CS 747, Autumn 2023: Lecture 6

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Autumn 2023

Markov Decision Problems

1. Definitions
   - Markov Decision Problem
   - Policy
   - Value Function
2. MDP planning
3. Policy evaluation

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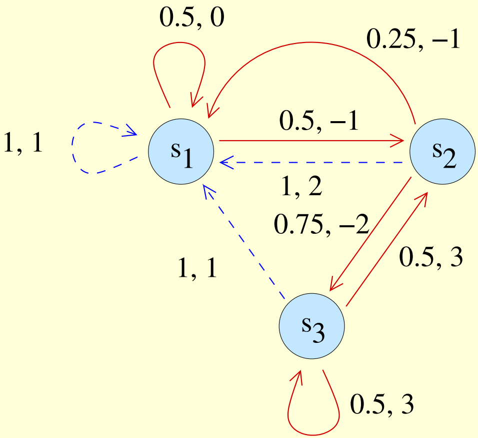
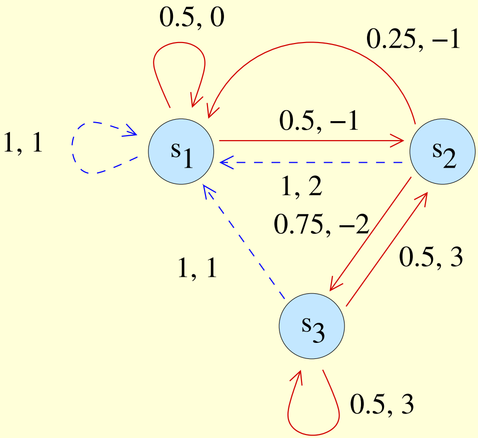
Markov Decision Problems (MDPs)



Markov Decision Problems (MDPs)

Elements of MDP $M = (S, A, T, R, \gamma)$.



S: a set of states.

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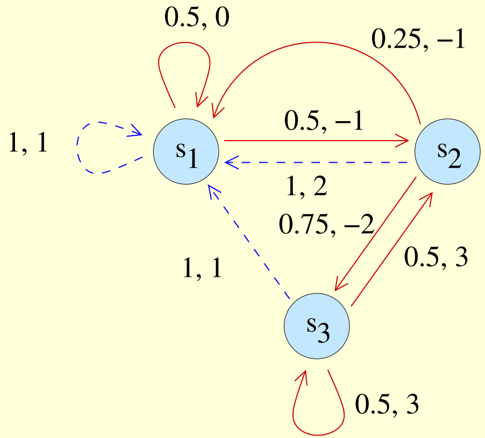

S: a set of states.

Let us assume $S = \{s_1, s_2, \ldots, s_n\}$, and hence $|S| = n$.

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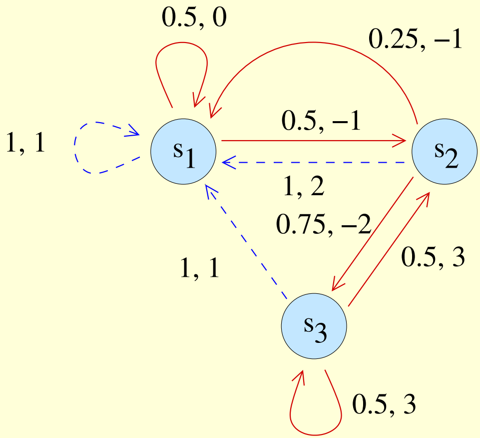
A: a set of actions.



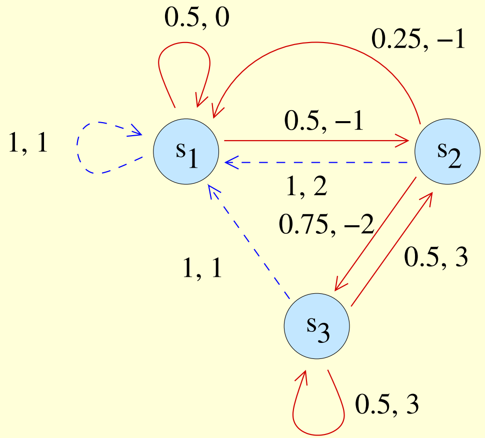
Markov Decision Problems (MDPs)

Elements of MDP $M = (S, A, T, R, \gamma)$.

A: a set of actions.

Let us assume $A = \{a_1, a_2, \ldots, a_k\}$, and hence $|A| = k$.

Here $A = \{\text{RED}, \text{BLUE}\}$.



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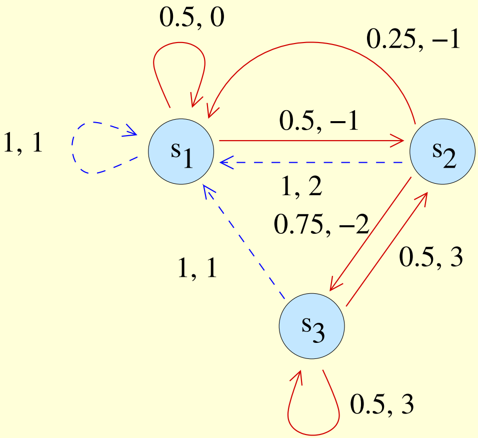
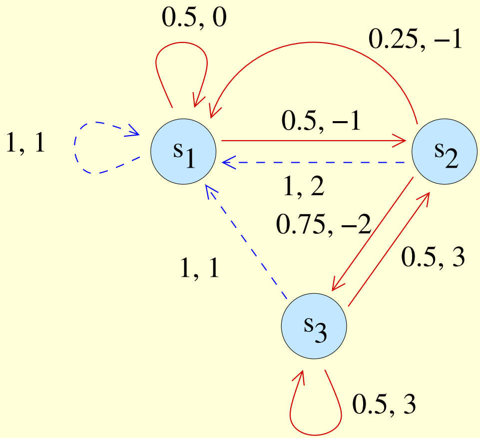


Markov Decision Problems (MDPs)

Elements of MDP $M = (S, A, T, R, \gamma)$.

T: a transition function.

- For $s, s' \in S, a \in A$: $T(s, a, s')$ is the probability of reaching s' by starting at s and taking action a.
- Thus, $T(s, a, \cdot)$ is a probability distribution over S.



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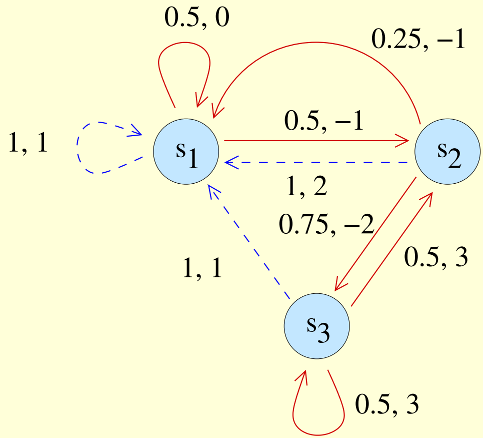
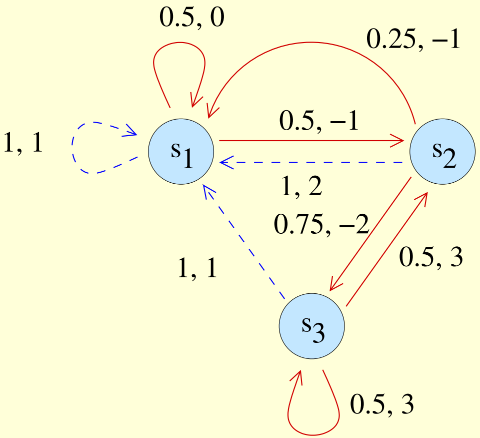


Markov Decision Problems (MDPs)

Elements of MDP $M = (S, A, T, R, \gamma)$.

R: a reward function.

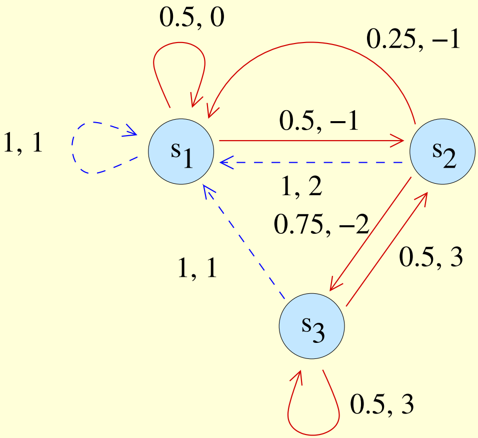
- For $s, s' \in S, a \in A$: $R(s, a, s')$ is the (numeric) reward for reaching s' by starting at s and taking action a.
- Assume rewards are from $[-R_{\max}, R_{\max}]$ for some $R_{\max} \geq 0$.



Markov Decision Problems (MDPs)

Elements of MDP $M = (S, A, T, R, \gamma)$.

γ: a discount factor—coming up.



Agent-Environment Interaction

$t = 0$

Agent is born in some state s^0, takes action a^0.
Environment generates and provides the agent
next state $s^1 \sim T(s^0, a^0, \cdot)$ and
reward $r^0 = R(s^0, a^0, s^1)$.

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$t = 1$

Agent is in state s^1, takes action a^1.
Environment generates and provides the agent
next state $s^2 \sim T(s^1, a^1, \cdot)$ and
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$\vdots$

Resulting trajectory: $s^0, a^0, r^0, s^1, a^1, r^1, s^2, \ldots$.

Describing the Agent’s Behaviour

$$\begin{tikzcd} \text{Agent} \arrow[r, shift left=2, "a^t"] & \text{Environment} \arrow[l, shift left=2, "{r^t, s^{t+1}}"] \end{tikzcd}$$

Describing the Agent's Behaviour

$$\text{Agent} \quad \underset{\xleftarrow{\; r^t,\, s^{t+1} \;}}{\xrightarrow{\; a^t \;}} \quad \text{Environment}$$

- How does the agent pick a^t?

Describing the Agent's Behaviour

$$\text{Agent} \quad \underset{r^t,\, s^{t+1}}{\overset{a^t}{\rightleftarrows}} \quad \text{Environment}$$

- How does the agent pick a^t?
  In principle, it can decide by looking at the preceding history

$$s^0, a^0, r^0, s^1, a^1, r^1, s^2, \ldots, s^t.$$

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  For now let us assume that a^t is picked based on s^t alone.

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- In other words, the agent follows a policy $\pi : S \to A$.

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  Observe that π is Markovian, deterministic, and stationary.

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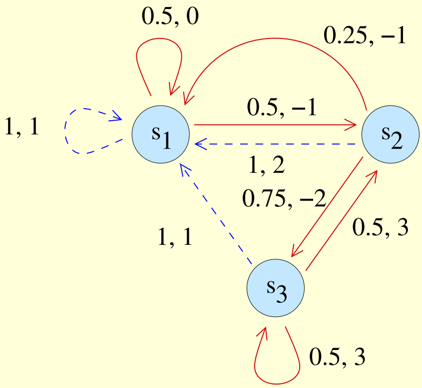
  For now let us assume that a^t is picked based on s^t alone.

- In other words, the agent follows a policy $\pi : S \to A$.
  Observe that π is Markovian, deterministic, and stationary.
  We will justify this choice in due course!

Illustration: Policy



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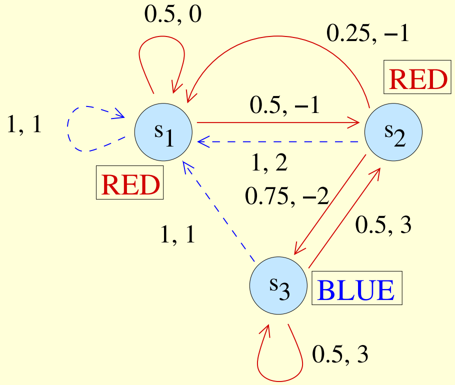
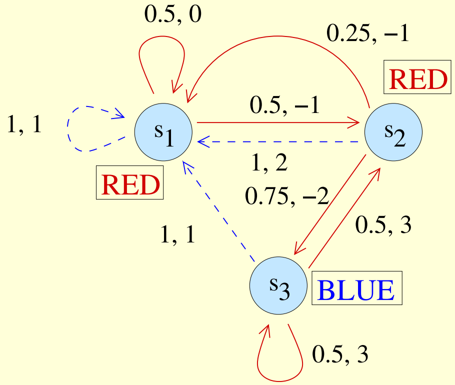


Illustration: Policy

- Illustrated policy π such that

$$\pi(s_1) = \text{RED}; \pi(s_2) = \text{RED}; \pi(s_3) = \text{BLUE}.$$



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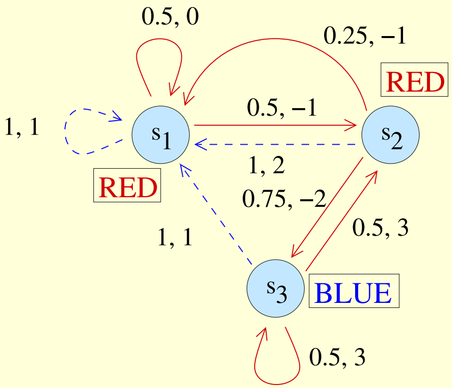
  What happens by "following" π, starting at s_1?



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- Illustrated policy π such that

  $\pi(s_1) =$ RED; $\pi(s_2) =$ RED; $\pi(s_3) =$ BLUE.

  What happens by "following" π, starting at s_1?

- s_1, RED, s_1, RED, s_2, RED, s_3, BLUE, s_1, ...
- s_1, RED, s_2, RED, s_1, RED, s_1, RED, s_1, ...
-

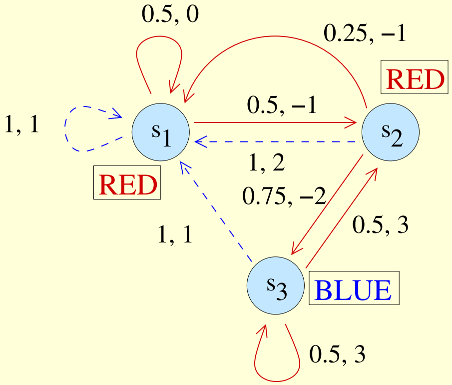
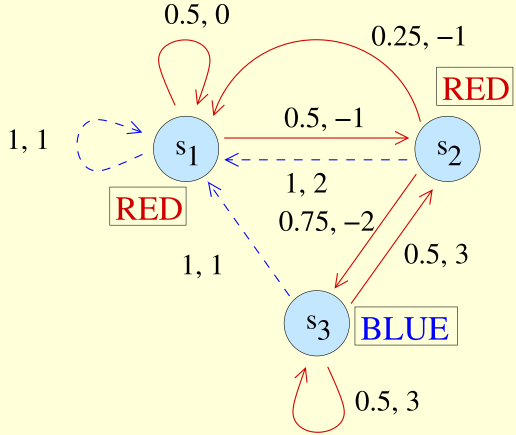


Illustration: Policy

- Let Π denote the set of all policies.



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- Let Π denote the set of all policies.
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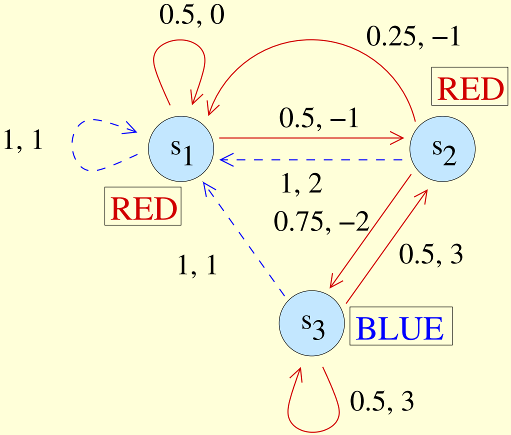

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- Let Π denote the set of all policies.
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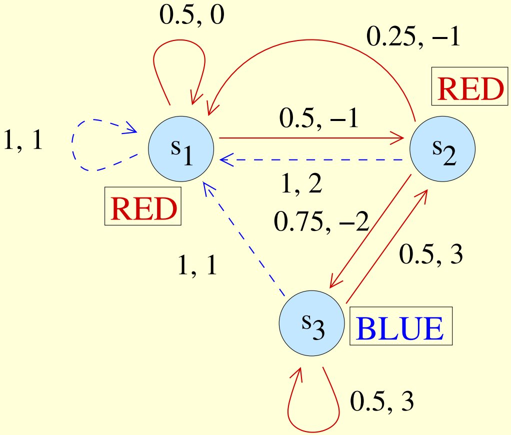

Illustration: Policy

- Let Π denote the set of all policies.
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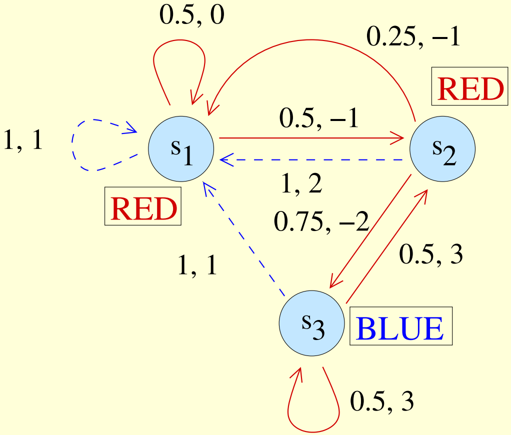
- Which $\pi \in \Pi$ is a "good" policy?



State Values for Policy π

- For $s \in S$, $V^\pi(s) \stackrel{\text{def}}{=} \mathbb{E}_\pi \left[r^0 + \quad r^1 + \quad\quad r^2 + \quad\quad r^3 + \ldots | s^0 = s \right]$,

State Values for Policy π

- For $s \in S$, $V^{\pi}(s) \stackrel{\text{def}}{=} \mathbb{E}_{\pi}\left[r^0 + \gamma r^1 + \gamma^2 r^2 + \gamma^3 r^3 + \ldots | s^0 = s\right]$, where $\gamma \in [0, 1)$ is a discount factor.

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- γ is an element of the MDP.
  Larger γ, farther the "lookahead".

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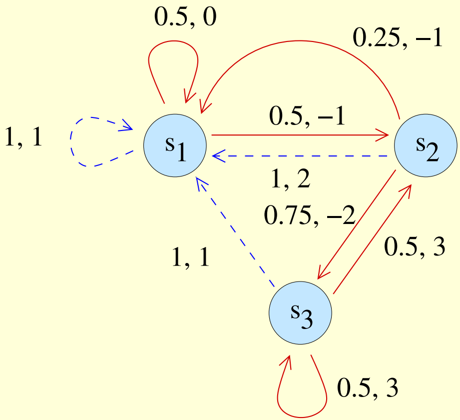

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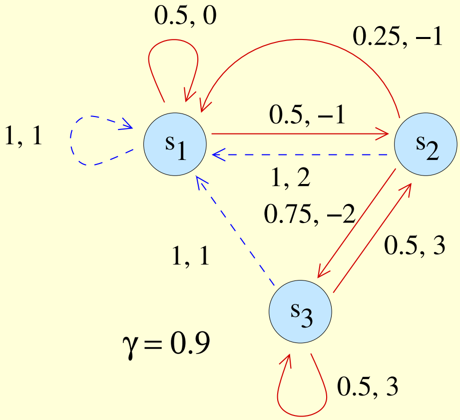

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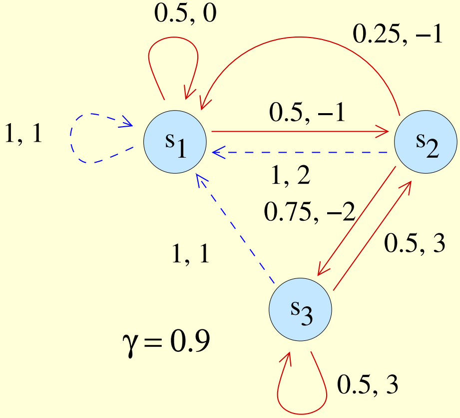
- γ is an element of the MDP. Larger γ, farther the "lookahead".
- $V^\pi(s)$ is the value of state s under policy π.



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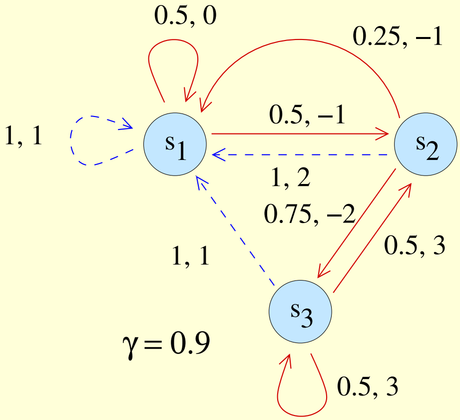
- $V^\pi(s)$ is the value of state s under policy π.

- $V^\pi : S \to \mathbb{R}$ is the value function of π.



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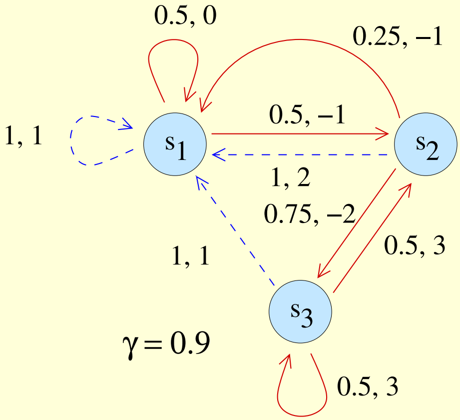
  "Larger is better".



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Optimal Policies

- Here are value functions from our example MDP.

π	$V^{\pi}(s_1)$	$V^{\pi}(s_2)$	$V^{\pi}(s_3)$
RRR	4.45	6.55	10.82
RRB	-5.61	-5.75	-4.05
RBR	2.76	4.48	9.12
RBB	2.76	4.48	3.48
BRR	10.0	9.34	13.10
BRB	10.0	7.25	10.0
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Which policy would you prefer?

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Which policy would you prefer?

Every MDP is guaranteed to have an optimal policy $\pi^{\star}$ s.t.

$$\forall \pi \in \Pi, \forall s \in S : V^{\pi^{\star}}(s) \geq V^{\pi}(s).$$

MDP Planning

MDP Planning problem: Given $M = (S, A, T, R, \gamma)$, find a policy $\pi^\star$ from the set of all policies Π such that $\forall s \in S, \forall \pi \in \Pi$: $V^{\pi^\star}(s) \geq V^{\pi}(s)$.

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- An MDP can have more than one optimal policy.

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- Every MDP is guaranteed to have a deterministic, Markovian, stationary optimal policy.
- An MDP can have more than one optimal policy.
- However, the value function of every optimal policy is the same, unique "optimal value function" $V^\star$.

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Structure of State Values

For $\pi \in \Pi, s \in S$: $V^{\pi}(s) \stackrel{\text{def}}{=} \mathbb{E}_{\pi}[r^0 + \gamma r^1 + \gamma^2 r^2 + \ldots | s^0 = s]$

Structure of State Values

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$$= \sum_{s' \in S} T(s, \pi(s), s') \mathbb{E}_{\pi}[r^0 + \gamma r^1 + \gamma^2 r^2 + \ldots | s^0 = s, s^1 = s']$$

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$$= \sum_{s' \in S} T(s, \pi(s), s') \mathbb{E}_{\pi}[r^0 | s^0 = s, s^1 = s']$$

$$+ \gamma \sum_{s' \in S} T(s, \pi(s), s') \mathbb{E}_{\pi}[r^1 + \gamma r^2 + \dots | s^0 = s, s^1 = s']$$

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Structure of State Values

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$$
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\end{aligned}
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- Policy evaluation: step of computing V^{π} for a given policy π.

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- This approach needs $\text{poly}(n, k) \cdot k^n$ arithmetic operations. We hope to be more efficient (wait for next week).