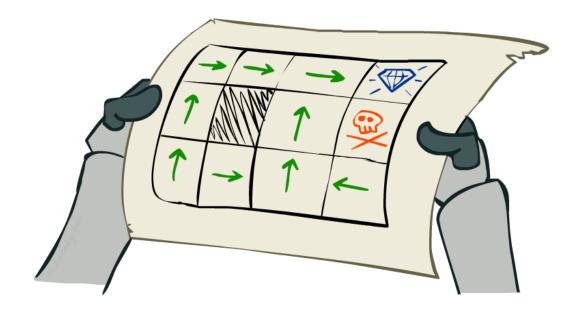
Advanced Topics in Al Solving MDPs





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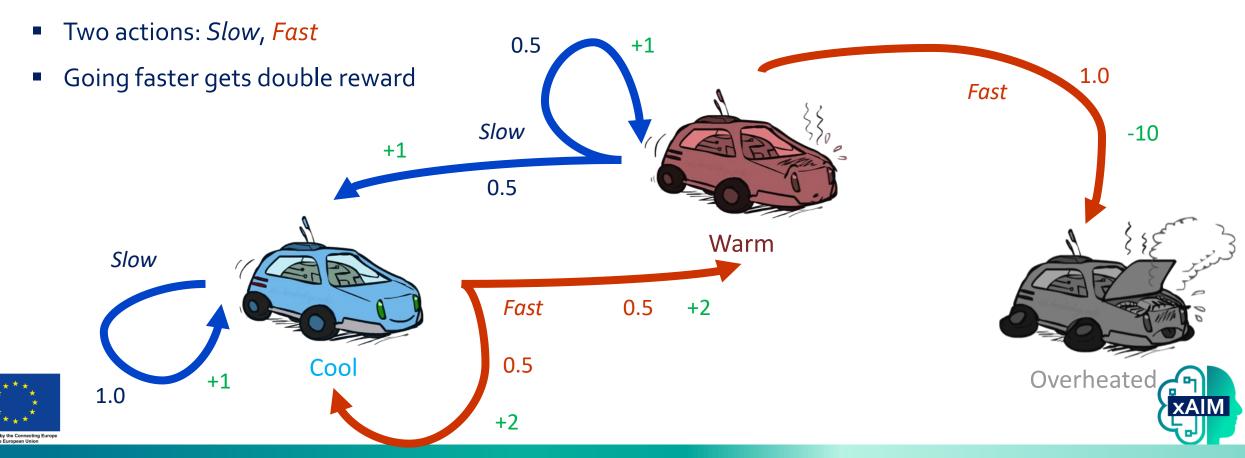
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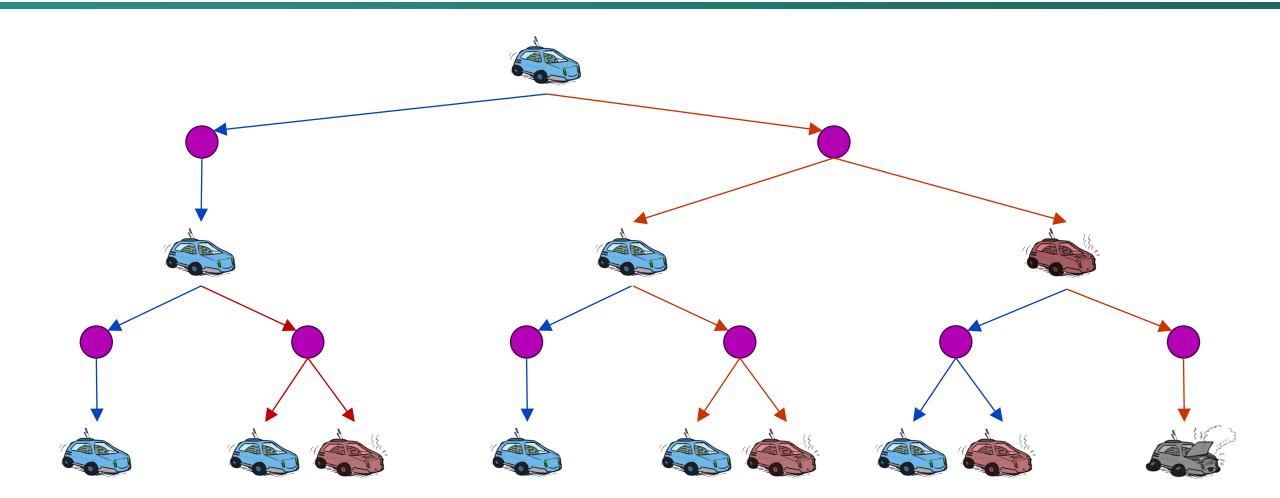
[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All materials are available at http://ai.berkeley.edu.]

Recall: Racing MDP

- A robot car wants to travel far, quickly
- Three states: Cool, Warm, Overheated



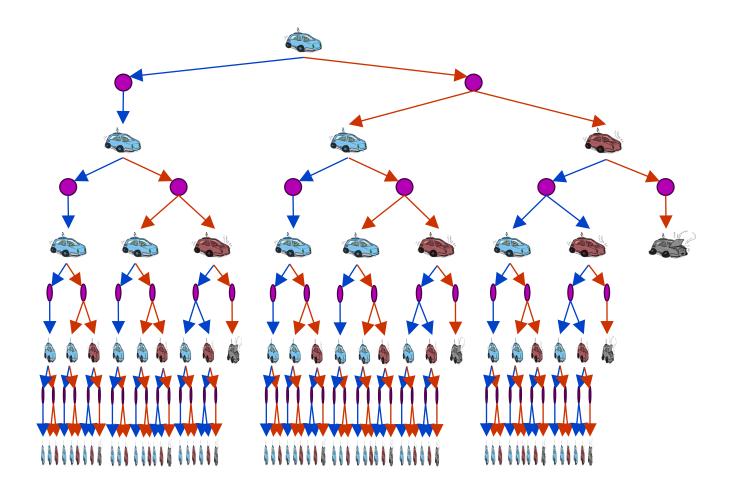
Racing Search Tree







Racing Search Tree

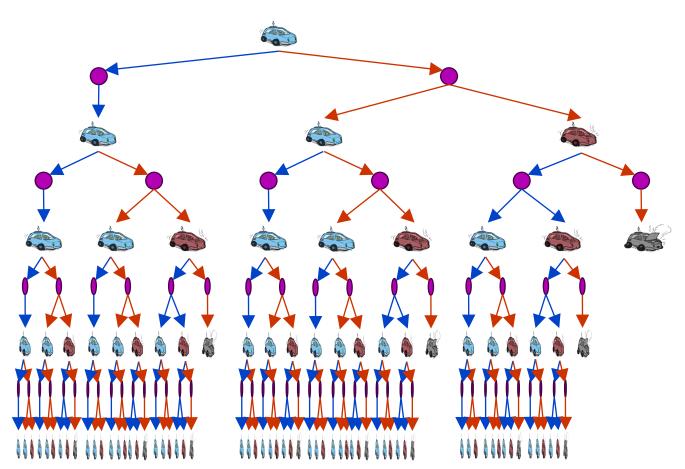






Racing Search Tree

- 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 γ < 1

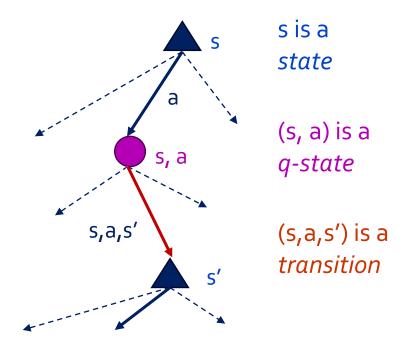






Optimal Quantities

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







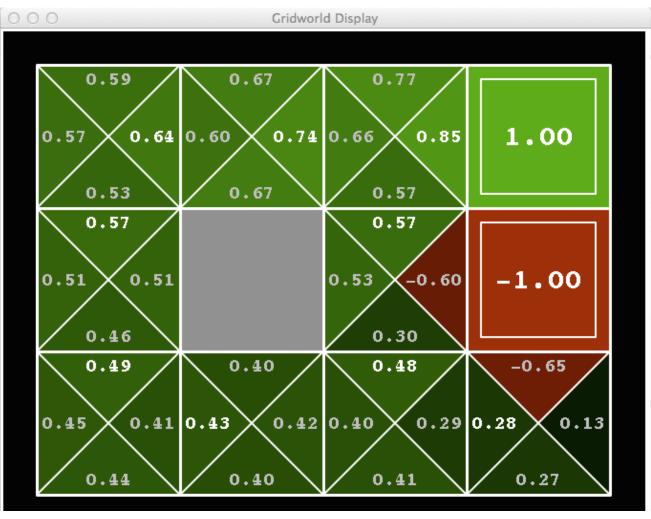
Gridworld V* Values

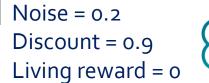
000	Gridworl	d Display	
0.64)	0.74)	0.85)	1.00
• 0.57		• 0.57	-1.00
• 0.49	∢ 0.43	▲ 0.48	∢ 0.28





Gridworld Q* Values

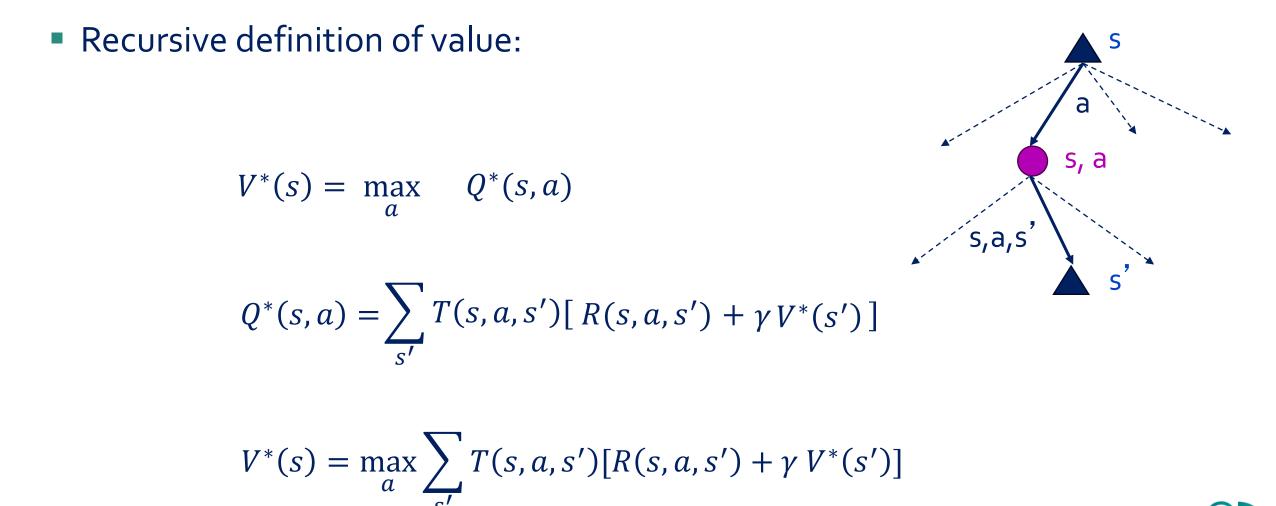




XAIM



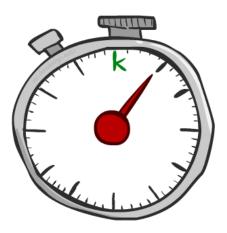
Values of States

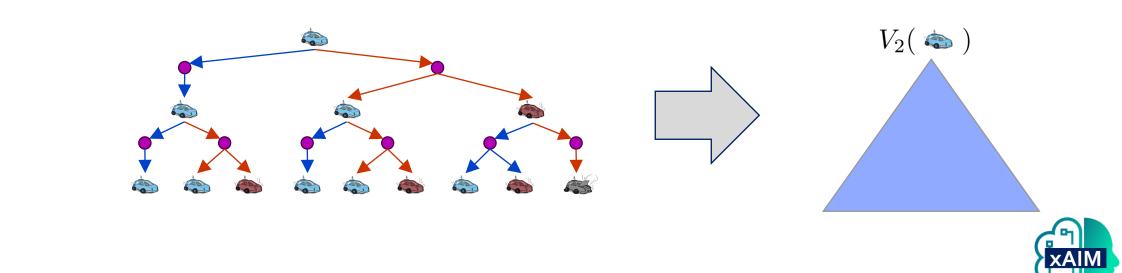




Time-Limited Values

- 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







0	C Cridworld Display			
	^	^	^	
	0.00	0.00	0.00	0.00
	^		^	
	0.00		0.00	0.00
	^	^	^	^
	0.00	0.00	0.00	0.00

VALUES AFTER 0 ITERATIONS





Gridworld Display				
	• 0.00	• 0.00	0.00 >	1.00
	0.00		∢ 0.00	-1.00
	^	^	^	
	0.00	0.00	0.00	0.00
				-

VALUES AFTER 1 ITERATIONS





0	○ ○ Gridworld Display			
	• 0.00	0.00)	0.72)	1.00
	• 0.00		• 0.00	-1.00
	• 0.00	• 0.00	• 0.00	0.00

VALUES AFTER 2 ITERATIONS





C	Gridworld Display			
	0.00)	0.52 →	0.78 ▸	1.00
	• 0.00		• 0.43	-1.00
	▲ 0.00	• 0.00	•	0.00

VALUES AFTER 3 ITERATIONS

Noise = 0.2 Discount = 0.9 Living reward = 0



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k=4

0	0	Gridworl	d Display	-
	0.37 ▸	0.66)	0.83)	1.00
	• 0.00		•	-1.00
	• 0.00	0.00 >	• 0.31	∢ 0.00

VALUES AFTER 4 ITERATIONS

Noise = 0.2 Discount = 0.9 Living reward = 0



00	0	Gridworl	d Display	
	0.51)	0.72)	0.84)	1.00
	▲ 0.27		• 0.55	-1.00
	• 0.00	0.22 →	▲ 0.37	∢ 0.13

VALUES AFTER 5 ITERATIONS





0 0	0	Gridworl	d Display	-
	0.59 →	0.73)	0.85)	1.00
	• 0.41		• 0.57	-1.00
	• 0.21	0.31 →	• 0.43	∢ 0.19

VALUES AFTER 6 ITERATIONS





0 0	Gridworl	d Display	-
0.62 ▸	0.74 →	0.85)	1.00
• 0.50		• 0.57	-1.00
• 0.34	0.36 →	• 0.45	◀ 0.24

VALUES AFTER 7 ITERATIONS





0	0	Gridworl	d Display	
	0.63)	0.74 →	0.85)	1.00
	• 0.53		• 0.57	-1.00
	• 0.42	0.39 →	• 0.46	∢ 0.26

VALUES AFTER 8 ITERATIONS





00	0	Gridworl	d Display	
	0.64 →	0.74 ▸	0.85)	1.00
	• 0.55		• 0.57	-1.00
	▲ 0.46	0.40 →	• 0.47	∢ 0.27

VALUES AFTER 9 ITERATIONS





0 0	C Gridworld Display			
	0.64 →	0.74 →	0.85)	1.00
	• 0.56		• 0.57	-1.00
	▲ 0.48	∢ 0.41	• 0.47	◀ 0.27

VALUES AFTER 10 ITERATIONS





000		Gridworld Display		-
	0.64)	0.74)	0.85)	1.00
	▲ 0.56		▲ 0.57	-1.00
	▲ 0.48	∢ 0.42	• 0.47	∢ 0.27

VALUES AFTER 11 ITERATIONS





Gridworld Display					
0.	64 ♪	0.74 →	0.85)	1.00	
0.			• 0.57	-1.00	
0.	49	◀ 0.42	• 0.47	∢ 0.28	

VALUES AFTER 12 ITERATIONS





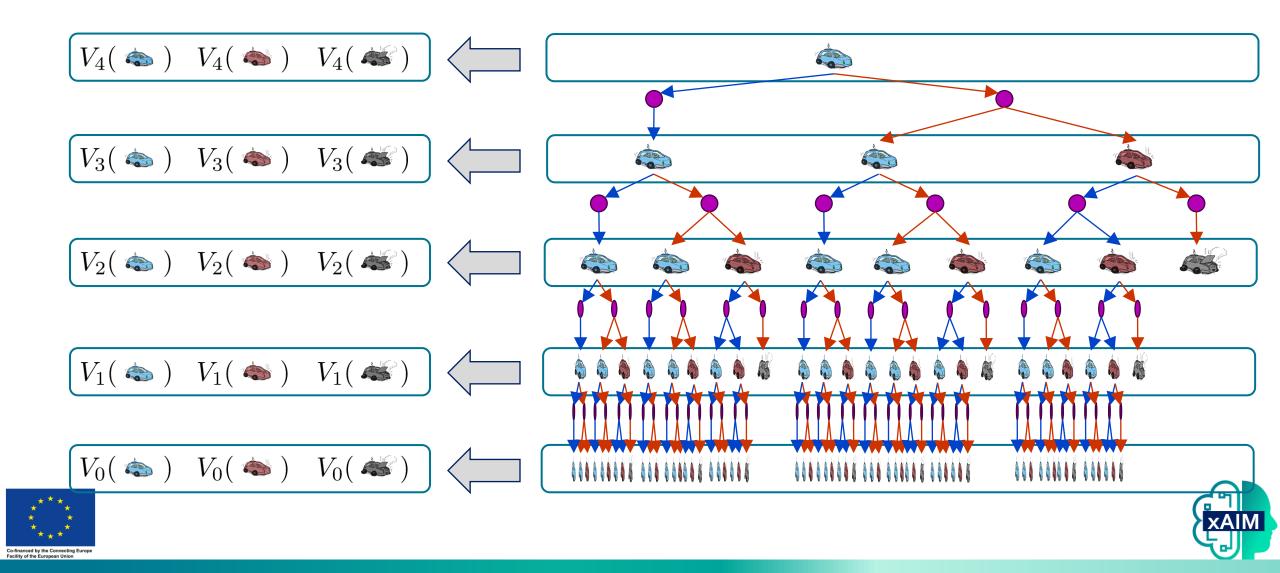
Gridworld Display			
0.64 →	0.74 →	0.85)	1.00
• 0.57		• 0.57	-1.00
• 0.49	∢ 0.43	▲ 0.48	∢ 0.28

VALUES AFTER 100 ITERATIONS



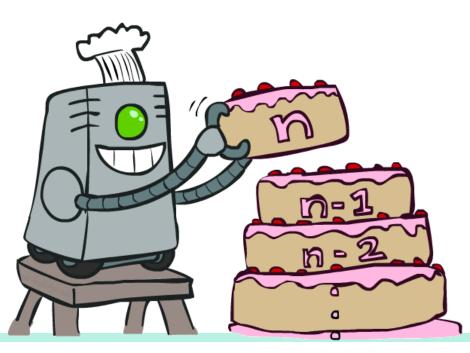


Computing Time-Limited Values



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Next: Value Iteration





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