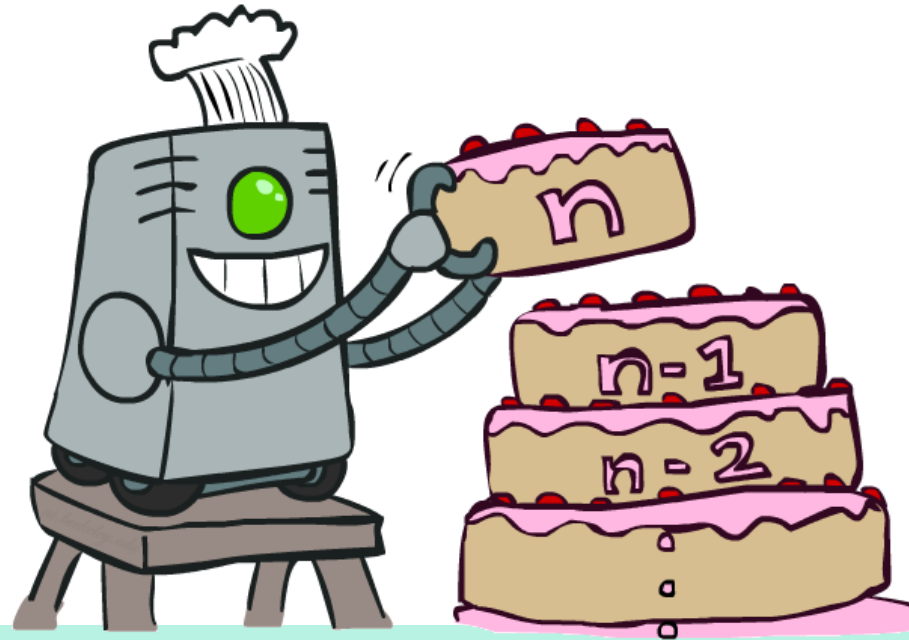


Advanced Topics in AI

Value Iteration



Instructor: Prof. Dr. techn. Wolfgang Nejdl

Leibniz University Hannover



[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>.]



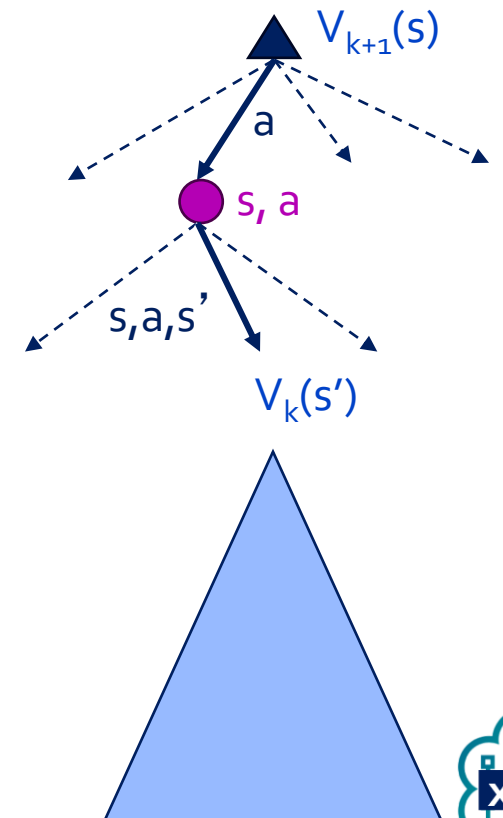
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Value Iteration

- 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, which yields V^*
- 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

V_1

S: 1

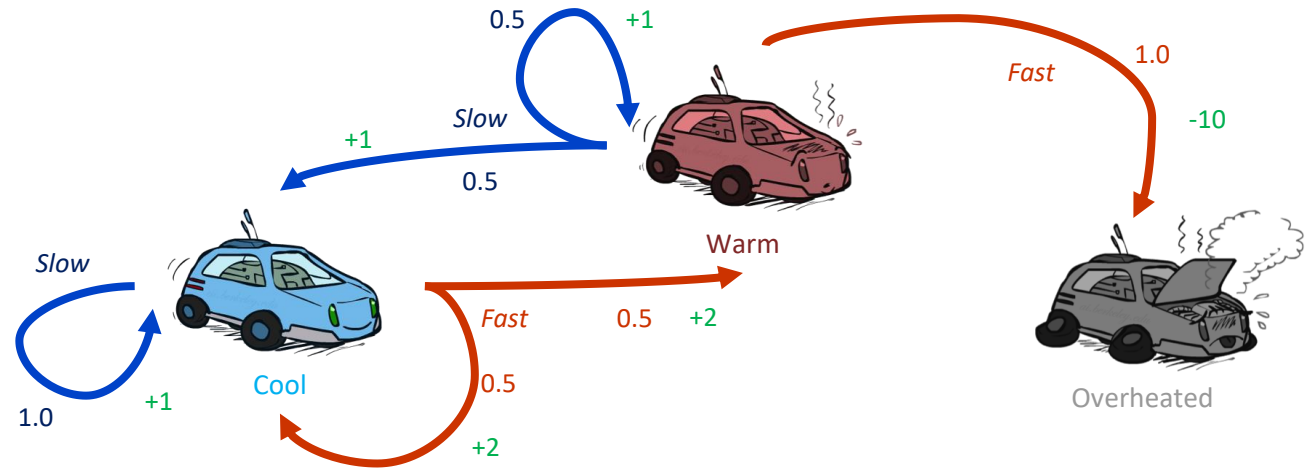
F: $0.5 * 2 + 0.5 * 2 = 2$

V_0

0

0

0



Assume no discount!

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

Example: Value Iteration



V_2



V_1

2

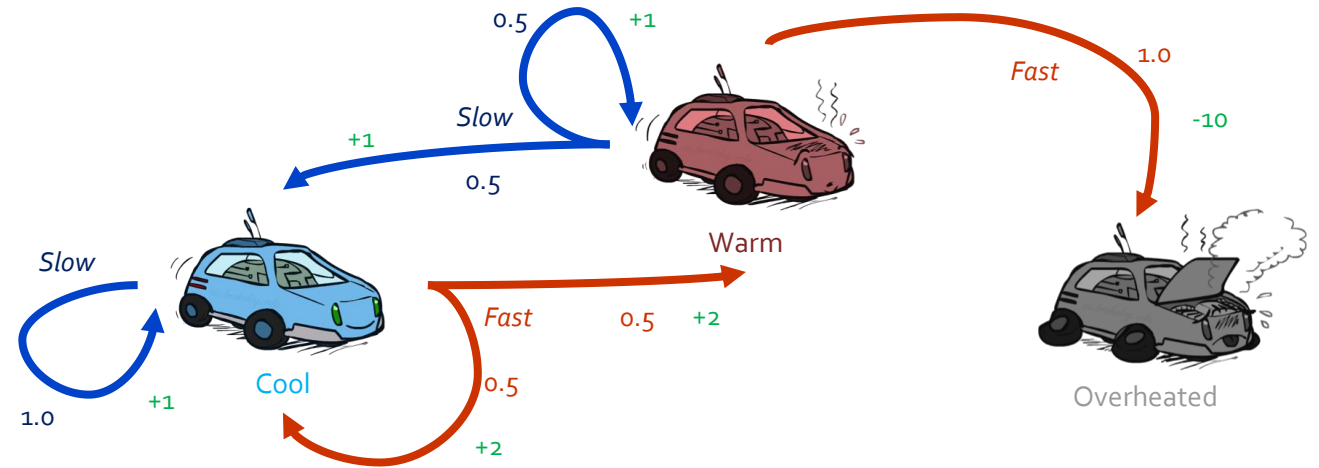
S: $0.5 * 1 + 0.5 * 1 = 1$
F: -10

V_0

0

0

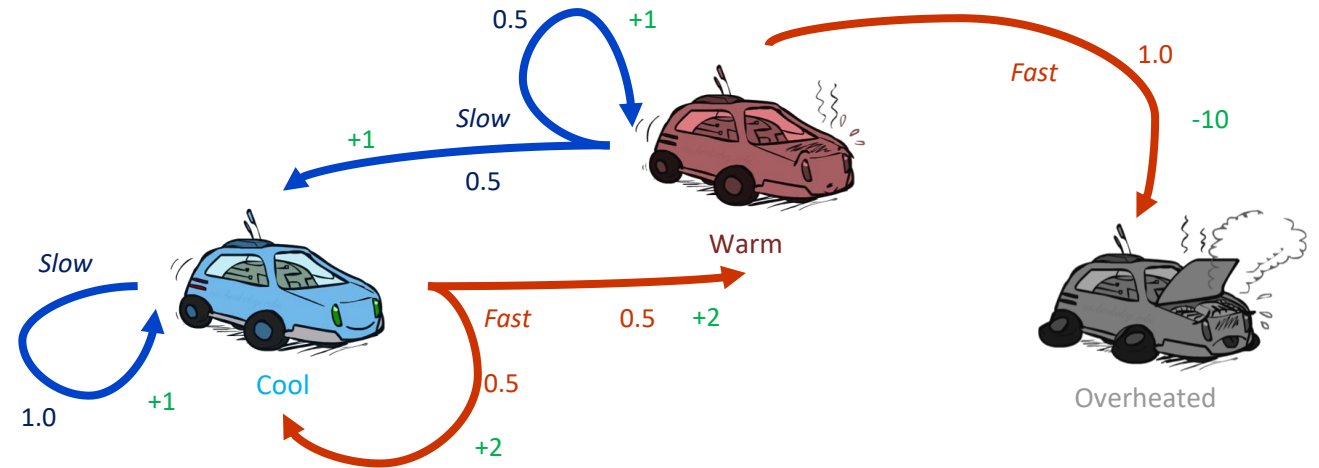
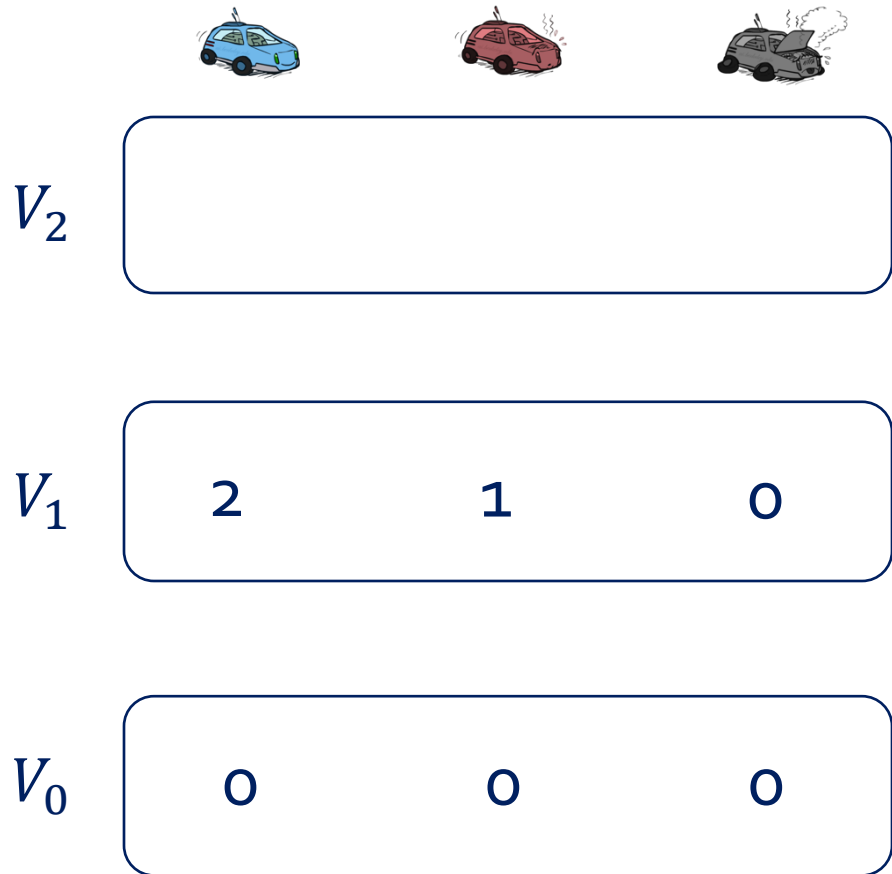
0



Assume no discount!

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

Example: Value Iteration



Assume no discount!

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

Example: Value Iteration



V_2

S: $1+2=3$

F: $0.5*(2+2)+0.5*(2+1)=3.5$

V_1

2

1

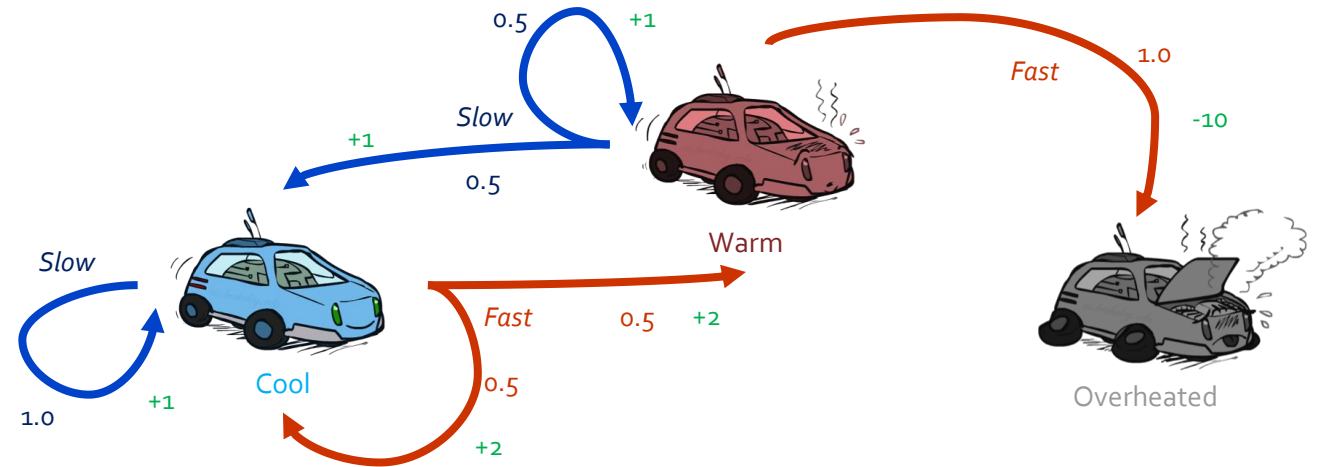
0

V_0

0

0




0

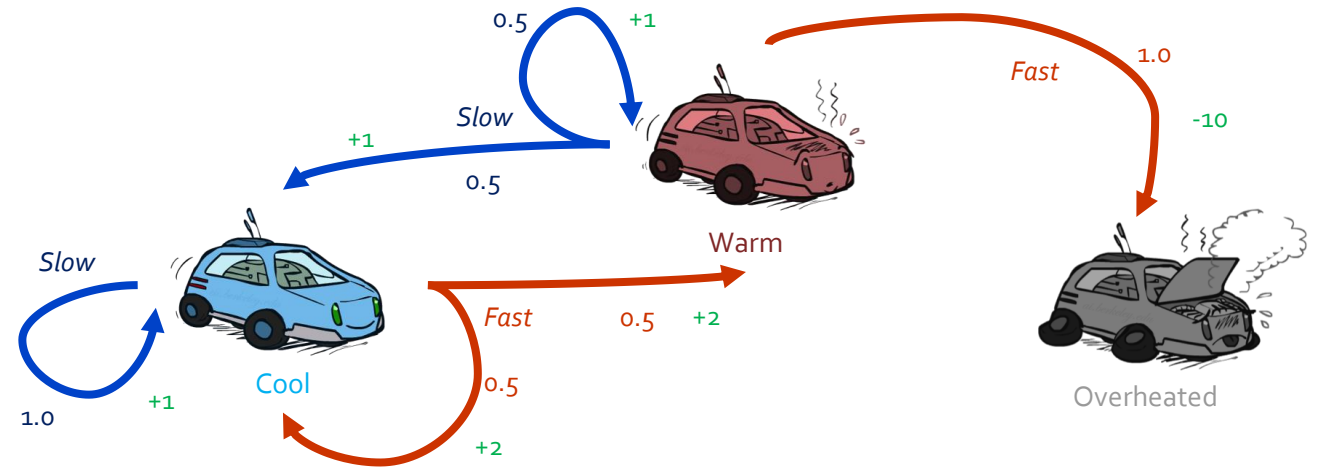


Assume no discount!

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

Example: Value Iteration

			
V_2	3.5	2.5	0
V_1	2	1	0
V_0	0	0	0

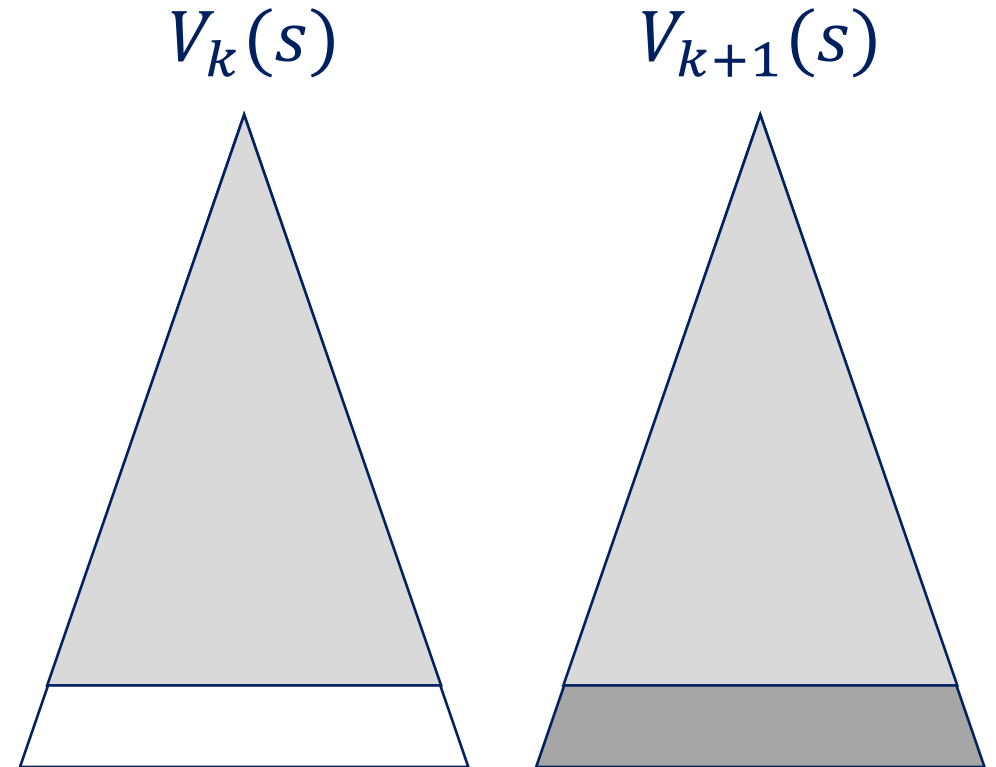


Assume no discount!

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

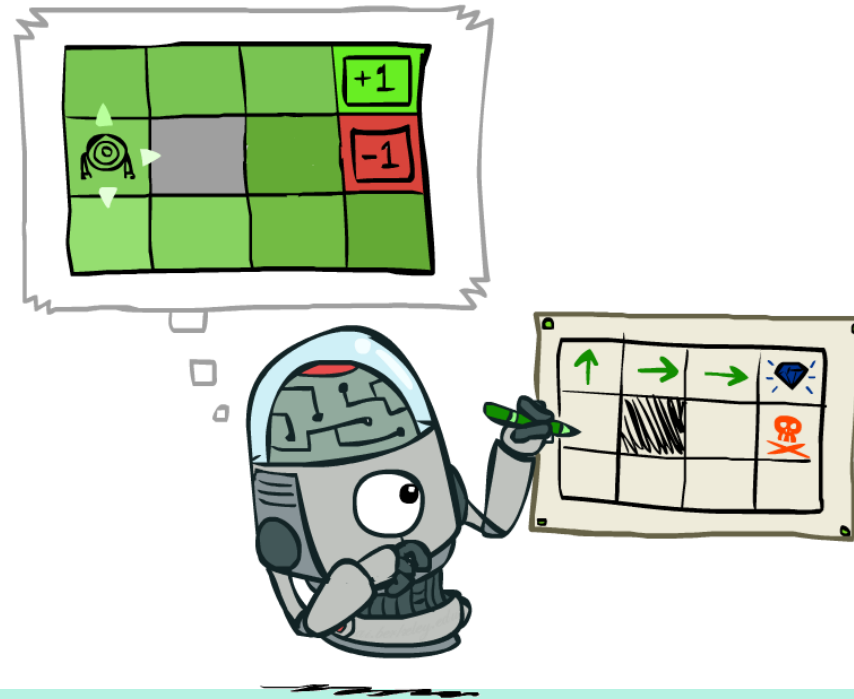
Convergence

- How do we know the V_k vectors are going to converge? (assuming $0 < \gamma < 1$)
- Proof 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 $\gamma^k \max |R|$ different
 - So as k increases, the values converge



Advanced Topics in AI

Next: Policy-based methods



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