Last Time

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- How do we reason about the **future consequences** of actions in an MDP?

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- How do we reason about the **future consequences** of actions in an MDP?
- What are the basic **algorithms for solving MDPs**?

Guiding Questions

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- Does value iteration always converge?
- Is the value function unique?

Value Iteration: The Bellman Operator

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Algorithm: Value Iteration

while $\|V - V'\|_\infty < \epsilon$

$\quad V \leftarrow V'$

$\quad V' \leftarrow B[V]$

return V'

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$$B[V](s) = \max_{a \in A} \left(R(s,a) + \gamma E\left[V(s') \right] \right)$$

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Theorem 1: Let $\{V_1, \ldots, V_\infty\}$ be a sequence of value functions for a discrete MDP generated by the recurrence $V_{k+1} = B[V_k]$. If $\gamma < 1$, then $\lim_{k \to \infty} V_k = V^*$.

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Contraction Mappings

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Definition: A *contraction mapping* on metric space (M, d) is a function $f : M \to M$ satisfying

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Script: contraction_mapping.jl

Banach's Theorem

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$$\|B[V_1] - B[V_2]\|_\infty = \max_{s \in S} |B[V_1](s) - B[V_2](s)|$$

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By Banach's theorem (part 1), $\hat{V} = B[\hat{V}]$. Since $\hat{V}$ satisfies Bellman's equation, it is optimal and $\hat{V} = V^*$.

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3. There are a finite number of possible policies
4. By (1), (2), and (3), the policy will improve until it finds the optimal policy, and it will always find the optimal policy.

Guiding Questions

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- Does value iteration always converge?
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Break

Conservation MDP