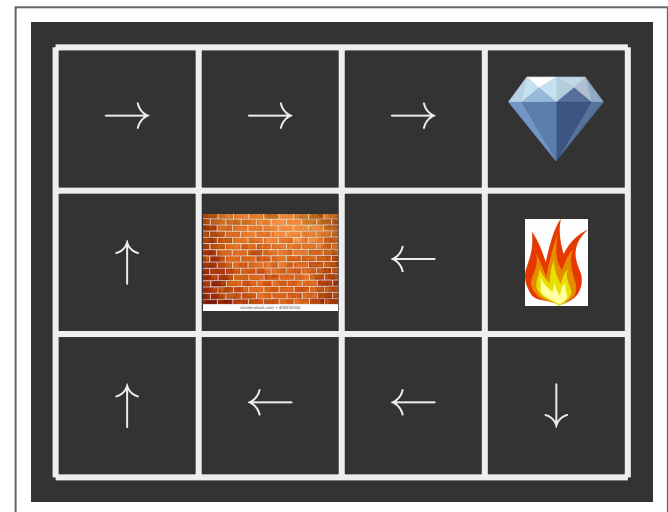
- A policy π gives an action for each state
- An optimal policy is one that maximizes expected utility if followed
- An explicit policy defines a reflex agent

Expectimax did not compute entire policies

- It computed the action for a single state only

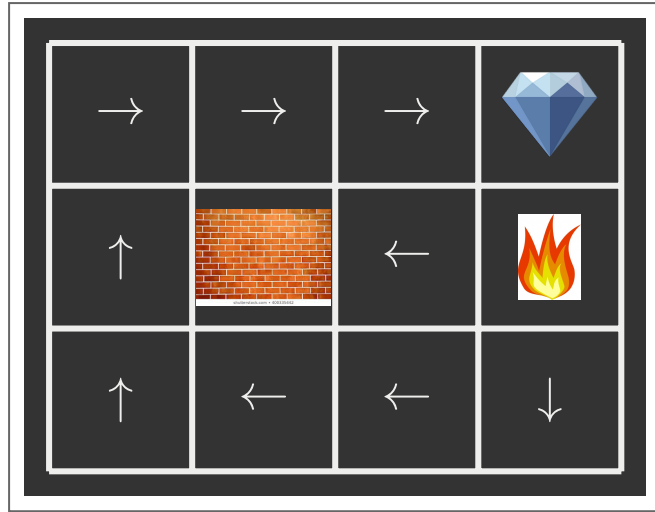


Andrey Markov (1856-1922)

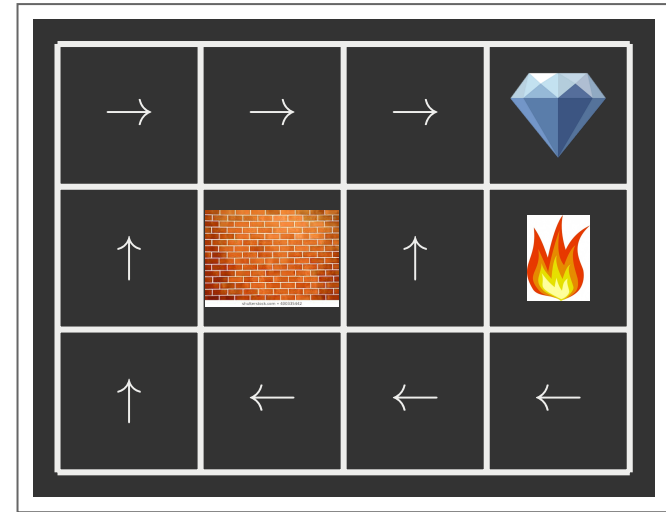


OPTIMAL POLICIES

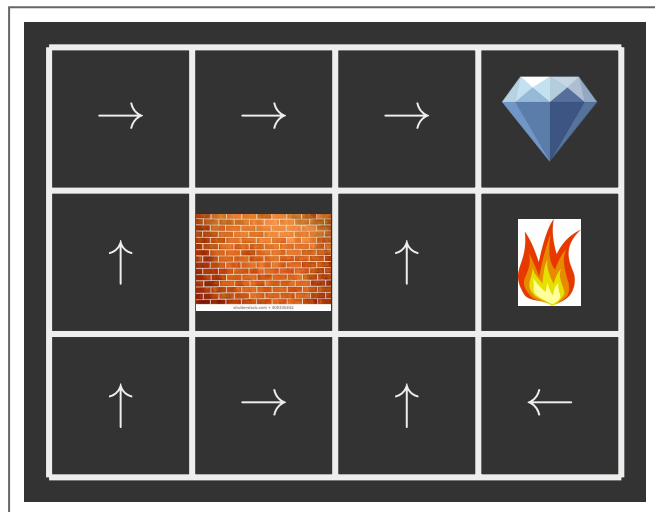
Optimal policy when
 $R(s, a, s') = -0.01$ for
 all non terminals s .



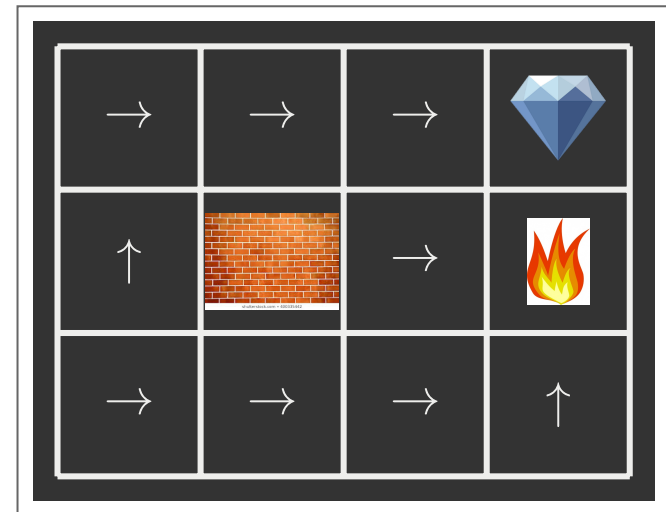
$$R(s) = -0.01$$



$$R(s) = -0.03$$



$$R(s) = -0.4$$



$$R(s) = -2.0$$

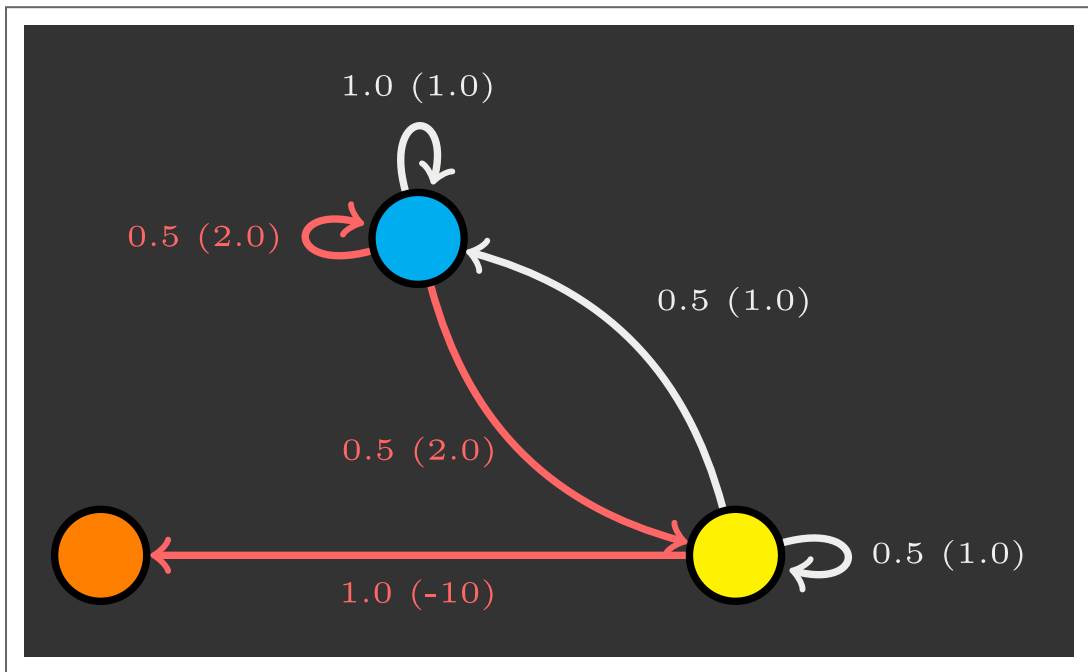
EXAMPLE: CAR RACING

A robot car wants to travel far, quickly

Three states: Cool, Warm, Overheated

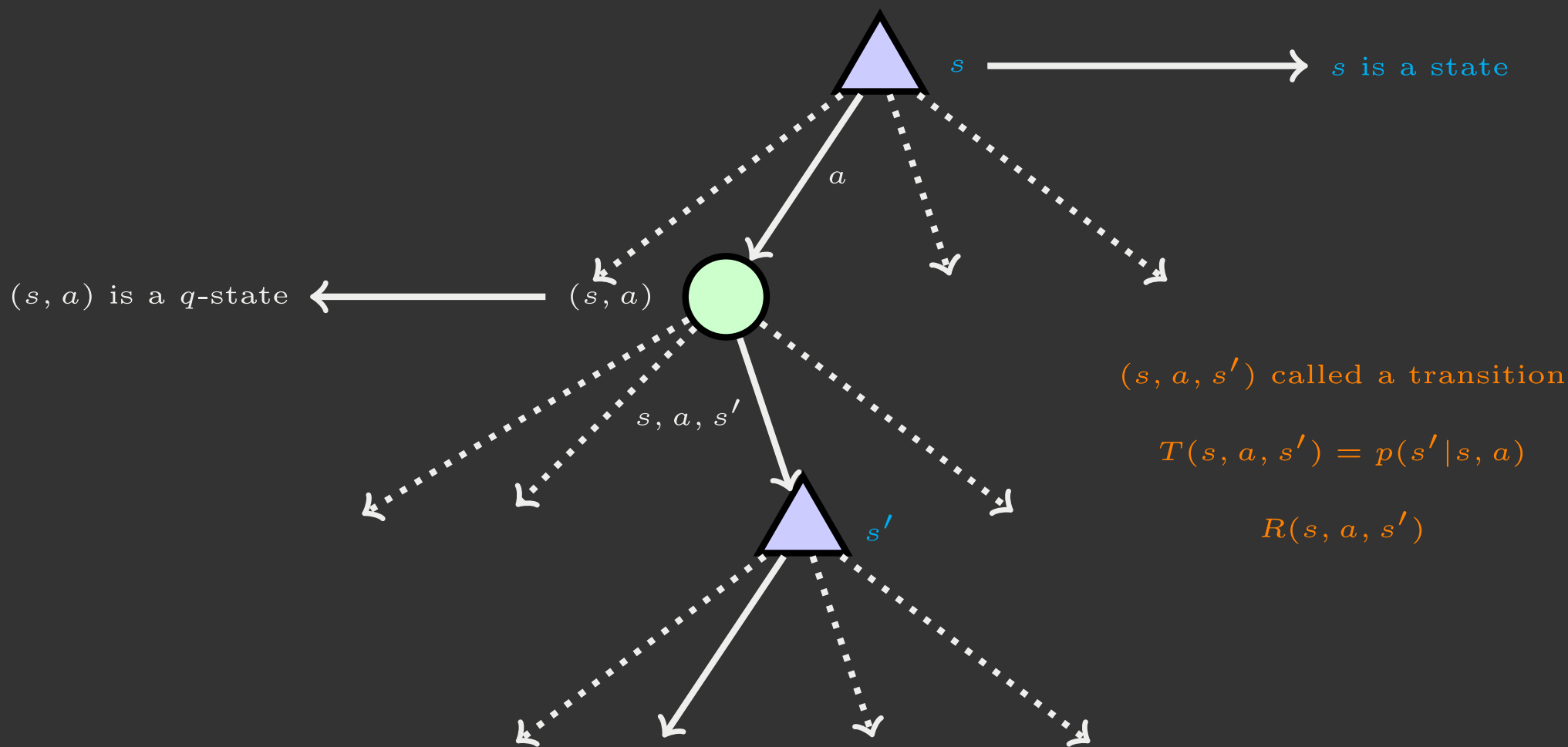
Two actions: Slow, Fast

Going faster gets double reward



MDP SEARCH TREE

Each MDP state projects an expectimax-like search tree



UTILITY 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 is reasonable to maximize the sum of rewards

It is also reasonable to prefer rewards now to rewards later

One solution: values of rewards decay exponentially



Worth Now



Worth Next Step



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

Assumption: if we assume stationary preferences:

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

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:

$$U([r_0, r_1, r_2, \dots]) = r_0 + \gamma r_1 + \gamma^2 r_2 + \dots$$

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 non-stationary policies (π depends on time left)
- Discounting: use $0 < \gamma < 1$

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

- 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)

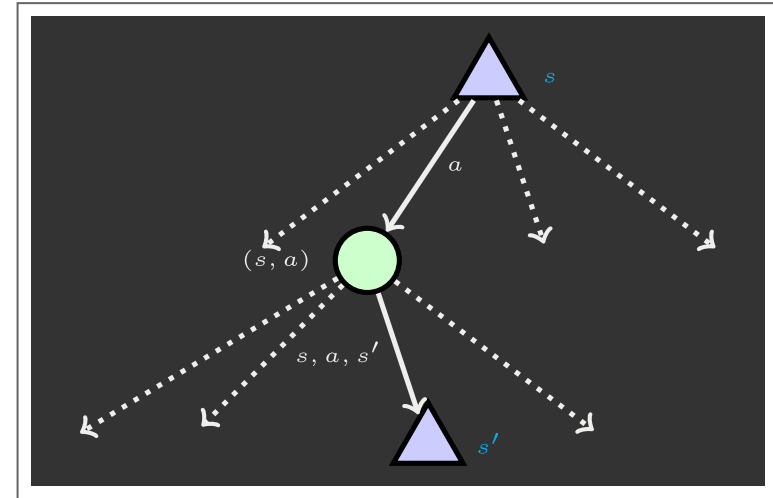
RECAP: DEFINING MDPS

Markov decision processes:

- Set of states \mathcal{S}
- Start state s_0
- Set of actions \mathcal{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





Speaker notes

