

Markov Decision Processes

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Sequence of Actions

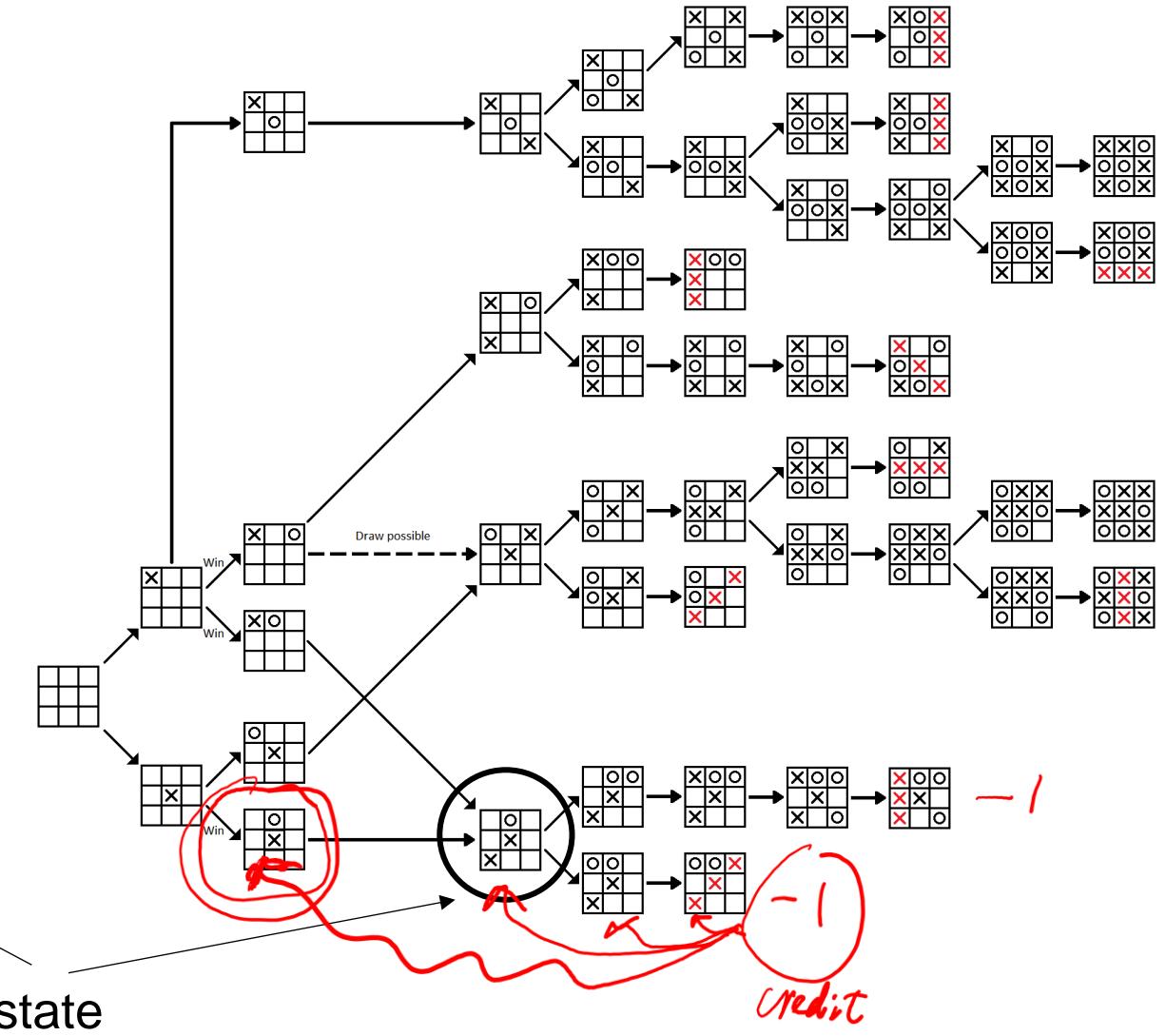


To win the game, the learner has to take a sequence of actions $a_1 \rightarrow a_2 \rightarrow \dots \rightarrow a_H$.

The effect of a particular action may not be revealed instantaneously.

- Some effect may be revealed instantaneously
- Some may be revealed later

Sequence of Actions



Interaction Protocol (Episodic Setting)



For episode $t = 1, 2, \dots, T$:

$$h \leftarrow 1$$

Environment generates initial state $s_{t,1}$

While episode t has not ended:

Learner chooses an action $a_{t,h}$

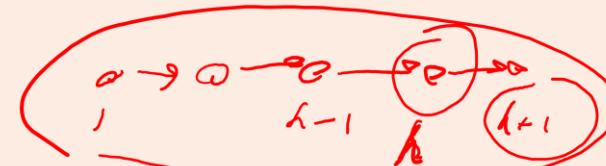
Learner observes instantaneous reward $r_{t,h}$ with $\mathbb{E}[r_{t,h}] = R(s_{t,h}, a_{t,h})$

Environment generates next state $s_{t,h+1} \sim P(\cdot | s_{t,h}, a_{t,h})$

$$h \leftarrow h + 1$$

Markov assumption:

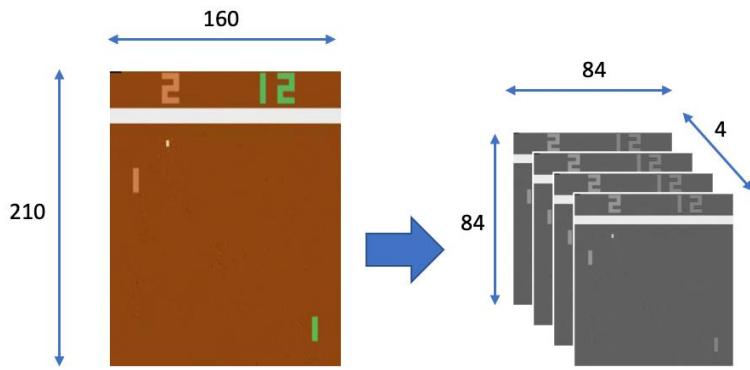
$r_{t,h}$ and $s_{t,h+1}$ are conditionally independent of $(s_{t,1}, a_{t,1}, \dots, s_{t,h-1}, a_{t,h-1})$ given $s_{t,h}$



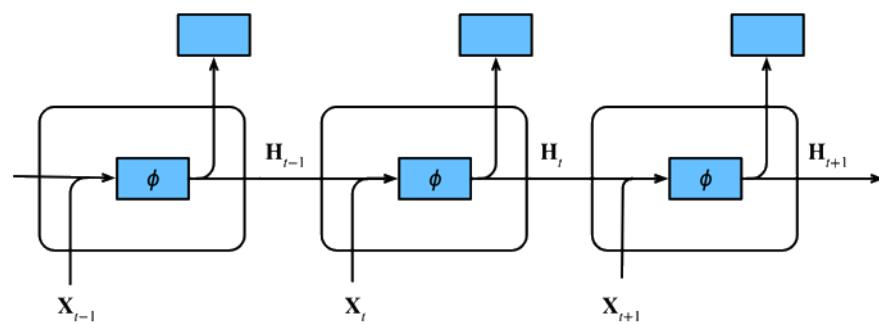
Goal: maximize
$$\sum_{t=1}^T \sum_{h=1}^{\tau_t} R(s_{t,h}, a_{t,h})$$

τ_t : length of episode t

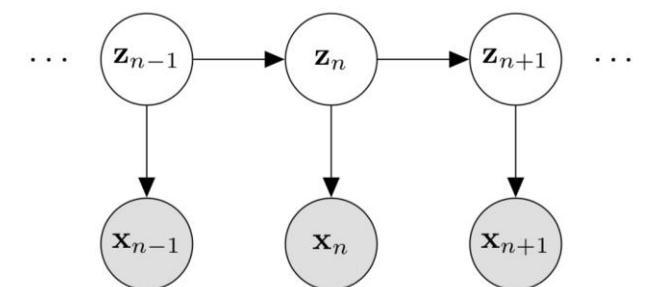
From Observations to States



Stacking recent observations



Recurrent neural network



Hidden Markov model

Regret (Episodic Setting)

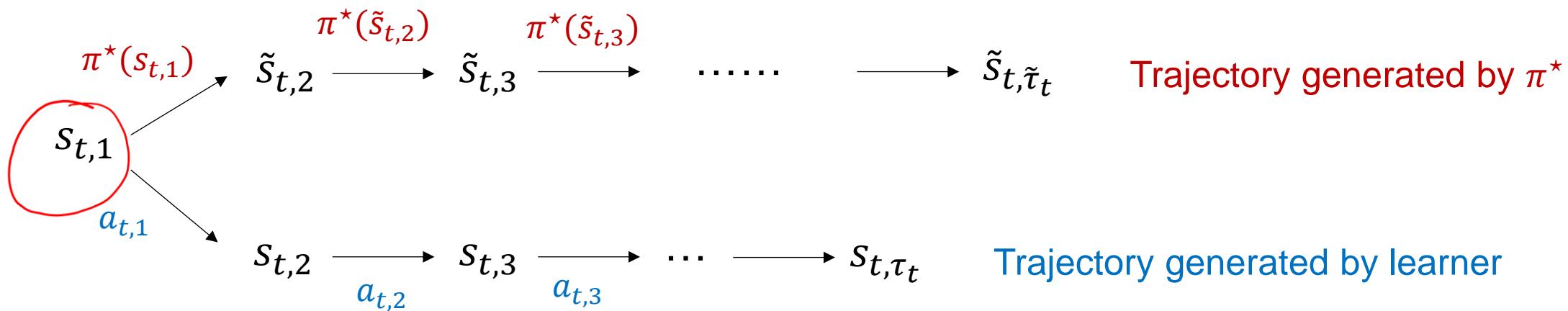
$$\pi^*: S \rightarrow A$$

$$\text{Regret} = \max_{\pi^*} \mathbb{E}^{\pi^*} \left[\sum_{t=1}^T \sum_{h=1}^{\tilde{\tau}_t} R(\tilde{s}_{t,h}, \pi^*(\tilde{s}_{t,h})) \right] - \sum_{t=1}^T \sum_{h=1}^{\tau_t} R(s_{t,h}, a_{t,h})$$

Benchmark

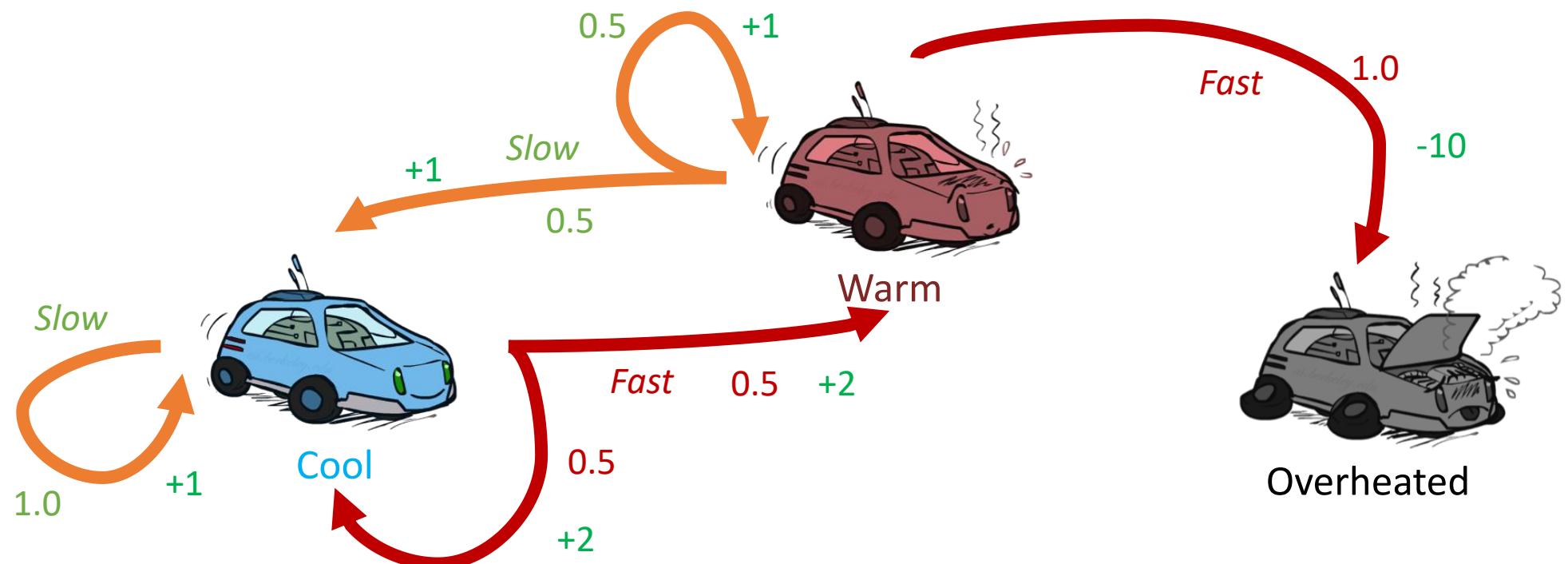
CB

$$\max_{\pi^*} \sum_{t=1}^T R(x_t, \pi^*(x_t)) - \sum_{t=1}^T R(x_t, a_t)$$



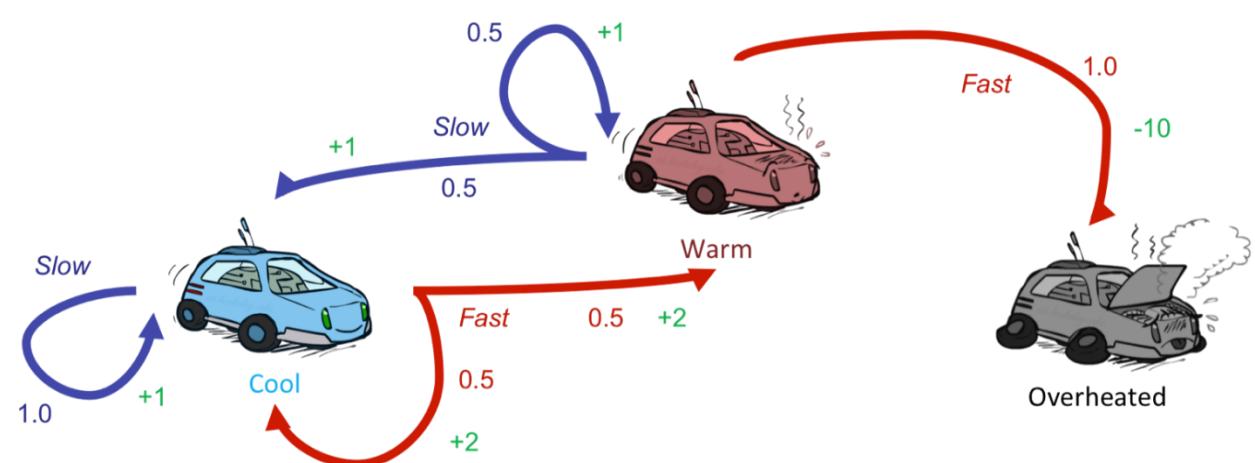
Example: Racing

- A robot car wants to travel far, quickly
- Three states: Cool, Warm, Overheated
- Two actions: Slow, Fast
- Going faster gets double reward



Example: Racing

s	a	s'	$P(s' s, a)$	$R(s, a)$
	Slow		1.0	+1
	Fast		0.5	+2
	Fast		0.5	+2
	Slow		0.5	+1
	Slow		0.5	+1
	Fast		1.0	-10
	(end)		1.0	0



Formulations

- Interaction Protocol
 - Fixed-Horizon
 - Variable-Horizon (Goal-Oriented)
 - Infinite-Horizon
- Performance Metric
 - Total Reward
 - Average Reward
 - Discounted Reward
- Policy
 - Markov policy
 - Stationary policy

Horizon = Length of an episode

Interaction Protocols (1/3): Fixed-Horizon

Horizon length is a fixed number H

$h \leftarrow 1$

Observe initial state $s_1 \sim \rho$

While $h \leq H$:

 Choose action a_h

 Observe reward r_h with $\mathbb{E}[r_h] = R(s_h, a_h)$

 Observe next state $s_{h+1} \sim P(\cdot | s_h, a_h)$

Examples: games with a fixed number of time

Interaction Protocols (2/3): Goal-Oriented

The learner interacts with the environment until reaching **terminal states** $\mathcal{T} \subset \mathcal{S}$

$h \leftarrow 1$

Observe initial state $s_1 \sim \rho$

While $s_h \notin \mathcal{T}$:

 Choose action a_h

 Observe reward r_h with $\mathbb{E}[r_h] = R(s_h, a_h)$

 Observe next state $s_{h+1} \sim P(\cdot | s_h, a_h)$

$h \leftarrow h + 1$

Examples: video games, robotics tasks, personalized recommendations, etc.

Interaction Protocols (3/3): Infinite-Horizon

The learner continuously interacts with the environment

$h \leftarrow 1$

~~Observe initial state $s_1 \sim \rho$~~

Loop forever:

Choose action a_h

Observe reward r_h with $\mathbb{E}[r_h] = R(s_h, a_h)$

Observe next state $s_{h+1} \sim P(\cdot | s_h, a_h)$

$h \leftarrow h + 1$

Examples: network management, inventory management

Formulations

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Performance Metric

Total Reward (for episodic setting):

$$\sum_{h=1}^{\tau} r_h$$

(τ : the step where the episode ends)

Average Reward (for infinite-horizon setting):

$$\lim_{H \rightarrow \infty} \frac{1}{H} \sum_{h=1}^H r_h$$

Discounted Total Reward (for episodic or infinite-horizon):

$$\sum_{h=1}^{\tau} \gamma^{h-1} r_h$$

τ : the step where the episode ends, or ∞ in the infinite-horizon case

$\gamma \in [0,1)$: discount factor

$$\underline{\gamma = 0.99}$$

Interaction Protocols vs. Performance Metrics

	“natural” objective	
Fixed-Horizon	----->	Total Reward
Goal-Oriented	----->	Total Reward Could be unbounded
Infinite-horizon	----->	Average Reward Could have constant change for an infinitesimal change in policy

Discounted Total Reward?
Focusing more on the **recent** reward

There is a potential mismatch between our ultimate goal and what we optimized.

Formulations

- Interaction Protocol
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 - Infinite-Horizon
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Policy for MDPs

$$\pi = (\underbrace{\pi_1, \pi_2, \dots, \pi_H, \dots}_{\uparrow})$$

Markov Policy

$$a_h \sim \pi_h(\cdot | s_h) \in \Delta_A$$
$$a_h = \pi_h(s_h) \in A$$

h : step index

(space of dist)

For **fixed-horizon** setting, there exists an optimal policy in this class



Stationary Policy \subseteq Markov Policy

$$a_h \sim \pi(\cdot | s_h)$$
$$a_h = \pi(s_h)$$

For **infinite-horizon/goal-oriented** settings, there exists an optimal policy in this class



✗ Fixed-horizon (Markov Policy) (total reward)

✓ Goal-oriented (Stationary Policy) (Discounted reward)

A stationary policy specifies

$$\pi(\text{Slow} \mid \text{Cool})$$

$$\pi(\text{Fast} \mid \text{Cool})$$

$$\pi(\text{Slow} \mid \text{Warm})$$

$$\pi(\text{Fast} \mid \text{Warm})$$

A Markov policy specifies

$$\pi_h(\text{Slow} \mid \text{Cool})$$

$$\pi_h(\text{Fast} \mid \text{Cool})$$

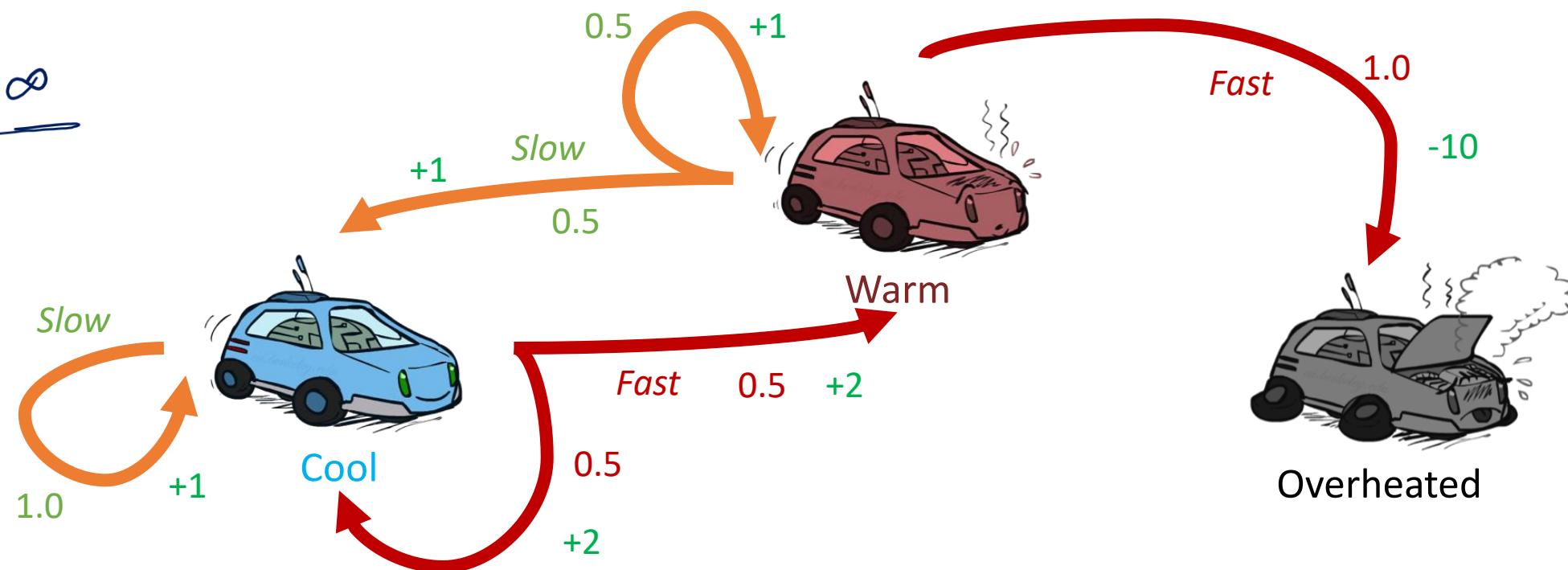
$$\pi_h(\text{Slow} \mid \text{Warm})$$

$$\pi_h(\text{Fast} \mid \text{Warm})$$

$$\forall h$$

$$H=5$$

$$H=\infty$$

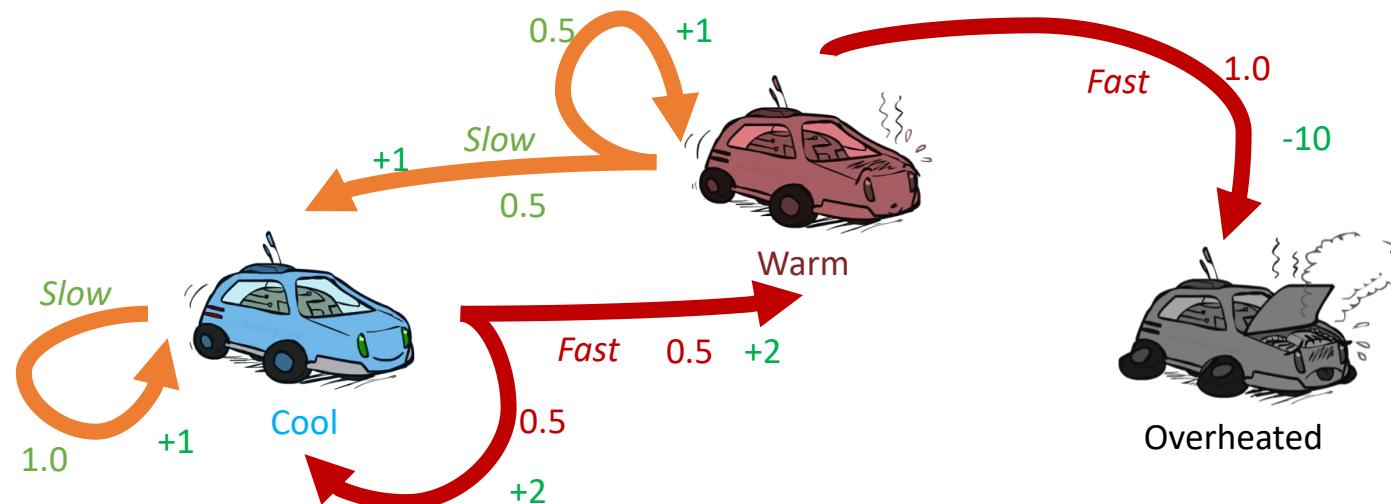


Value Iteration

(Fixed-Horizon)

Two Tasks

- Policy Evaluation:** Calculate the expected total reward of a given policy
What is the expected total reward for the policy $\pi(\text{cool}) = \text{fast}$, $\pi(\text{warm}) = \text{slow}$?
- Policy Optimization:** Find the best policy
What is the policy that achieves the highest expected total reward?

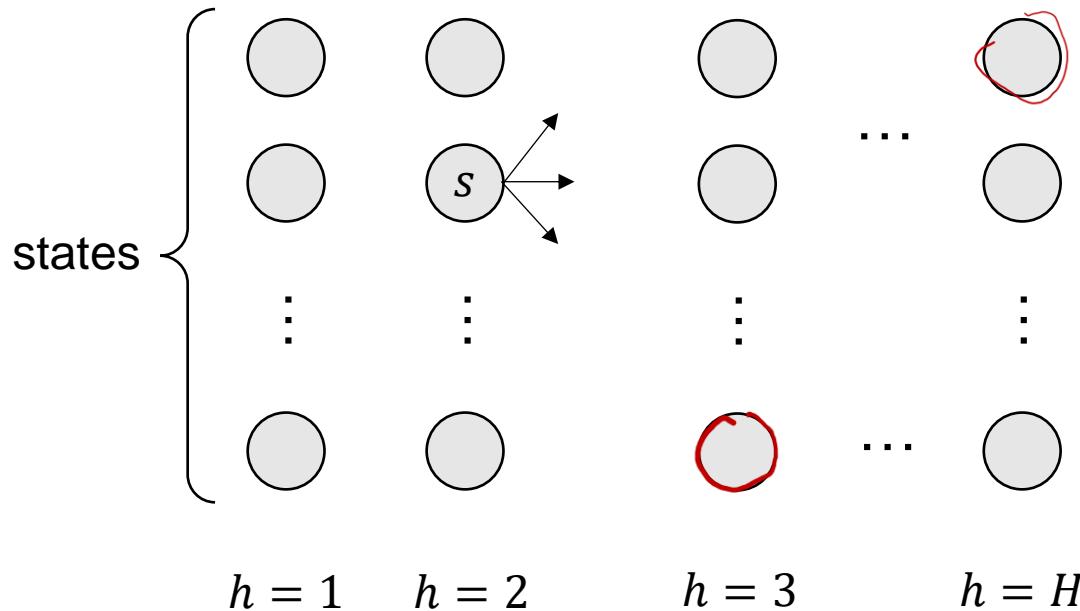


Value Iteration for Policy Evaluation

$$\pi = (\pi_1, \dots, \pi_H)$$

$$\mathbb{E}^\pi \left[\sum_{h=1}^H R(s_t, a_t) \right]$$

$$Q_h^\pi(s, a) = \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid (s_h, a_h) = (s, a) \right]$$



State transition: $P(s'|s, a)$

Reward: $R(s, a)$

$\boxed{V_1(s)}$

expected future
 $= \sum_s p(s) V_1(s)$

$$V_h^\pi(s) = \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid s_h = s \right] \quad R(s, a)$$

Backward induction:

$$Q_H^\pi(s, a) = R(s, a)$$

$$V_{H+1}^\pi(s) = 0 \quad \forall s$$

For $h = H, \dots, 1$: for all s, a

$$Q_h^\pi(s, a) = R(s, a) + \underbrace{\sum_{s'} P(s'|s, a) V_{h+1}^\pi(s')}_{\text{Expected total reward of } \pi \text{ from step } h+1}$$

$$V_h^\pi(s) = \sum_a \pi_h(a|s) Q_h^\pi(s, a)$$

Bellman Equation

Q_h^π is called “the state-action value functions of policy π ”

V_h^π is called “the state value function of policy π ”

Both can be just called “**value functions**”

$$Q_h^\pi(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) V_{h+1}^\pi(s')$$

$$V_h^\pi(s) = \sum_a \pi_h(a|s) Q_h^\pi(s, a)$$

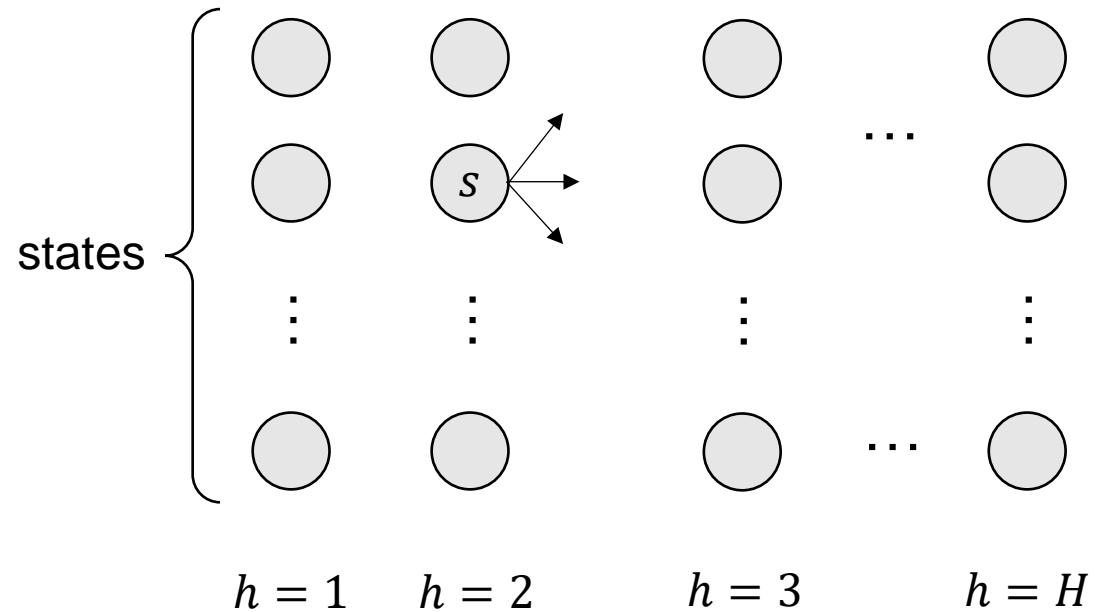
or

$$Q_h^\pi(s, a) = R(s, a) + \sum_{s', a'} P(s'|s, a) \pi_{h+1}(a'|s') Q_{h+1}^\pi(s', a')$$

or

$$V_h^\pi(s) = \sum_a \pi_h(a|s) \left(R(s, a) + \sum_{s'} P(s'|s, a) V_{h+1}^\pi(s') \right)$$

Value Iteration for Policy Optimization



State transition: $P(s'|s, a)$

Reward: $R(s, a)$

$$Q_h^*(s, a) = \max_{\pi \in \Pi_M} \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid (s_h, a_h) = (s, a) \right]$$

$$V_h^*(s) = \max_{\pi \in \Pi_M} \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid s_h = s \right]$$

Backward induction:

$$V_{H+1}^*(s) = 0 \quad \forall s$$

For $h = H, \dots, 1$: for all s, a

$$Q_h^*(s, a) = R(s, a) + \underbrace{\sum_{s'} P(s'|s, a) V_{h+1}^*(s')}_{\text{Expected optimal total reward from step } h+1}$$

$$V_h^*(s) = \max_a Q_h^*(s, a) \quad \pi_h^*(s) = \operatorname{argmax}_a Q_h^*(s, a)$$

Exercise

s	a	s'	$P(s' s, a)$	$R(s, a)$
	Slow		1.0	+1
	Fast		0.5	+2
	Fast		0.5	+2
	Slow		0.5	+1
	Slow		0.5	+1
	Fast		1.0	-10
	(end)		1.0	0

$$Q_3^*(s, a) = R(s, a)$$

$$Q_3^*(\text{cool, slow}) = 1$$

$$Q_3^*(\text{cool, fast}) = 2$$

$$Q_3^*(\text{warm, slow}) = 1$$

$$Q_3^*(\text{warm, fast}) = -10 \quad \}$$

$$V_3^*(s)$$

$$\underline{V_3^*(\text{cool}) = 2} \quad \boxed{}$$

$$V_3^*(\text{warm}) = 1 \quad \boxed{}$$

$$Q_2^*(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) V_3^*(s') \quad \checkmark$$

$$Q_2^*(\text{cool, slow}) = 1 + V_3^*(\text{cool}) = 3$$

$$Q_2^*(\text{cool, fast}) = 2 + 0.5 V_3^*(\text{cool}) + 0.5 V_3^*(\text{warm}) = 3.5$$

$$Q_2^*(\text{warm, slow}) = 1 + 0.5 V_3^*(\text{cool}) + 0.5 V_3^*(\text{warm}) = 2.5$$

$$Q_2^*(\text{warm, fast}) = -10$$

$$V_2^*(s)$$

$$V_2^*(\text{cool}) = 3.5 \quad \pi_2^*(\text{cool}) \approx \text{fast}$$

$$V_2^*(\text{warm}) = 2.5 \quad \pi_2^*(\text{warm}) \approx \text{slow}$$

Assume $H = 3$

Bellman Optimality Equation

Q_h^* : optimal state-action value functions
 V_h^* : optimal state value functions
or “optimal value functions”

$$Q_h^*(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) V_{h+1}^*(s')$$

$$V_h^*(s) = \max_a Q_h^*(s, a)$$

or

$$Q_h^*(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) \left(\max_{a'} Q_{h+1}^*(s', a') \right)$$

or

$$V_h^*(s) = \max_a \left(R(s, a) + \sum_{s'} P(s'|s, a) V_{h+1}^*(s') \right)$$

$$\pi_h^*(s) = \operatorname{argmax}_a Q_h^*(s, a)$$

Recall: Regret

$$\text{Regret} = \max_{\pi^*} \mathbb{E}^{\pi^*} \left[\sum_{t=1}^T \sum_{h=1}^{\tilde{\tau}_t} R(\tilde{s}_{t,h}, \pi^*(\tilde{s}_{t,h})) \right] - \sum_{t=1}^T \sum_{h=1}^{\tau_t} R(s_{t,h}, a_{t,h})$$

$$\mathbb{E}[\text{Regret}] = \mathbb{E} \left[\sum_{t=1}^T \left(\underline{V_1^*(s_{t,1})} - \underline{V_1^{\pi_t}(s_{t,1})} \right) \right]$$

$$= \mathbb{E} \left[\sum_{t=1}^T \left(\underline{V_1^*(\rho)} - \underline{\underline{V_1^{\pi_t}(\rho)}} \right) \right]$$

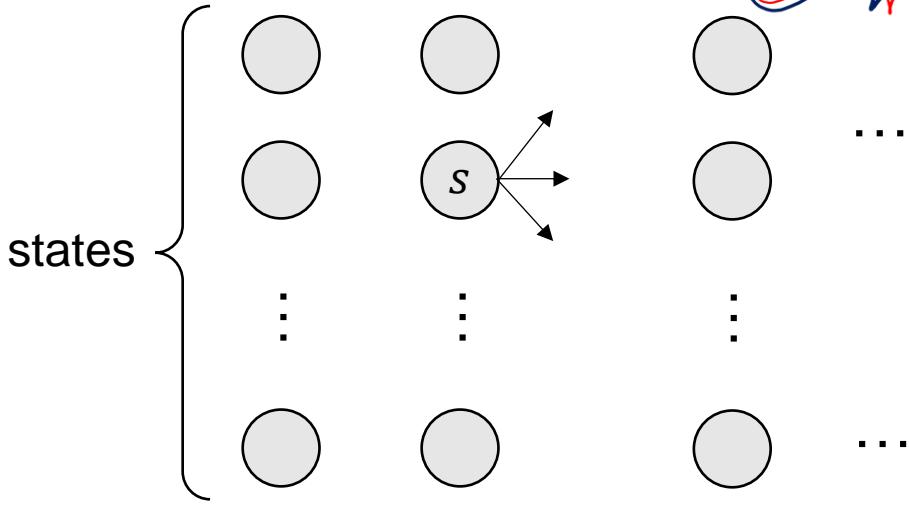
$$\boxed{V_1^\pi(\rho) \triangleq \mathbb{E}_{s \sim \rho}[V_1^\pi(s)]}$$

$$\underline{s_{t,1}} \sim \rho$$

Value Iteration

(Discounted Variable-Horizon)

Value Iteration for Policy Evaluation



$$\begin{array}{ccc} h = 1 & h = 2 & h = 3 \\ \text{weight} & 1 & \gamma \\ & & \gamma^2 \end{array}$$

State transition: $P(s'|s, a)$

Reward: $R(s, a)$

$$Q_i^\pi(s, a) = R(s, a) + \mathbb{E} \left[\gamma \sum_{h=2}^i R(s_h, a_h) \mid s_2 \sim P(\cdot | s, a) \right]$$

$$Q_i^\pi(s, a) = \mathbb{E}^\pi \left[\sum_{h=1}^i \gamma^{h-1} R(s_h, a_h) \mid (s_1, a_1) = (s, a) \right]$$

$$V_i^\pi(s) = \mathbb{E}^\pi \left[\sum_{h=1}^i \gamma^{h-1} R(s_h, a_h) \mid s_1 = s \right]$$

For fixed horizon
 $i = (H+1) - h$

$$Q^\pi(s, a) = Q_\infty^\pi(s, a) \quad V^\pi(s) = V_\infty^\pi(s)$$

$$V_0^\pi(s) = 0 \quad \forall s \quad \boxed{V_{H+1}^\pi(s) = 0} \quad \text{fixed horizon}$$

For $i = 1, 2, 3, \dots$: for all s, a

$$Q_i^\pi(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V_{i-1}^\pi(s')$$

$$V_i^\pi(s) = \sum_a \pi(a|s) Q_i^\pi(s, a)$$

If $|Q_i^\pi(s, a) - Q_{i-1}^\pi(s, a)| \leq \epsilon$ for all s, a : **terminate**

$$\underline{Q(s, a)} \approx \underline{Q_i^\pi(s, a)}$$

$$\left\{
 \begin{aligned}
 Q^{\pi}(s, a) &= \mathbb{E}^{\pi} \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_1 = s, a_1 = a \right] \\
 V^{\pi}(s) &= \mathbb{E}^{\pi} \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_1 = s \right] = \sum_a \pi(a|s) \mathbb{E}^{\pi} \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_1 = s, a_1 = a \right] \\
 Q^{\pi}(s, a) &= R(s, a) + \mathbb{E}^{\pi} \left[\sum_{h=2}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_2 \sim p(\cdot|s, a) \right] = \sum_a \pi(a|s) Q^{\pi}(s, a) \\
 &= R(s, a) + \gamma \sum_{s'} p(s'|s, a) \mathbb{E}^{\pi} \left[\sum_{h=2}^{\infty} \gamma^{h-2} R(s_h, a_h) \mid s_2 = s' \right] \\
 &= R(s, a) + \gamma \sum_{s'} p(s'|s, a) \mathbb{E}^{\pi} \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_1 = s' \right] \\
 &= R(s, a) + \gamma \sum_{s'} p(s'|s, a) V^{\pi}(s')
 \end{aligned}
 \right.$$

Bellman Equation

$$\hat{Q}^\pi(s, a) = Q_\infty^\pi(s, a)$$

$$\underset{s \sim p}{\mathbb{E}} [V^\pi(s)]$$

$$Q^\pi(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^\pi(s')$$

$$V^\pi(s) = \sum_a \pi(a|s) Q^\pi(s, a)$$

or

$$Q^\pi(s, a) = R(s, a) + \gamma \sum_{s', a'} P(s'|s, a) \pi(a'|s') Q^\pi(s', a')$$

or

$$V^\pi(s) = \sum_a \pi(a|s) \left(R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^\pi(s') \right)$$

Convergence

$$\nexists \left| Q_i^\pi(s, a) - Q_{i-1}^\pi(s, a) \right| \leq \varepsilon \quad \forall s, a \quad (*)$$

1. Value Iteration for policy evaluation will terminate.
2. When it terminates, it holds that

$$|Q_i^\pi(s, a) - Q^\pi(s, a)| \leq \frac{\epsilon}{1 - \gamma} \quad \forall s, a$$

$$\begin{aligned}
 Q_i^\pi(s, a) &= R(s, a) + \gamma \sum_{s', a'} p(s' | s, a) \pi(a' | s') Q_{i-1}^\pi(s', a') \\
 &= R(s, a) + \sum_{s', a'} p(s' | s, a) \pi(a' | s') Q_i^\pi(s', a') + \gamma \sum_{s', a'} p(s' | s, a) \pi(a' | s') (Q_{i-1}^\pi(s', a') - Q_i^\pi(s', a')) \\
 &\in [-\varepsilon, \varepsilon]
 \end{aligned}$$

If (*) holds, then the last term can be upper bounded by $\gamma \cdot \varepsilon \leq \varepsilon$

$$\Rightarrow \left| Q_i^\pi(s, a) - \left(R(s, a) + \gamma \sum_{s', a'} p(s' | s, a) \pi(a' | s') Q_i^\pi(s', a') \right) \right| \leq \varepsilon$$

Convergence

1. Value Iteration for policy evaluation will terminate.
2. When it terminates, it holds that

$$|Q_i^\pi(s, a) - Q^\pi(s, a)| \leq \frac{\epsilon}{1 - \gamma} \quad \forall s, a$$

Proof strategy: (not the simplest proof)

- 1) Prove that VI will terminate (i.e., $\max_{s,a} |Q_i^\pi(s, a) - Q_{i-1}^\pi(s, a)| \leq \epsilon$ will eventually hold)
- 2) At termination,

$$\text{BellmanError}(Q_i^\pi) = \max_{s,a} \left| Q_i^\pi(s, a) - \left(R(s, a) + \gamma \sum_{s',a'} P(s'|s, a) \pi(a'|s') Q_i^\pi(s', a') \right) \right| \leq \epsilon$$

- 3) Use the **Value error $\leq (1 - \gamma)^{-1}$ Bellmen Error lemma** to claim

$$|Q_i^\pi(s, a) - Q^\pi(s, a)| \leq \frac{\epsilon}{1 - \gamma}.$$

Convergence (A More General Statement of 2.)

Value error $\leq (1 - \gamma)^{-1}$ Bellmen Error

Let $f: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ be **any** function (not necessarily generated by Value Iteration)

If

$$\left| f(s, a) - \left(R(s, a) + \gamma \sum_{s', a'} P(s'|s, a) \pi(a'|s') f(s', a') \right) \right| \leq \epsilon \quad \forall s, a$$

then

$$|f(s, a) - Q^\pi(s, a)| \leq \frac{\epsilon}{1 - \gamma} \quad \forall s, a$$

Given π , Assume we have

$$\underline{f(s,a)} \stackrel{\geq}{\leq} R(s,a) + \gamma \sum_{s',a'} p(s'|s,a) \pi(a'|s') f(s',a') - \varepsilon$$

$\forall s,a$

$$Q^\pi(s,a) = R(s,a) + \gamma \sum_{s',a'} p(s'|s,a) \pi(a'|s') Q^\pi(s',a')$$

$\forall s,a$

$$\underline{f(s,a) - Q^\pi(s,a)} \leq \gamma \sum_{s',a'} p(s'|s,a) \pi(a'|s') (f(s',a') - Q^\pi(s',a')) + \varepsilon$$

$\forall s,a$

$$\leq \gamma \max_{s',a'} (f(s',a') - Q^\pi(s',a')) + \varepsilon$$

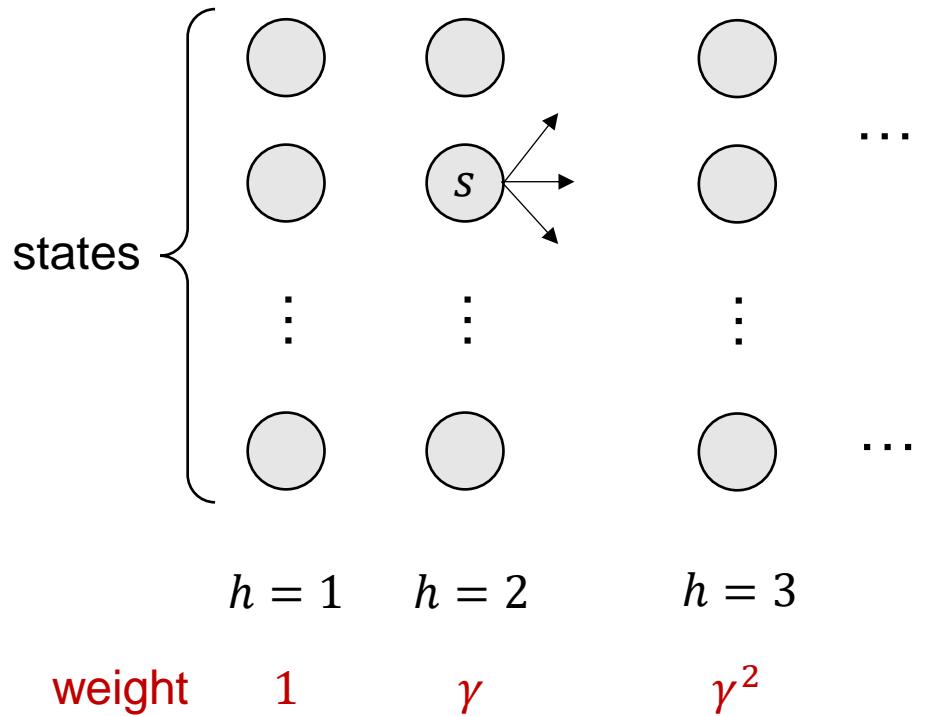
$$\Rightarrow \max_{s,a} (f(s,a) - Q^\pi(s,a)) \leq \gamma \max_{s',a'} (f(s',a') - Q^\pi(s',a')) + \varepsilon$$

Similarly:

$$\Rightarrow (\cancel{\max_{s,a}}) \max_{s,a} (f(s,a) - Q^\pi(s,a)) \leq \frac{\varepsilon}{1-\gamma}$$

$$\min_{s,a} (f(s,a) - Q^\pi(s,a)) \geq -\frac{\varepsilon}{1-\gamma}$$

Value Iteration for Policy Optimization



State transition: $P(s'|s, a)$

Reward: $R(s, a)$

$$Q_i^*(s, a) = \max_{\pi} \mathbb{E}^{\pi} \left[\sum_{h=1}^i \gamma^{h-1} R(s_h, a_h) \mid (s_0, a_0) = (s, a) \right]$$

$$V_i^*(s) = \max_{\pi} \mathbb{E}^{\pi} \left[\sum_{h=1}^i \gamma^{h-1} R(s_h, a_h) \mid s_0 = s \right]$$

$$Q^*(s, a) = Q_{\infty}^*(s, a) \quad V^*(s) = V_{\infty}^*(s)$$

$$V_0^*(s) = 0 \quad \forall s$$

For $i = 1, 2, 3, \dots$: for all s, a

≠ $Q^*(s, a)$

$$Q_i^*(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V_{i-1}^*(s')$$

$$V_i^*(s) = \max_a Q_i^*(s, a)$$

If $|Q_i^*(s, a) - Q_{i-1}^*(s, a)| \leq \epsilon$ for all s, a : **terminate**

Bellman Optimality Equation

$$\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$$

$$Q^*(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^*(s')$$

$$V^*(s) = \max_a Q^*(s, a)$$

or

$$Q^*(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) \max_{a'} Q^*(s', a')$$

or

$$V^*(s) = \max_a \left(R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^*(s') \right)$$

Convergence

$$|Q_i(s, a) - Q_{i-1}(s, a)| \leq \epsilon$$

1. Value Iteration for policy optimization will terminate.
2. When it terminates, it holds that

$$|Q_i^*(s, a) - Q^*(s, a)| \leq \frac{\epsilon}{1 - \gamma} \quad \forall s, a$$

3. When it terminates, it holds that

$$V^*(s) - V^{\hat{\pi}}(s) \leq \frac{2\epsilon}{(1 - \gamma)^2} \quad \forall s$$

where $\hat{\pi}(s) = \operatorname{argmax}_a Q_i^*(s, a)$

$$\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$$

Convergence (A More General Statement of 2.)

Value error $\leq (1 - \gamma)^{-1}$ Bellmen Error

Let $f: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ be **any** function (not necessarily generated by Value Iteration)

If

$$\left| f(s, a) - \left(R(s, a) + \gamma \sum_{s'} P(s'|s, a) \max_{a'} f(s', a') \right) \right| \leq \epsilon \quad \forall s, a$$

then

$$|f(s, a) - Q^*(s, a)| \leq \frac{\epsilon}{1 - \gamma} \quad \forall s, a$$

Convergence (A More General Statement of 3.)

Suboptimality $\leq (1 - \gamma)^{-1}$ Value Error

Let $f: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ be **any** function (not necessarily generated by Value Iteration)

If

$$|f(s, a) - Q^*(s, a)| \leq \epsilon \quad \forall s, a$$

then

$$V^*(s) - V^{\pi_f}(s) \leq \frac{2\epsilon}{1 - \gamma} \quad \forall s$$

where $\pi_f(s) = \operatorname{argmax}_a f(s, a)$

Review:



pure exploration

$$\hat{R}(a)$$

estimated value function

pure exploitation

$$a_t = \underset{a}{\operatorname{argmax}} \hat{R}(a)$$

$$\hat{a}^* = \underset{a}{\operatorname{argmax}} \hat{R}(a)$$

$$a^* = \underset{a}{\operatorname{argmax}} R(a)$$

$$\forall a \quad |R(a) - \hat{R}(a)| \leq \varepsilon$$

$$R(\hat{a}) - R(\hat{a}) = \underbrace{\hat{R}(a^*) - \hat{R}(\hat{a})}_{\leq 0} + \underbrace{R(a^*) - \hat{R}(a^*)}_{\leq \varepsilon} + \underbrace{\hat{R}(\hat{a}) - R(\hat{a})}_{\leq \varepsilon}$$

$$\leq 0$$

$$\leq \varepsilon$$

$$\leq \varepsilon$$

$$\leq 2\varepsilon$$

Summary (Fixed Horizon)

Definitions

$$Q_h^\pi(s, a) \triangleq \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid (s_h, a_h) = (s, a) \right]$$

$$V_h^\pi(s) \triangleq \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid s_h = s \right]$$

Relations (Bellman Equations)

$$Q_h^\pi(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) V_{h+1}^\pi(s')$$

$$V_h^\pi(s) = \sum_a \pi_h(a|s) Q_h^\pi(s, a)$$

Calculation (VI)

Calculate
 $Q_h^\pi(s, a), V_h^\pi(s) \forall s, a$
from $h = H$ to $h = 1$

$$Q_h^*(s, a) \triangleq \max_\pi \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid (s_h, a_h) = (s, a) \right]$$

$$V_h^*(s) \triangleq \max_\pi \mathbb{E}^\pi \left[\sum_{k=h}^H R(s_k, a_k) \mid s_h = s \right]$$

$$Q_h^*(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) V_{h+1}^*(s')$$

$$V_h^*(s) = \max_a Q_h^*(s, a)$$

Calculate
 $Q_h^*(s, a), V_h^*(s) \forall s, a$
from $h = H$ to $h = 1$

Summary (Discounted Variable Horizon)

Definitions

$$Q^\pi(s, a) = \mathbb{E}^\pi \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid (s_1, a_1) = (s, a) \right]$$

$$V^\pi(s) = \mathbb{E}^\pi \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_1 = s \right]$$

Relations (Bellman Equations)

$$Q^\pi(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^\pi(s')$$

$$V^\pi(s) = \sum_a \pi(a|s) Q^\pi(s, a)$$

Calculation (VI)

Calculate
 $Q_i^\pi(s, a), V_i^\pi(s) \forall s, a$
for $i = 1, 2, \dots$
until convergence

$$Q^*(s, a) = \max_{\pi} \mathbb{E}^\pi \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid (s_1, a_1) = (s, a) \right]$$

$$V^*(s) = \max_{\pi} \mathbb{E}^\pi \left[\sum_{h=1}^{\infty} \gamma^{h-1} R(s_h, a_h) \mid s_1 = s \right]$$

$$Q^*(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^*(s')$$

$$V^*(s) = \max_a Q^*(s, a)$$

Calculate
 $Q_i^*(s, a), V_i^*(s) \forall s, a$
for $i = 1, 2, \dots$
until convergence

Policy Iteration

Policy Optimization

Policy Iteration

$$\pi_i : S \rightarrow A$$

Policy Iteration

For $i = 1, 2, \dots$

$$\forall s, \quad \pi_i(s) \leftarrow \underset{a}{\operatorname{argmax}} Q^{\pi_{i-1}}(s, a)$$

$\pi_i(s) \neq \underset{a}{\operatorname{argmax}} Q^{\pi_i}(s, a)$

Requires an inner
VI for policy evaluation algo

Theorem (monotonic improvement). Policy Iteration ensures

$$\forall s, a, \quad Q^{\pi_i}(s, a) \geq Q^{\pi_{i-1}}(s, a)$$

When converged (i.e., $\pi_i = \pi_{i-1}$), we have $\pi_i = \pi^*$.

(We will prove this later.)

Generalized Policy Iteration

$N = \infty \Rightarrow$ Policy Iteration

(Sub-routine:
VI for policy evaluation)

$N = 1 \Rightarrow$ Value Iteration for policy optimization

For $i = 1, 2, \dots$

$$\pi_i(s) = \max_a Q_i(s, a)$$

$$Q_i(s, a) = \underbrace{Q}_{\text{Policy update}}^{\pi_{i-1}}(s, a) \quad (\text{inductive prove this})$$

$$Q \leftarrow Q_i$$

Repeat for N times:

$$Q_{i+1}(s, a) \leftarrow R(s, a) + \gamma \sum_{s', a'} P(s'|s, a) \pi_i(a'|s') Q_i(s', a')$$

$$Q_{i+1} \leftarrow Q$$

perform Value iteration to evaluate π_i

Value update

$(s, a) \rightarrow R$

Notice: in value iteration for PO, there may not exist a policy π such that $Q_i = Q^\pi$

In contrast, in policy iteration we have $Q_i = Q^{\pi_{i-1}}$

VI for PO can be viewed as PI with **incomplete policy evaluation**

$$Q_i = Q^{\pi_{i-1}}$$

Summary

- Value Iteration for Policy Optimization (VI for PO)
 - Is essentially a **dynamic programming** algorithm
 - Finds the value functions of the optimal policy
- Value Iteration for Policy Evaluation (VI for PE)
 - Also a **dynamic programming** algorithm
 - Finds the value functions of the given policy
- Policy Iteration (PI)
 - An iterative policy improvement algorithm (for PO)
 - Each iteration involves a policy evaluation subtask
- VI for PO and PI can be viewed as special cases of Generalized PI



Performance Difference Lemma

Unanswered Questions

- For an estimation $\hat{Q}(s, a) \approx Q^*(s, a)$ with error, how can we bound

$$V^*(\rho) - V^{\hat{\pi}}(\rho) \quad \text{where } \hat{\pi}(s) = \operatorname{argmax}_a \hat{Q}(s, a)?$$

- How to show that Policy Iteration leads to monotonic policy improvement?
- Also, how are these methods related to the third challenge of online RL: credit assignment?

Performance Difference Lemma

$$\sum_{s,a} d_\rho^{\pi'}(s) \pi'(a|s) Q^\pi(s,a) = \sum_{s,a} d_\rho^{\pi'}(s,a) Q^\pi(s,a)$$

$$\sum_{s,a} d_\rho^{\pi'}(s) \pi(a|s) Q^\pi(s,a) = \sum_s d_\rho^{\pi'}(s) V^\pi(s)$$

For any two stationary policies π' and π in the discounted setting,

$$\mathbb{E}_{s \sim \rho} [V^{\pi'}(s)] - \mathbb{E}_{s \sim \rho} [V^\pi(s)] = \sum_{s,a} d_\rho^{\pi'}(s) (\pi'(a|s) - \pi(a|s)) Q^\pi(s,a)$$

$$\sum_{k=1}^{\infty} \gamma^{k-1} = \frac{1}{1-\gamma}$$

$$= \sum_{s,a} d_\rho^{\pi'}(s,a) (Q^\pi(s,a) - V^\pi(s))$$

$$d_\rho^\pi(s) \triangleq \mathbb{E}^\pi \left[\sum_{h=1}^{\infty} \gamma^{h-1} \mathbb{I}\{s_h = s\} \mid s_1 \sim \rho \right]$$

$$d_\rho^\pi(s,a) \triangleq \mathbb{E}^\pi \left[\sum_{h=1}^{\infty} \gamma^{h-1} \mathbb{I}\{(s_h, a_h) = (s, a)\} \mid s_1 \sim \rho \right]$$

Discounted occupancy measure on state s

$$\sum_a d_\rho^{\pi'}(s,a) = d_\rho^{\pi'}(s)$$

$$= d_\rho^\pi(s) \pi(a|s)$$

Performance Difference Lemma

We can also swap the roles of π' and π and apply the same lemma

$$\mathbb{E}_{s \sim \rho}[V^\pi(s)] - \mathbb{E}_{s \sim \rho}[V^{\pi'}(s)] = \sum_{s,a} d_\rho^\pi(s) (\pi(a|s) - \pi'(a|s)) Q^{\pi'}(s, a)$$

$$\times (-1) \Rightarrow \mathbb{E}_{s \sim \rho}[V^{\pi'}(s)] - \mathbb{E}_{s \sim \rho}[V^\pi(s)] = \sum_{s,a} d_\rho^{\pi'}(s) (\pi'(a|s) - \pi(a|s)) Q^\pi(s, a)$$

||

Original version:

$$\mathbb{E}_{s \sim \rho}[V^{\pi'}(s)] - \mathbb{E}_{s \sim \rho}[V^\pi(s)] = \sum_{s,a} d_\rho^{\pi'}(s) (\pi'(a|s) - \pi(a|s)) Q^\pi(s, a)$$

Performance Difference Lemma (Fixed-Horizon)

For any two Markov policies π' and π in the fixed-horizon setting,

$$\begin{aligned}\mathbb{E}_{s_1 \sim \rho} [V_1^{\pi'}(s_1)] - \mathbb{E}_{s_1 \sim \rho} [V_1^{\pi}(s_1)] &= \sum_{h=1}^H \sum_{s,a} d_{\rho,h}^{\pi'}(s) (\pi'_h(a|s) - \pi_h(a|s)) \underline{Q_h^{\pi}(s, a)} \\ &= \sum_{h=1}^H \sum_{s,a} d_{\rho,h}^{\pi'}(s, a) (Q_h^{\pi}(s, a) - V_h^{\pi}(s))\end{aligned}$$

$$\underline{d_{\rho,h}^{\pi}(s)} \triangleq \mathbb{E}^{\pi} [\mathbb{I}\{s_h = s\} \mid s_1 \sim \rho] = \mathbb{P}^{\pi}(s_h = s \mid s_1 \sim \rho)$$

$$d_{\rho,h}^{\pi}(s, a) \triangleq \mathbb{E}^{\pi} [\mathbb{I}\{(s_h, a_h) = (s, a)\} \mid s_1 \sim \rho] = \mathbb{P}^{\pi}((s_h, a_h) = (s, a) \mid s_1 \sim \rho)$$

The Meaning of Performance Difference Lemma

It tells us how **credit** are assigned to each state/step

The sub-optimality of a policy π :

$$\mathbb{E}_{s \sim \rho}[V^*(s)] - \mathbb{E}_{s \sim \rho}[V^\pi(s)]$$

If π is highly sub-optimal, then we can always find

- 1) An (s, a) -pair on the path of π such that $V^*(s) - Q^*(s, a)$ is positive and large
- 2) An (s, a) -pair on the path of π^* such that $Q^\pi(s, a) - V^\pi(s)$ is positive and large

If π puts a lot of probability $\pi(a|s)$ on an action with large $V^*(s) - Q^*(s, a)$

$$= \sum_{s,a} d_\rho^\pi(s) (\pi^*(a|s) - \pi(a|s)) Q^*(s, a)$$

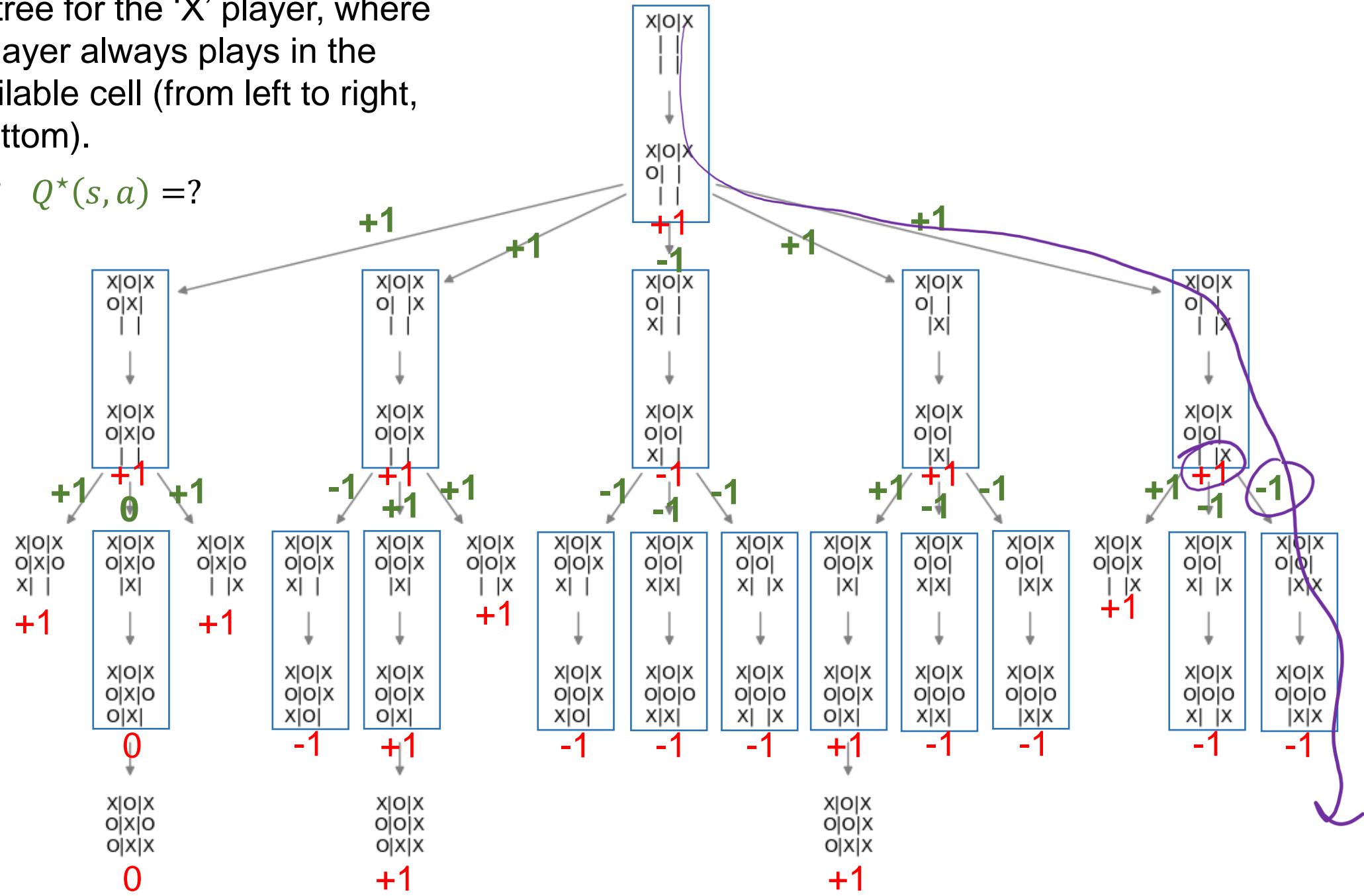
$$= \sum_{s,a} d_\rho^\pi(s, a) (V^*(s) - Q^*(s, a)) \geq 0 \quad \checkmark$$

$$= \sum_{s,a} d_\rho^{\pi^*}(s) (\pi^*(a|s) - \pi(a|s)) Q^\pi(s, a)$$

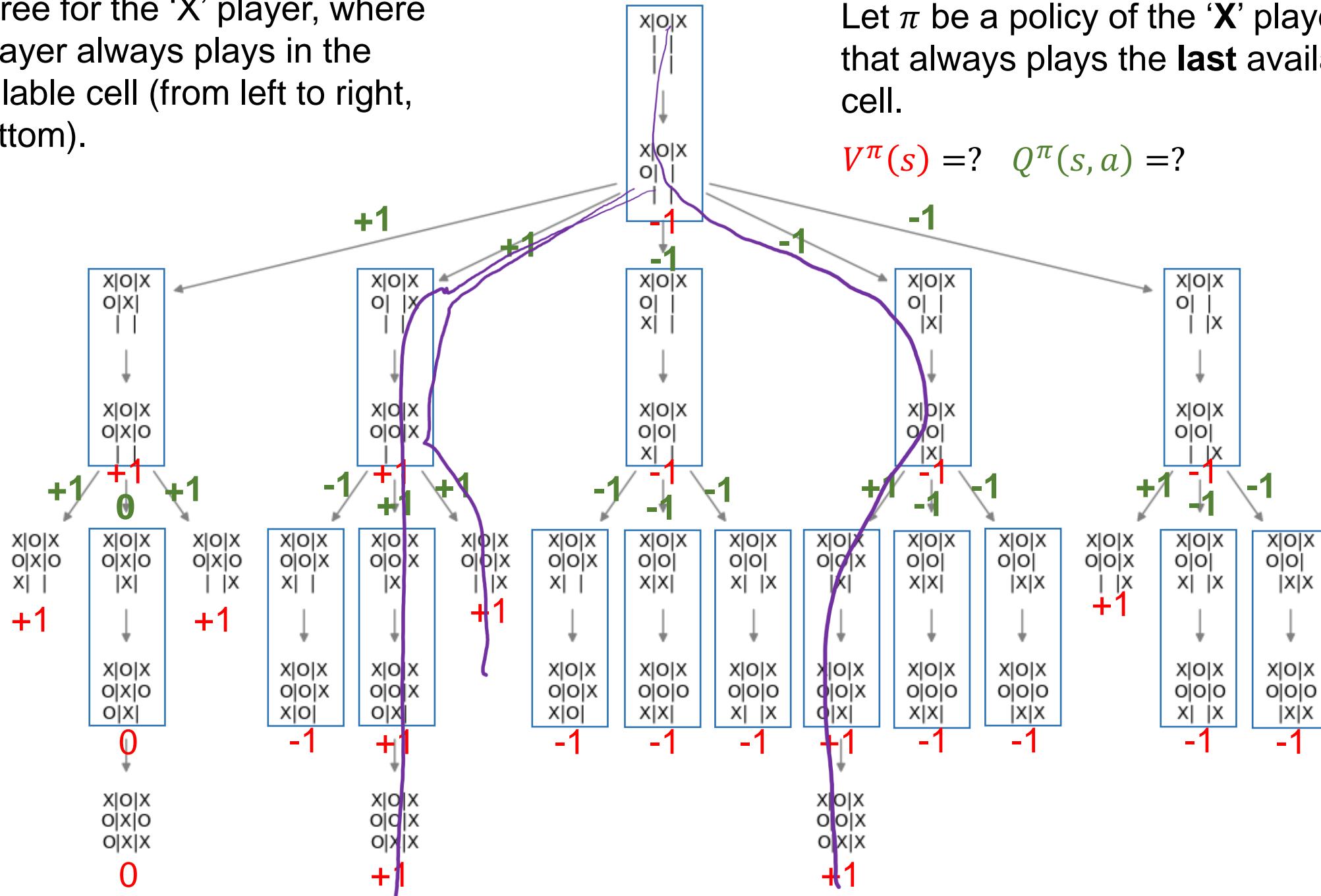
$$= \sum_{s,a} d_\rho^{\pi^*}(s, a) (Q^\pi(s, a) - V^\pi(s)) \quad \checkmark$$

A game tree for the 'X' player, where the 'O' player always plays in the **first** available cell (from left to right, top to bottom).

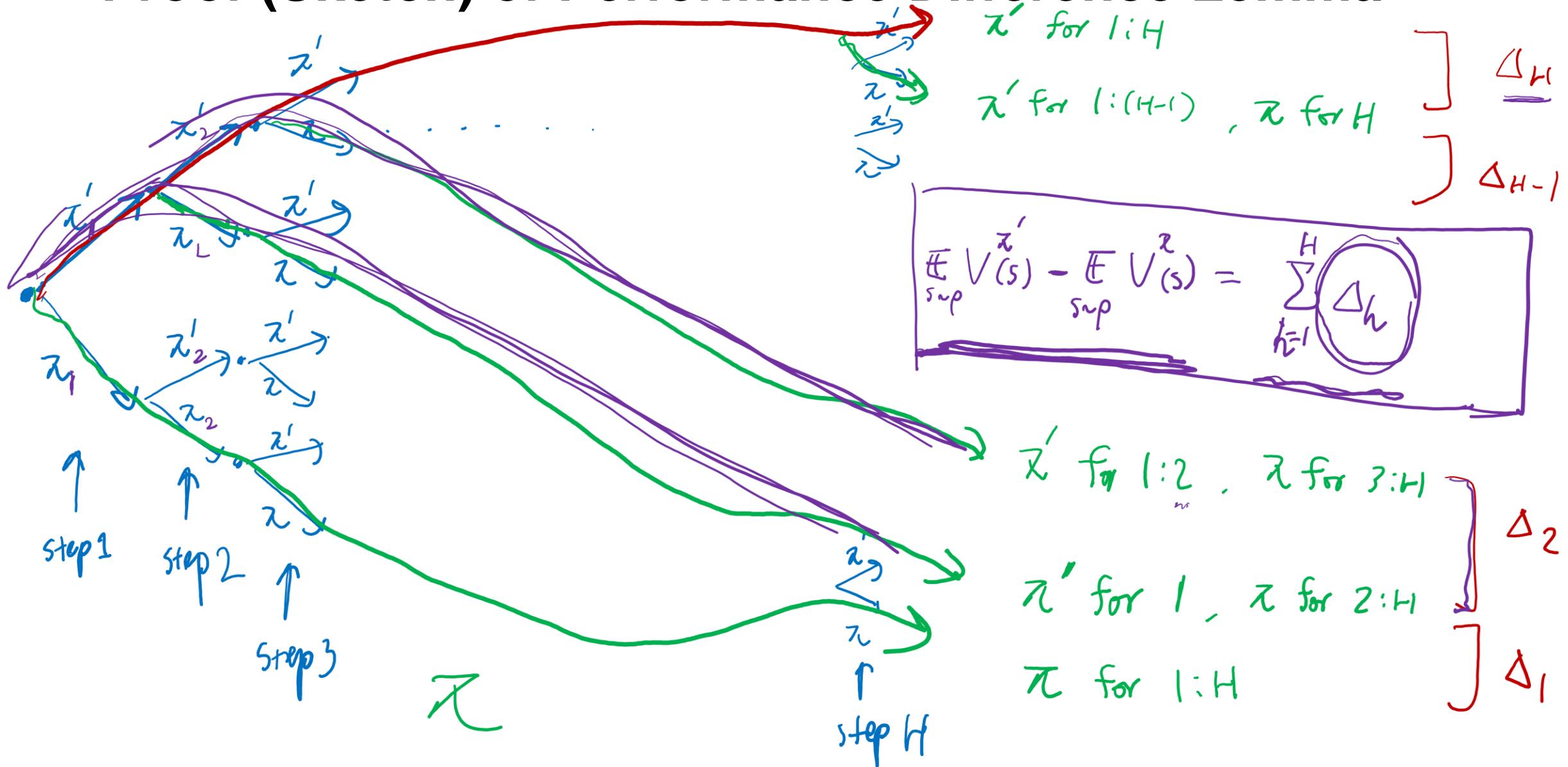
$$V^*(s) = ? \quad Q^*(s, a) = ?$$



A game tree for the 'X' player, where the 'O' player always plays in the **first** available cell (from left to right, top to bottom).



Proof (Sketch) of Performance Difference Lemma



Now focus on calculating Δ_h

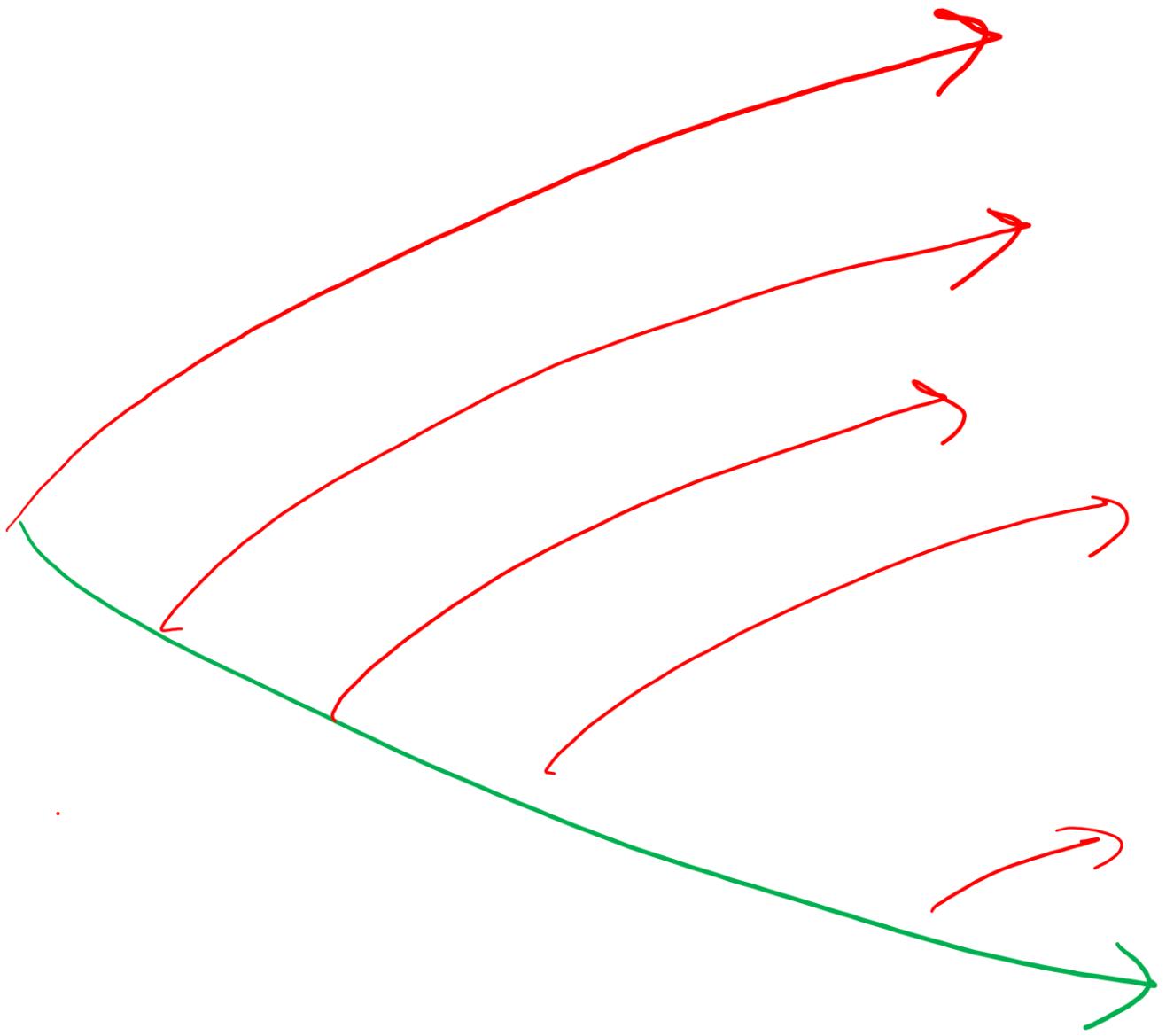
$Q^\pi(s_h, a_h) = \text{return by picking } a_h \text{ on } s_h, \text{ then follow } \pi \text{ afterwards}$

$$\begin{aligned}\pi^{\circledcirc} &= \pi' \text{ for step } 1:h, \pi \text{ for } (h+1):H \\ \underline{\pi^{\circledast}} &= \pi' \text{ for step } 1:(h-1), \pi \text{ for } h:H\end{aligned}\quad \text{only differ in step } h$$

$$\mathbb{E}^{\pi^{\circledcirc}} \left[\sum_{k=1}^H r(s_k, a_k) \mid s_1 \sim p \right] - \mathbb{E}^{\pi^{\circledast}} \left[\sum_{k=1}^H r(s_k, a_k) \mid s_1 \sim p \right]$$

$$= \mathbb{E}^{\pi^{\circledcirc}} \left[\sum_{k=h}^H r(s_k, a_k) \mid \underbrace{s_1 \sim p}_{s_h \sim d_{p,h}} \right] - \mathbb{E}^{\pi^{\circledast}} \left[\sum_{k=h}^H r(s_k, a_k) \mid \underbrace{s_1 \sim p}_{s_h \sim d_{p,h}} \right]$$

$$\begin{aligned}&= \mathbb{E}_{s_h \sim d_{p,h}^{x'}, a_h} \left[\sum_{a_h} \pi'(a_h \mid s_h) Q^\pi(s_h, a_h) \right] - \mathbb{E}_{s_h \sim d_{p,h}^{x'}, a_h} \left[\sum_{a_h} \pi(a_h \mid s_h) Q_h^\pi(s_h, a_h) \right] \\ &\approx \sum_{s_h, a_h} d_{p,h}^{x'}(s_h) (\pi'(a_h \mid s_h) - \pi(a_h \mid s_h)) Q^\pi(s_h, a_h)\end{aligned}$$



Unanswered Question 1

Suboptimality $\leq (1 - \gamma)^{-1}$ Value Error

Let $f: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ be **any** function

If

$$|f(s, a) - Q^*(s, a)| \leq \epsilon \quad \forall s, a$$

then

$$\underbrace{V^*(s) - V^{\pi_f}(s)}_{\text{Suboptimality}} \leq \frac{2\epsilon}{1 - \gamma} \quad \forall s$$

where $\pi_f(s) = \operatorname{argmax}_a f(s, a)$

$$|f(s,a) - Q^*(s,a)| \leq \varepsilon$$

$$\sum_a (\pi^*(a|s) - \pi_f(a|s)) f(s,a) = \sum_a \pi^*(a|s) f(s,a) - \max_a f(s,a) \leq 0$$

$\pi_f(s) = \underset{a}{\operatorname{argmax}} f(s,a)$

$$\begin{aligned} \mathbb{E}_{s \sim p} [V^{\pi^*}(s)] - \mathbb{E}_{s \sim p} [V^{\pi_f}(s)] &= \sum_{s,a} d_p^{\pi_f}(s) \left(\pi^*(a|s) - \pi_f(a|s) \right) \overbrace{Q^*(s,a)} \\ &= \sum_{s,a} d_p^{\pi_f}(s) \left(\pi^*(a|s) - \pi_f(a|s) \right) \overbrace{f(s,a)} \leq 0 \\ &\quad + \sum_{s,a} d_p^{\pi_f}(s) \left(\pi^*(a|s) - \pi_f(a|s) \right) \overbrace{(Q^*(s,a) - f(s,a))} \\ &\leq \sum_{s,a} d_p^{\pi_f}(s) \left| \pi^*(a|s) - \pi_f(a|s) \right| \varepsilon \\ &\leq \left(\sum_s d_p^{\pi_f}(s) \right) 2\varepsilon = \frac{2\varepsilon}{1-\gamma} \end{aligned}$$

Unanswered Question 2

$$\pi_i(s) = \arg\max_a Q^{\pi_{i-1}}(s, a)$$

Policy Iteration ensures

$$\forall s, a, \quad Q^{\pi_i}(s, a) \geq Q^{\pi_{i-1}}(s, a)$$

$Q^{\pi_i}(s, a) = R(s, a) + \gamma \sum_{s'} p(s'|s, a) V^{\pi_i}(s')$
 $Q^{\pi_{i-1}}(s, a) = \underbrace{\sum_s}_{V^{\pi_{i-1}}(s)}$

When converged (i.e., $\pi_i = \pi_{i-1}$), we have $\pi_i = \pi^*$.

$$\begin{aligned} \mathbb{E}_{s \sim p} \left[V^{\pi_i}(s) \right] - \mathbb{E}_{s \sim p} \left[V^{\pi_{i-1}}(s) \right] &= \sum_{s, a} d_p^{\pi_i}(s) \left(\underline{\pi_i(a|s)} - \underline{\pi_{i-1}(a|s)} \right) \underline{Q^{\pi_{i-1}}(s, a)} \\ &= \sum_s d_p^{\pi_i}(s) \left(\underbrace{\max_a Q^{\pi_{i-1}}(s, a)}_{\geq 0} - \sum_a \pi_{i-1}(a|s) \underline{Q^{\pi_{i-1}}(s, a)} \right) \end{aligned}$$

$$\forall s, \quad V^{\pi_i}(s) \geq V^{\pi_{i-1}}(s) \quad \geq 0$$

If $\pi_i = \pi_{i-1} = \hat{\pi} \Rightarrow Q^{\hat{\pi}}$ satisfies Bellman Optimality Equation $\Rightarrow \text{Bellman Error}(Q^{\hat{\pi}}) = 0 \Rightarrow Q^{\hat{\pi}} = Q^*$
 Value error $\leq \frac{1}{1-\gamma}$ Bellman error

Recap: MDP

- Definitions of $Q^\pi(s, a), V^\pi(s), Q^*(s, a), V^*(s)$
- Bellman equations (related to dynamic programming)
- Value Iteration to approximate $Q^\pi(s, a)/V^\pi(s)$ or $Q^*(s, a)/V^*(s)$
- Policy Iteration to find π^* --- involving $Q^\pi(s, a)/V^\pi(s)$ approximation
- Unified by Generalized Policy Iteration
- Performance difference lemma to decompose $\mathbb{E}_{s \sim \rho} [V^{\pi'}(s)] - \mathbb{E}_{s \sim \rho} [V^\pi(s)]$
 - Credit assignment
 - $= \sum_{s,a} d_\rho^\pi(s, a) (V^{\pi'}(s) - Q^{\pi'}(s, a))$ (helpful in analyzing VI by letting $\pi' = \pi^*$)
 - $= \sum_{s,a} d_\rho^{\pi'}(s, a) (Q^\pi(s, a) - V^\pi(s))$ (helpful in analyzing PI by letting $\pi' = \pi_{i+1}$)

Next

- Our discussion indicates there are two potential ways to find optimal policy
 - Value-Iteration-based: approximate $\hat{Q}(s, a) \approx Q^*(s, a)$ and let $\hat{\pi}(s) = \operatorname{argmax}_a \hat{Q}(s, a)$
 - Policy-Iteration-based: approximate $\hat{Q}(s, a) \approx Q^\pi(s, a)$ and let $\hat{\pi}(s) = \operatorname{argmax}_a \hat{Q}(s, a)$
 - ... or something in between (based on generalized policy iteration)
- RL algorithms we will discuss:
 - Performing approximate VI or PI using samples