Week 3: Model-free Prediction and Control

Bolei Zhou

The Chinese University of Hong Kong

September 20, 2020

This Week's Plan

1. Last week
   1. MDP, policy evaluation, policy iteration and value iteration for solving a known MDP
2. This week
   1. Model-free prediction: Estimate value function of an unknown MDP
   2. Model-free control: Optimize value function of an unknown MDP

Review on the control in MDP

1. When the MDP is known?
   1. Both R and P are exposed to the agent
   2. Therefore we can run policy iteration and value iteration
2. Policy iteration: Given a known MDP, compute the optimal policy and the optimal value function
   1. Policy evaluation: iteration on the Bellman expectation backup

$$v_i(s) = \sum_{a \in \mathcal{A}} \pi(a|s)(R(s,a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s,a) v_{i-1}(s'))$$

   2. Policy improvement: greedy on action-value function q

$$q_{\pi_i}(s,a) = R(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) v_{\pi_i}(s')$$

$$\pi_{i+1}(s) = \arg\max_a q_{\pi_i}(s,a)$$

Review on the control in MDP

1. Value iteration: Given a known MDP, compute the optimal value function
2. Iteration on the Bellman optimality backup

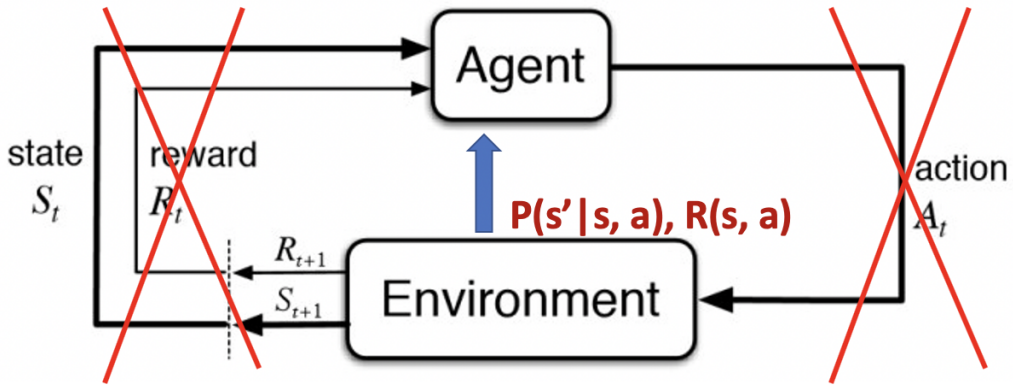
$$v_{i+1}(s) \leftarrow \max_{a \in \mathcal{A}} R(s,a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s,a) v_i(s')$$

3. To retrieve the optimal policy after the value iteration:

$$\pi^*(s) \leftarrow \arg\max_{a} R(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) v_{end}(s') \tag{1}$$

RL with knowing how the world works

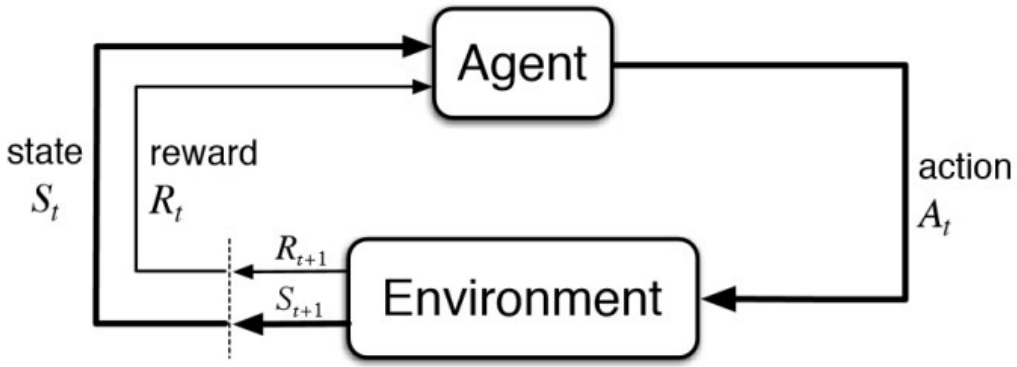
1. Both of the policy iteration and value iteration assume the direct access to the dynamics and rewards of the environment



2. In a lot of real-world problems, MDP model is either unknown or known by too big or too complex to use
   1. Atari Game, Game of Go, Helicopter, Portfolio management, etc

Model-free RL: Learning by interaction

1. Model-free RL can solve the problems through interaction with the environment



2. No more direct access to the known transition dynamics and reward function
3. Trajectories/episodes are collected by the agent's interaction with the environment
4. Each trajectory/episode contains $\{S_1, A_1, R_2, S_2, A_2, R_t, ..., S_T\}$

Model-free prediction: policy evaluation without the access to the model

1. Estimating the expected return of a particular policy if we don't have access to the MDP models
    1. Monte Carlo policy evaluation
    2. Temporal Difference (TD) learning

Monte-Carlo Policy Evaluation

1. Return: $G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + ...$ under policy π
2. $v^\pi(s) = \mathbb{E}_{\tau \sim \pi}[G_t | s_t = s]$, thus expectation over trajectories τ generated by following π
3. MC simulation: we can simply sample a lot of trajectories, compute the actual returns for all the trajectories, then average them
4. MC policy evaluation uses empirical mean return instead of expected return
5. MC does not require MDP dynamics/rewards, no bootstrapping, and does not assume state is Markov.
6. Only applied to episodic MDPs (each episode terminates)

Monte-Carlo Policy Evaluation

1. To evaluate state $v(s)$
   1. Every time-step t that state s is visited in an episode,
   2. Increment counter $N(s) \leftarrow N(s) + 1$
   3. Increment total return $S(s) \leftarrow S(s) + G_t$
   4. Value is estimated by mean return $v(s) = S(s)/N(s)$
2. By law of large numbers, $v(s) \rightarrow v^{\pi}(s)$ as $N(s) \rightarrow \infty$

Incremental Mean

Mean from the average of samples $x_1, x_2, ...$

$$\begin{aligned}
\mu_t &= \frac{1}{t}\sum_{j=1}^{t} x_j \\
&= \frac{1}{t}\left(x_t + \sum_{j=1}^{t-1} x_j\right) \\
&= \frac{1}{t}(x_t + (t-1)\mu_{t-1}) \\
&= \mu_{t-1} + \frac{1}{t}(x_t - \mu_{t-1})
\end{aligned}$$

Incremental MC Updates

1. Collect one episode $(S_1, A_1, R_2, ..., S_t)$
2. For each state s_t with computed return G_t

$$N(S_t) \leftarrow N(S_t) + 1$$
$$v(S_t) \leftarrow v(S_t) + \frac{1}{N(S_t)}(G_t - v(S_t))$$

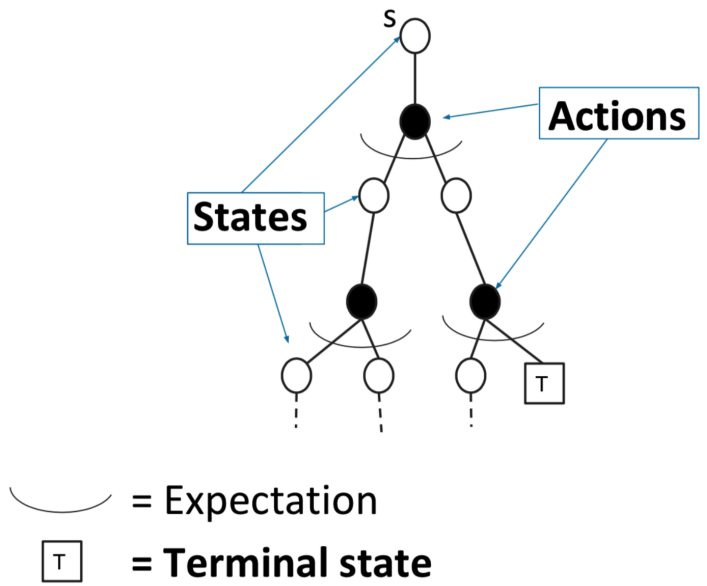
3. Or use a running mean (old episodes are forgotten). Good for non-stationary problems.

$$v(S_t) \leftarrow v(S_t) + \alpha(G_t - v(S_t))$$

Difference between DP and MC for policy evaluation

1. Dynamic Programming (DP) computes v_i by bootstrapping the rest of the expected return by the value estimate v_{i-1}
2. Iteration on Bellman expectation backup:

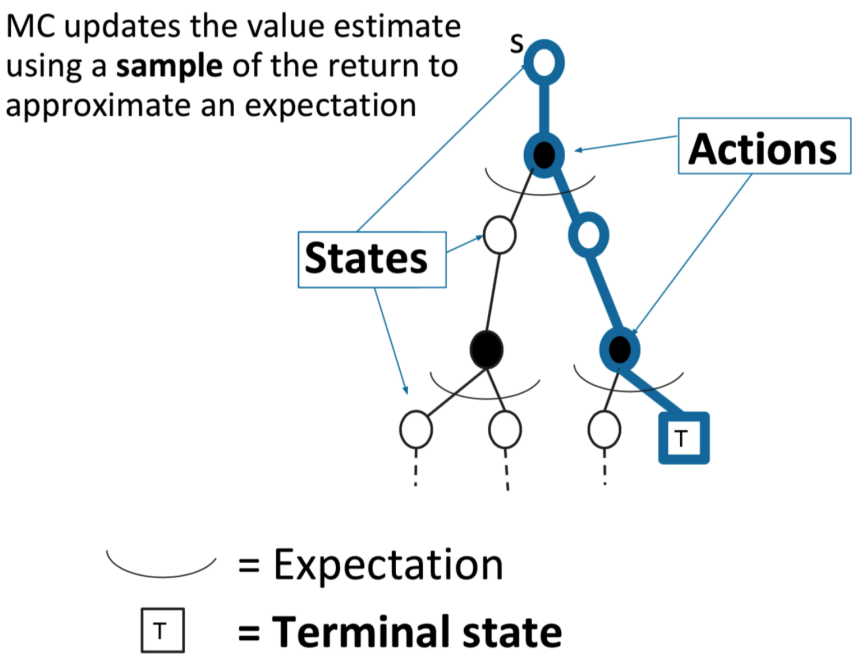
$$v_i(s) \leftarrow \sum_{a \in \mathcal{A}} \pi(a|s) \Big(R(s,a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s,a) v_{i-1}(s') \Big)$$



Difference between DP and MC for policy evaluation

1. MC updates the empirical mean return with one sampled episode

$$v(S_t) \leftarrow v(S_t) + \alpha(G_{i,t} - v(S_t))$$



Advantages of MC over DP

1. MC works when the environment is unknown
2. Working with sample episodes has a huge advantage, even when one has complete knowledge of the environment's dynamics, for example, transition probability is complex to compute
3. Cost of estimating a single state's value is independent of the total number of states. So you can sample episodes starting from the states of interest then average returns

Temporal-Difference (TD) Learning

1. TD methods learn directly from episodes of experience
2. TD is model-free: no knowledge of MDP transitions/rewards
3. TD learns from incomplete episodes, by bootstrapping

Temporal-Difference (TD) Learning

1. Objective: learn v_π online from experience under policy π
2. Simplest TD algorithm: TD(0)
   1. Update $v(S_t)$ toward estimated return $R_{t+1} + \gamma v(S_{t+1})$

$$v(S_t) \leftarrow v(S_t) + \alpha(R_{t+1} + \gamma v(S_{t+1}) - v(S_t))$$

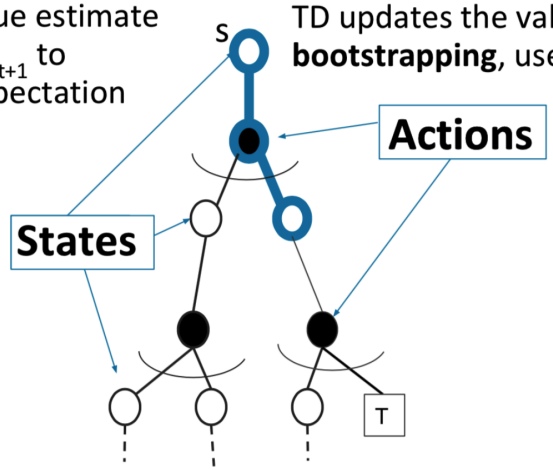
3. $R_{t+1} + \gamma v(S_{t+1})$ is called TD target
4. $\delta_t = R_{t+1} + \gamma v(S_{t+1}) - v(S_t)$ is called the TD error
5. Comparison: Incremental Monte-Carlo
   1. Update $v(S_t)$ toward actual return G_t given an episode i

$$v(S_t) \leftarrow v(S_t) + \alpha(G_{i,t} - v(S_t))$$

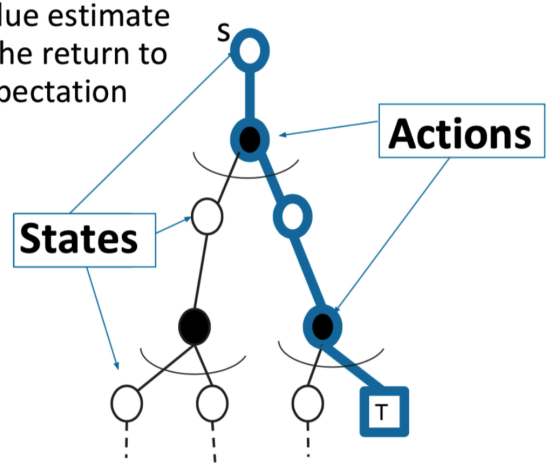
Advantages of TD over MC

TD updates the value estimate using a **sample** of s_{t+1} to approximate an expectation

TD updates the value estimate by **bootstrapping**, uses estimate of $V(s_{t+1})$



MC updates the value estimate using a **sample** of the return to approximate an expectation



= Expectation

T = **Terminal state**

Comparison of TD and MC

1. TD can learn online after every step
2. MC must wait until end of episode before return is known

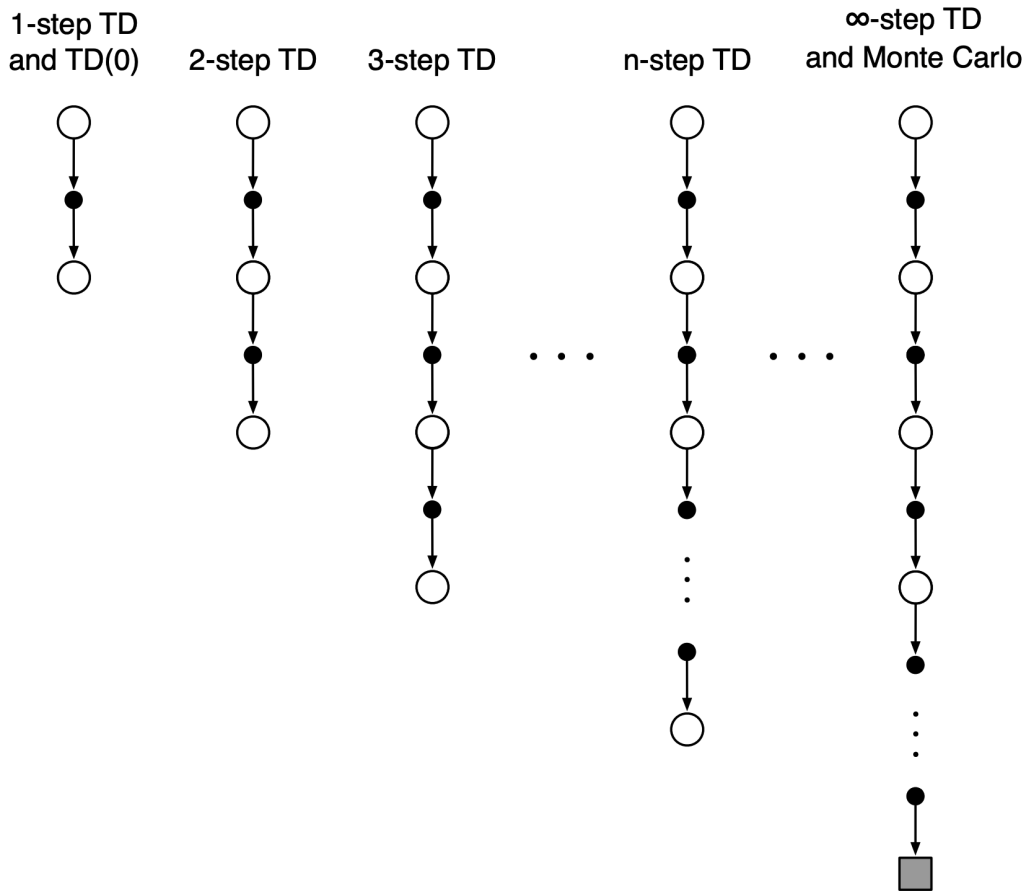
3. TD can learn from incomplete sequences
4. MC can only learn from complete sequences

5. TD works in continuing (non-terminating) environments
6. MC only works for episodic (terminating) environments

7. TD exploits Markov property, more efficient in Markov environments
8. MC does not exploit Markov property, more effective in non-Markov environments

n-step TD

1. *n*-step TD methods that generalize both one-step TD and MC.
2. We can shift from one to the other smoothly as needed to meet the demands of a particular task.



n-step TD prediction

1. Consider the following n-step returns for $n = 1, 2, \infty$

$$\begin{aligned} n = 1 (TD) \quad & G_t^{(1)} = R_{t+1} + \gamma v(S_{t+1}) \\ n = 2 \quad & G_t^{(2)} = R_{t+1} + \gamma R_{t+2} + \gamma^2 v(S_{t+2}) \\ & \vdots \\ n = \infty (MC) \quad & G_t^{\infty} = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{T-t-1} R_T \end{aligned}$$

2. Thus the n-step return is defined as

$$G_t^n = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{n-1} R_{t+n} + \gamma^n v(S_{t+n})$$

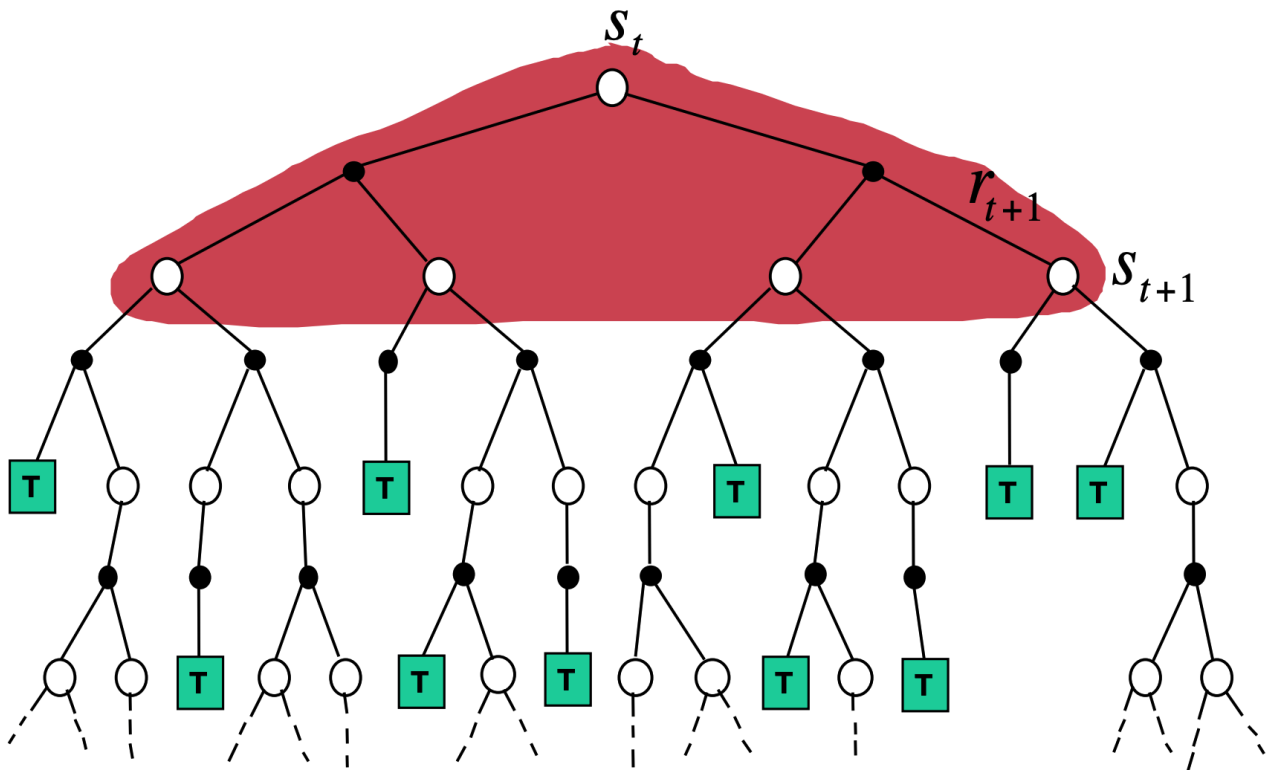
3. n-step TD: $v(S_t) \leftarrow v(S_t) + \alpha \Big(G_t^n - v(S_t) \Big)$

Bootstrapping and Sampling for DP, MC, and TD

1. Bootstrapping: update involves an estimate
   1. MC does not bootstrap
   2. DP bootstraps
   3. TD bootstraps
2. Sampling: update samples an expectation
   1. MC samples
   2. DP does not sample
   3. TD samples

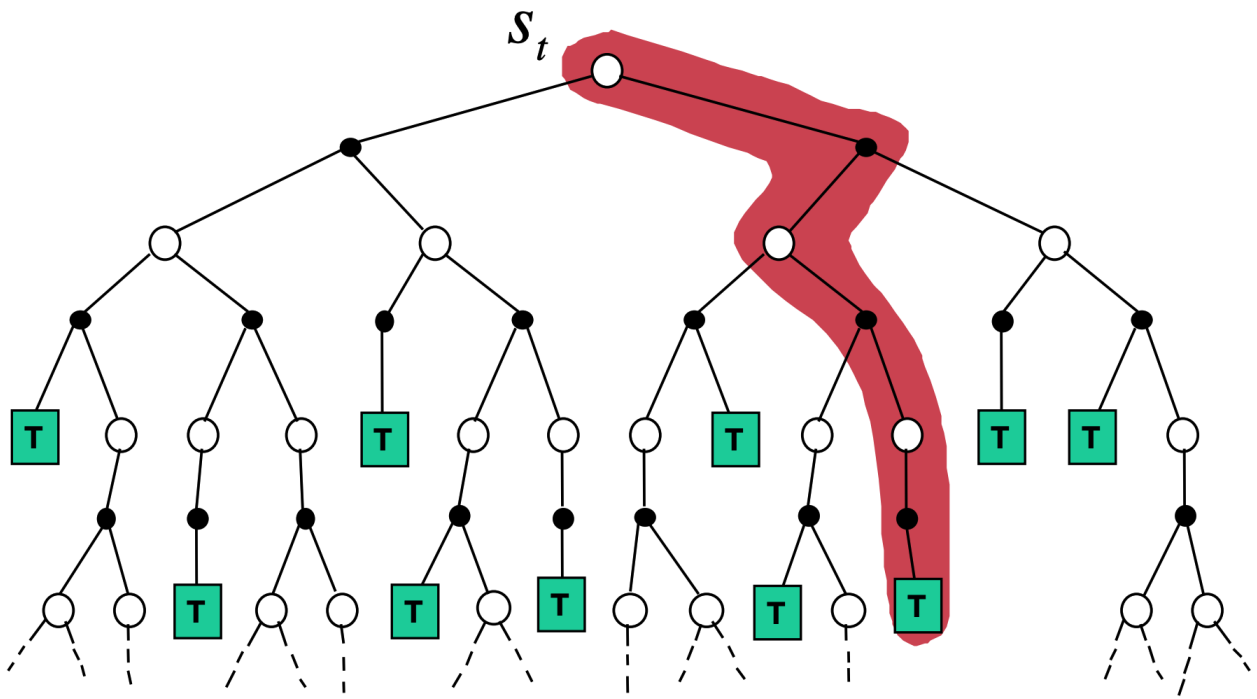
Unified View: Dynamic Programming Backup

$$v(S_t) \leftarrow \mathbb{E}_\pi[R_{t+1} + \gamma v(S_{t+1})]$$



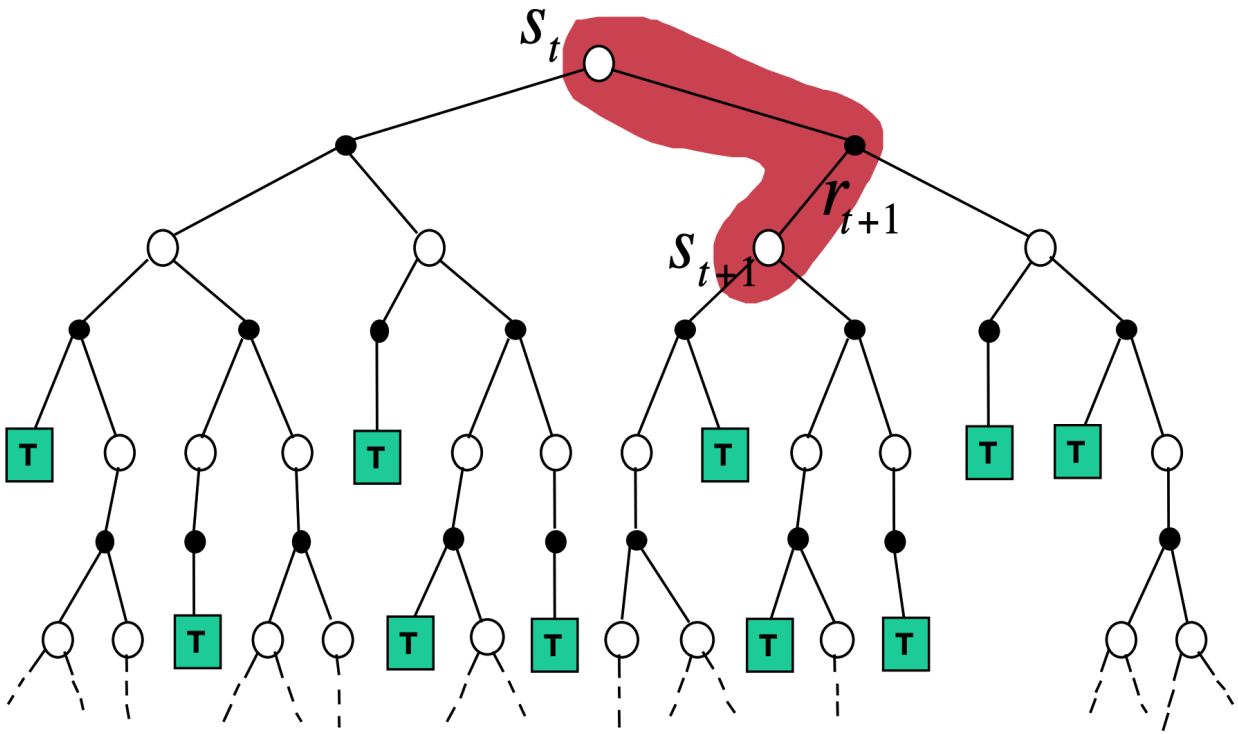
Unified View: Monte-Carlo Backup

$$v(S_t) \leftarrow v(S_t) + \alpha(G_t - v(S_t))$$

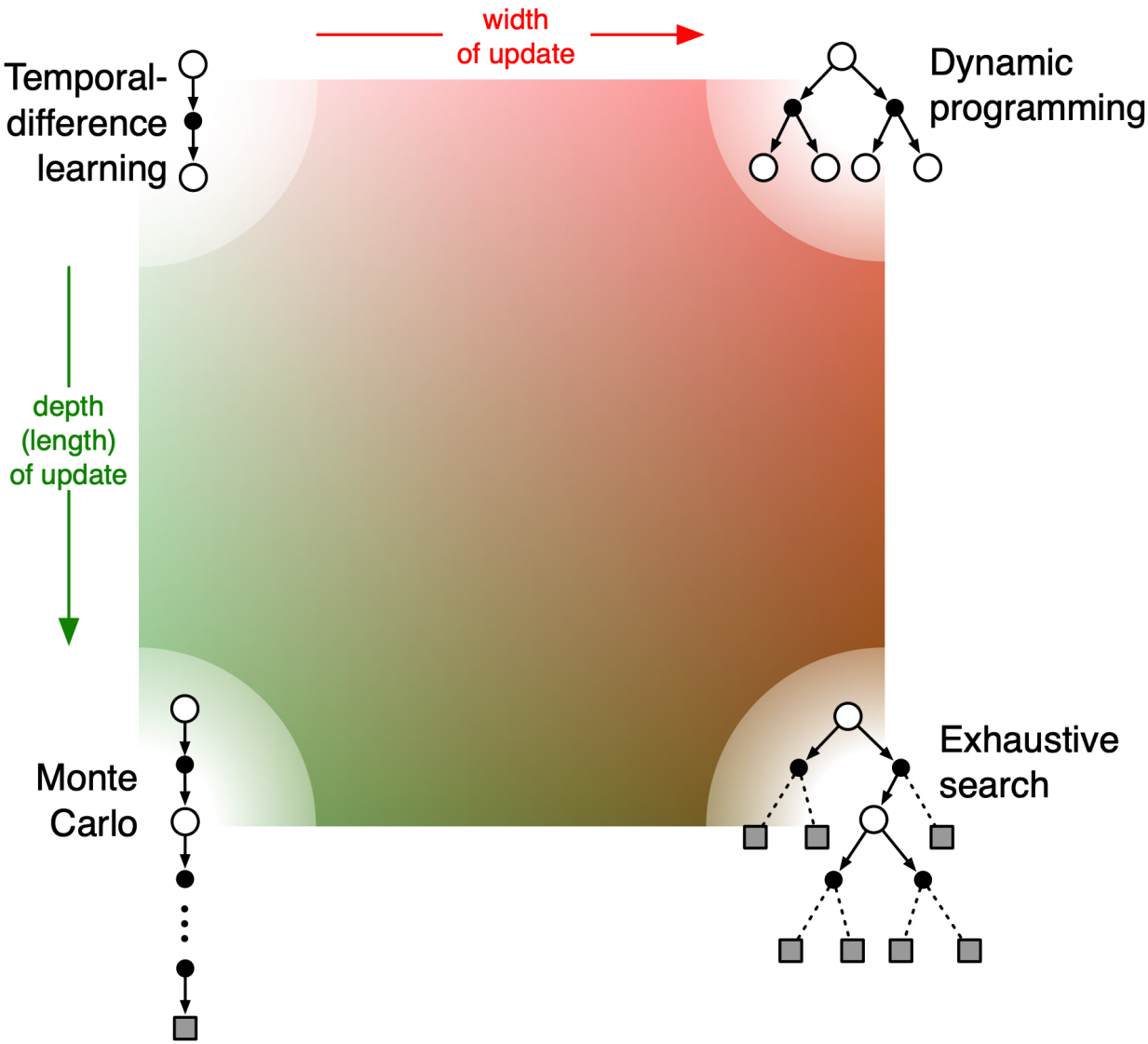


Unified View: Temporal-Difference Backup

$$TD(0) : v(S_t) \leftarrow v(S_t) + \alpha(R_{t+1} + \gamma v(s_{t+1}) - v(S_t))$$



Unified View of Reinforcement Learning



Summary

1. Model-free prediction
    1. Evaluate the state value by only interacting with the environment
    2. Many algorithms can do it: Dynamic Programming, Temporal Difference Learning, Monte-Carlo

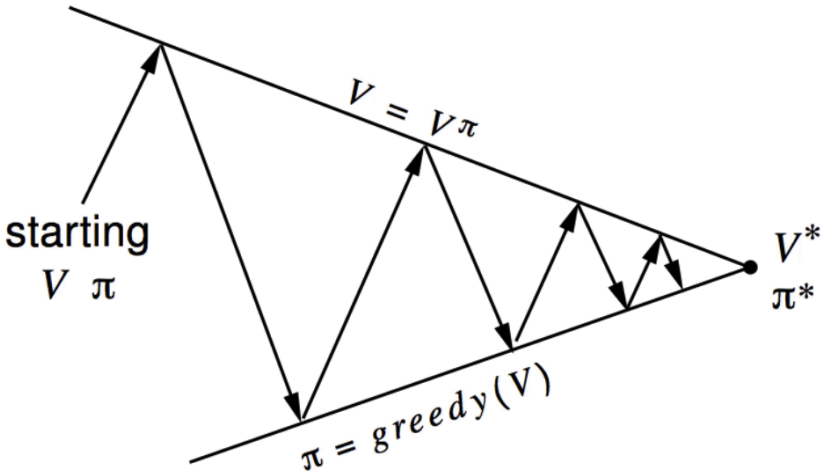
Model-free Control for MDP

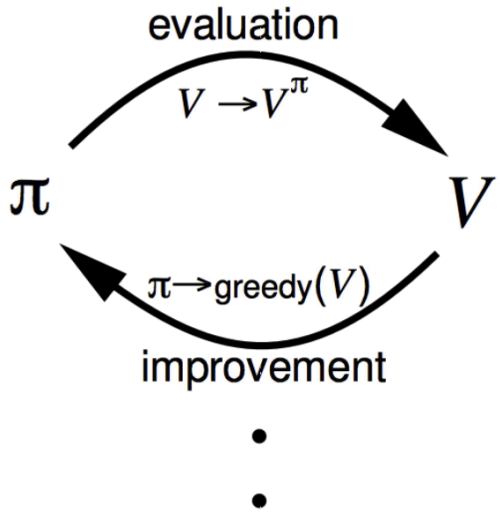
1. Model-free control:
   1. Optimize the value function of an unknown MDP
   2. Generate a optimal control policy
2. But is there model-based control? What is it? will come back to it
3. Generalized Policy Iteration (GPI) with MC or TD in the loop

Revisiting Policy Iteration

1. Iterate through the two steps:
   1. Evaluate the policy π (computing v given current π)
   2. Improve the policy by acting greedily with respect to v_π

$$\pi' = \text{greedy}(v_\pi) \tag{2}$$

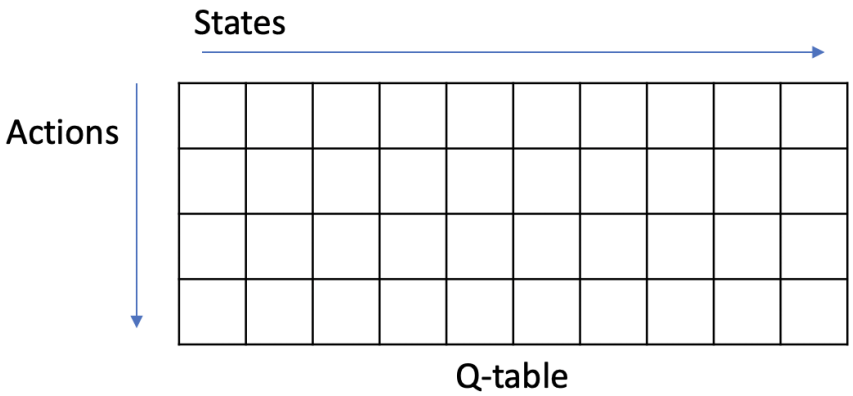




Policy Iteration for a Known MDP

1. compute the state-action value of a policy π:

$$q_{\pi_i}(s,a) = R(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) v_{\pi_i}(s')$$



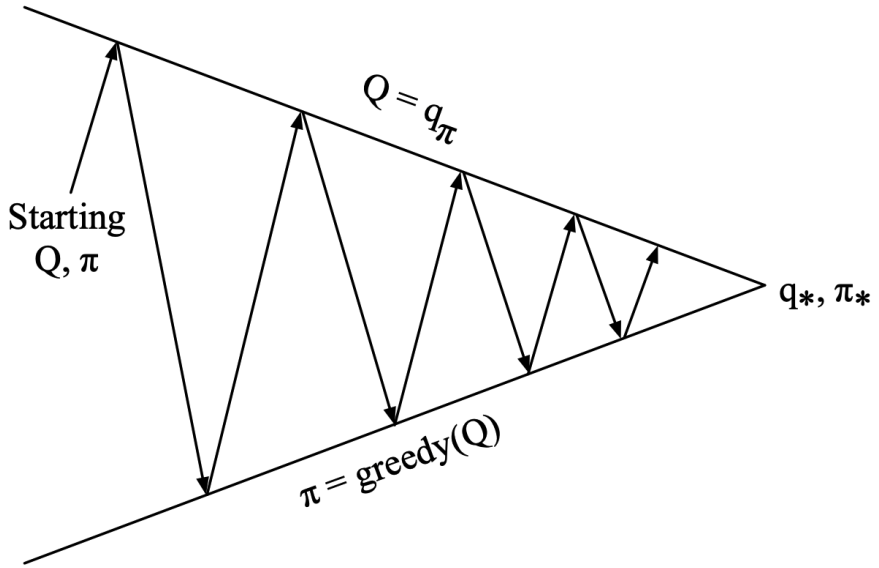
2. Compute new policy π_{i+1} for all $s \in \mathcal{S}$ following

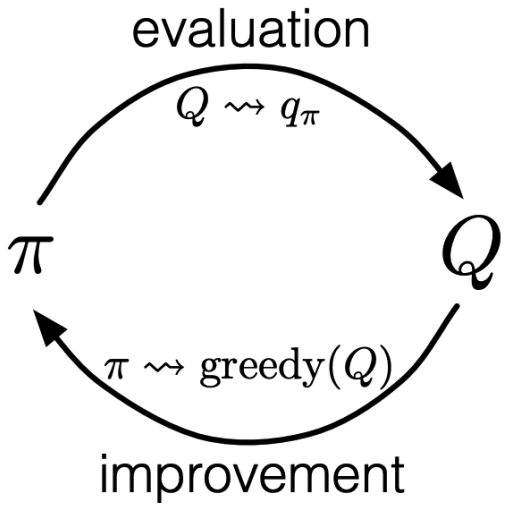
$$\pi_{i+1}(s) = \arg\max_a q_{\pi_i}(s,a) \tag{3}$$

3. Problem: What to do if there is neither $R(s,a)$ nor $P(s'|s,a)$ known/available?

Generalized Policy Iteration with Action-Value Function

Monte Carlo version of policy iteration





1. Policy evaluation: Monte-Carlo policy evaluation $Q = q_\pi$
2. Policy improvement: Greedy policy improvement?

$$\pi(s) = \arg\max_a q(s, a)$$

Monte Carlo with Exploring Starts

1. One assumption to obtain the guarantee of convergence in PI: Episode has exploring starts
2. Exploring starts can ensure all actions are selected infinitely often

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

Initialize:

$\pi(s) \in \mathcal{A}(s)$ (arbitrarily), for all $s \in \mathcal{S}$
$Q(s,a) \in \mathbb{R}$ (arbitrarily), for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$
$Returns(s,a) \leftarrow$ empty list, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$

Loop forever (for each episode):

Choose $S_0 \in \mathcal{S}$, $A_0 \in \mathcal{A}(S_0)$ randomly such that all pairs have probability > 0
Generate an episode from S_0, A_0, following π: $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$
$G \leftarrow 0$
Loop for each step of episode, $t = T-1, T-2, \ldots, 0$:
$G \leftarrow \gamma G + R_{t+1}$
Unless the pair S_t, A_t appears in $S_0, A_0, S_1, A_1 \ldots, S_{t-1}, A_{t-1}$:
Append G to $Returns(S_t, A_t)$
$Q(S_t, A_t) \leftarrow \text{average}(Returns(S_t, A_t))$
$\pi(S_t) \leftarrow \text{argmax}_a Q(S_t, a)$

Monte Carlo with ϵ-Greedy Exploration

1. Trade-off between exploration and exploitation (we will talk about this in later lecture)
2. ϵ-Greedy Exploration: Ensuring continual exploration
   1. All actions are tried with non-zero probability
   2. With probability $1 - \epsilon$ choose the greedy action
   3. With probability ϵ choose an action at random

$$\pi(a|s) = \begin{cases} \epsilon/|\mathcal{A}| + 1 - \epsilon & \text{if } a^* = \arg\max_{a \in \mathcal{A}} Q(s,a) \\ \epsilon/|\mathcal{A}| & \text{otherwise} \end{cases}$$

Monte Carlo with ϵ-Greedy Exploration

1. Policy improvement theorem: For any ϵ-greedy policy π, the ϵ-greedy policy π' with respect to q_π is an improvement, $v_{\pi'}(s) \geq v_\pi(s)$

$$
\begin{aligned}
q_\pi(s, \pi'(s)) &= \sum_{a \in \mathcal{A}} \pi'(a|s) q_\pi(s, a) \\
&= \frac{\epsilon}{|\mathcal{A}|} \sum_{a \in \mathcal{A}} q_\pi(s, a) + (1 - \epsilon) \max_a q_\pi(s, a) \\
&\geq \frac{\epsilon}{|\mathcal{A}|} \sum_{a \in \mathcal{A}} q_\pi(s, a) + (1 - \epsilon) \sum_{a \in \mathcal{A}} \frac{\pi(a|s) - \frac{\epsilon}{|\mathcal{A}|}}{1 - \epsilon} q_\pi(s, a) \\
&= \sum_{a \in \mathcal{A}} \pi(a|s) q_\pi(s, a) = v_\pi(s)
\end{aligned}
$$

Therefore, $v_{\pi'}(s) \geq v_\pi(s)$ from the policy improvement theorem

Monte Carlo with ϵ-Greedy Exploration

Algorithm 1

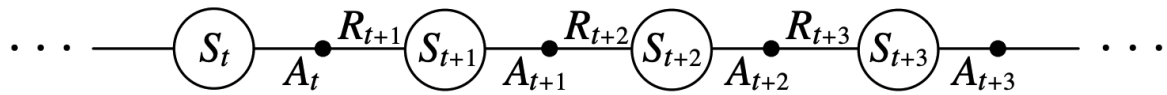
Initialize $Q(S, A) = 0, N(S, A) = 0, \epsilon = 1, k = 1$
$\pi_k = \epsilon$-greedy(Q)
loop
  Sample k-th episode $(S_1, A_1, R_2, ..., S_T) \sim \pi_k$
  for each state S_t and action A_t in the episode **do**
    $N(S_t, A_t) \leftarrow N(S_t, A_t) + 1$
    $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \frac{1}{N(S_t, A_t)}(G_t - Q(S_t, A_t))$
  end for
  $k \leftarrow k + 1, \epsilon \leftarrow 1/k$
  $\pi_k = \epsilon$-greedy(Q)
end loop

MC vs. TD for Prediction and Control

1. Temporal-difference (TD) learning has several advantages over Monte-Carlo (MC)
   1. Lower variance
   2. Online
   3. Incomplete sequences
2. So we can use TD instead of MC in our control loop
   1. Apply TD to $Q(S, A)$
   2. Use ϵ-greedy policy improvement
   3. Update every time-step rather than at the end of one episode

Recall: TD Prediction

1. An episode consists of an alternating sequence of states and state–action pairs:



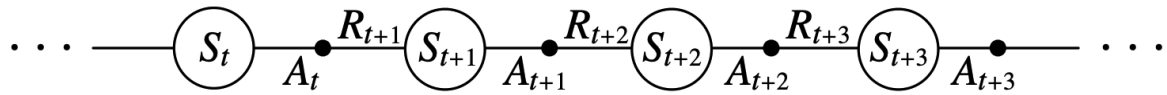
2. TD(0) method for estimating the value function $V(S)$

$$A_t \leftarrow \text{action given by } \pi \text{ for S}$$
$$\text{Take action } A_t, \text{ observe } R_{t+1} \text{ and } S_{t+1}$$
$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

3. How about estimating action value function $Q(S, A)$?

Sarsa: On-Policy TD Control

1. An episode consists of an alternating sequence of states and state–action pairs:



2. ϵ-greedy policy for one step, then bootstrap the action value function:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\Big]$$

3. The update is done after every transition from a nonterminal state S_t
4. TD target $\delta_t = R_{t+1} + \gamma Q(S_{t+1}, A_{t+1})$

Sarsa algorithm

Sarsa (on-policy TD control) for estimating $Q \approx q_*$

Initialize $Q(s,a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize S
  Choose A from S using policy derived from Q (e.g., ϵ-greedy)
  Repeat (for each step of episode):
    Take action A, observe R, S'
    Choose A' from S' using policy derived from Q (e.g., ϵ-greedy)
    $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma Q(S',A') - Q(S,A)\big]$
    $S \leftarrow S'$; $A \leftarrow A'$;
  until S is terminal

n-step Sarsa

1. Consider the following n-step Q-returns for $n = 1, 2, \infty$

$$\begin{aligned} n = 1 (Sarsa) \quad q_t^{(1)} &= R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) \\ n = 2 \quad\quad\quad q_t^{(2)} &= R_{t+1} + \gamma R_{t+2} + \gamma^2 Q(S_{t+2}, A_{t+2}) \\ &\vdots \\ n = \infty (MC) \quad q_t^{\infty} &= R_{t+1} + \gamma R_{t+2} + ... + \gamma^{T-t-1} R_T \end{aligned}$$

2. Thus the n-step Q-return is defined as

$$q_t^{(n)} = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{n-1} R_{t+n} + \gamma^n Q(S_{t+n}, A_{t+n})$$

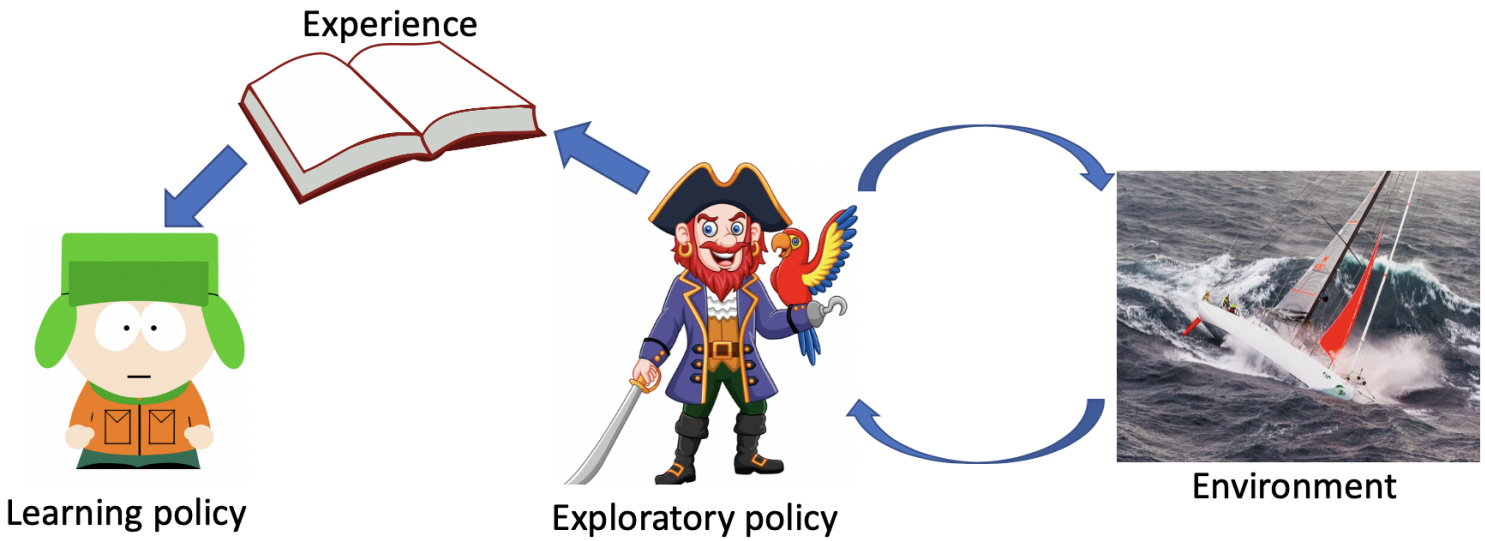
3. n-step Sarsa updates Q(s,a) towards the n-step Q-return:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \Big(q_t^{(n)} - Q(S_t, A_t) \Big)$$

On-policy Learning vs. Off-policy Learning

1. On-policy learning: Learn about policy π from the experience collected from π
    1. Behave non-optimally in order to explore all actions, then reduce the exploration. e.g., ϵ-greedy
2. Another important approach is **off-policy learning** which essentially uses **two different polices**:
    1. the one which is being learned about and becomes the optimal policy
    2. the other one which is more exploratory and is used to generate trajectories
3. Off-policy learning: Learn about policy π from the experience sampled from another policy μ
    1. π: target policy
    2. μ: behavior policy

Off-policy Learning



1. Following behaviour policy $\mu(a|s)$ to collect data

$$S_1, A_1, R_2, ..., S_T \sim \mu$$
$$\text{Update } \pi \text{ using } S_1, A_1, R_2, ..., S_T$$

2. It leads to many benefits:
   1. Learn about optimal policy while following exploratory policy
   2. Learn from observing humans or other agents
   3. Re-use experience generated from old policies $\pi_1, \pi_2, ..., \pi_{t-1}$

Off-Policy Control with Q Learning

1. Off-policy learning of action values $Q(s, a)$
2. No importance sampling is needed
3. Next action in TD target is selected from the alternative action $A' \sim \pi(.|S_t)$
4. update $Q(S_t, A_t)$ towards value of alternative action

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\big(R_{t+1} + \gamma Q(S_{t+1}, A') - Q(S_t, A_t)\big)$$

Off-Policy Control with Q-Learning

1. We allow both behavior and target policies to improve
2. The target policy π is greedy on $Q(s, a)$

$$\pi(S_{t+1}) = \arg\max_{a'} Q(S_{t+1}, a')$$

3. The behavior policy μ could be totally random, but we let it improve following ϵ-greedy on $Q(s, a)$
4. Thus Q-learning target:

$$\begin{aligned} R_{t+1} + \gamma Q(S_{t+1}, A') =& R_{t+1} + \gamma Q(S_{t+1}, \arg\max Q(S_{t+1}, a')) \\ =& R_{t+1} + \gamma \max_{a'} Q(S_{t+1}, a') \end{aligned}$$

5. Thus the Q-Learning update

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \Big[R_{t+1} + \gamma \max_{a} Q(S_{t+1}, a) - Q(S_t, A_t) \Big]$$

Q-learning algorithm

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Initialize $Q(s,a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize S
  Repeat (for each step of episode):
    Choose A from S using policy derived from Q (e.g., ϵ-greedy)
    Take action A, observe R, S'
    $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
    $S \leftarrow S'$
  until S is terminal

Comparison of Sarsa and Q-Learning

1. Sarsa: On-Policy TD control

   Choose action A_t from S_t using policy derived from Q with ϵ-greedy

   Take action A_t, observe R_{t+1} and S_{t+1}

   Choose action A_{t+1} from S_{t+1} using policy derived from Q with ϵ-greedy

   $$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\Big]$$

2. Q-Learning: Off-Policy TD control

   Choose action A_t from S_t using policy derived from Q with ϵ-greedy

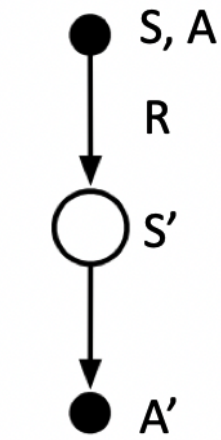
   Take action A_t, observe R_{t+1} and S_{t+1}

   Then 'imagine' A_{t+1} as $\arg\max Q(S_{t+1}, a')$ in the update target

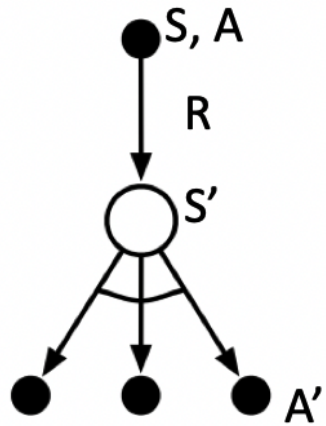
   $$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\Big]$$

Comparison of Sarsa and Q-Learning

1. Backup diagram for Sarsa and Q-learning



Sarsa

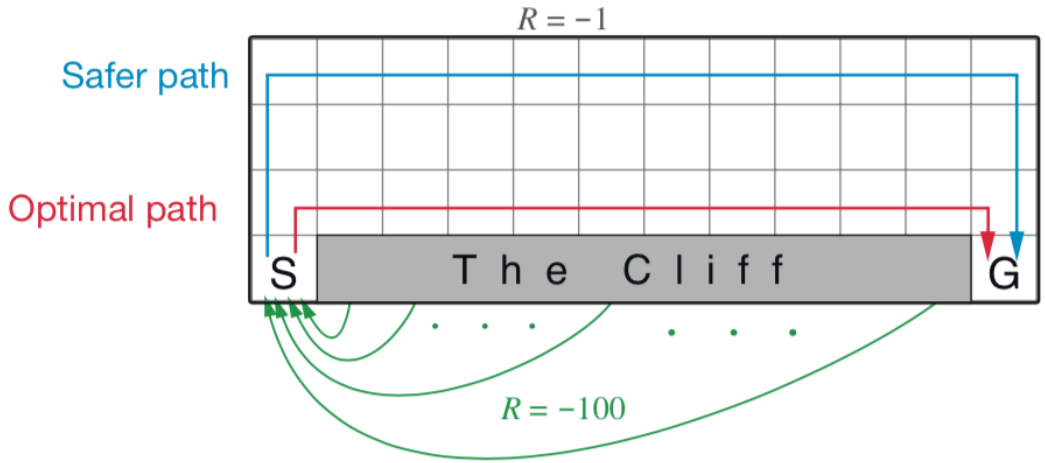


Q-learning

2. In Sarsa, A and A' are sampled from the same policy so it is on-policy
3. In Q Learning, A and A' are from different policies, with A being more exploratory and A' determined directly by the max operator

Example on Cliff Walk (Example 6.6 from Textbook)

https://github.com/cuhkrlcourse/RLexample/blob/master/modelfree/cliffwal

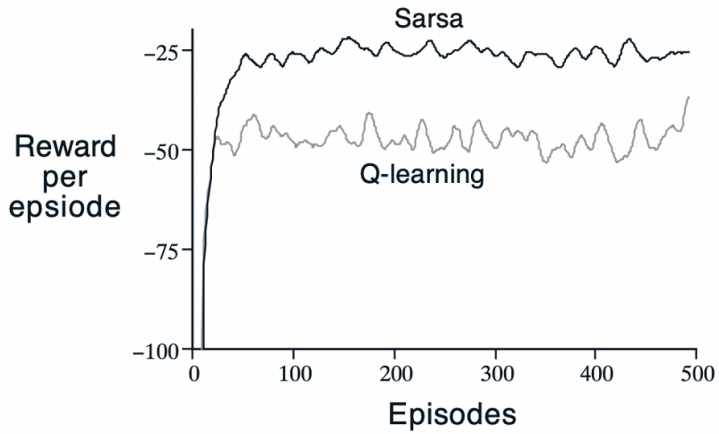


0	0	0	0	R	R	R	R	R	R	R	R
R	R	R	R	R	0	0	0	0	0	0	R
R	0	0	0	0	0	0	0	0	0	0	R
R	*	*	*	*	*	*	*	*	*	*	G

Result of Sarsa

0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
R	R	R	R	R	R	R	R	R	R	R	R
R	*	*	*	*	*	*	*	*	*	*	G

Result of Q-Learning



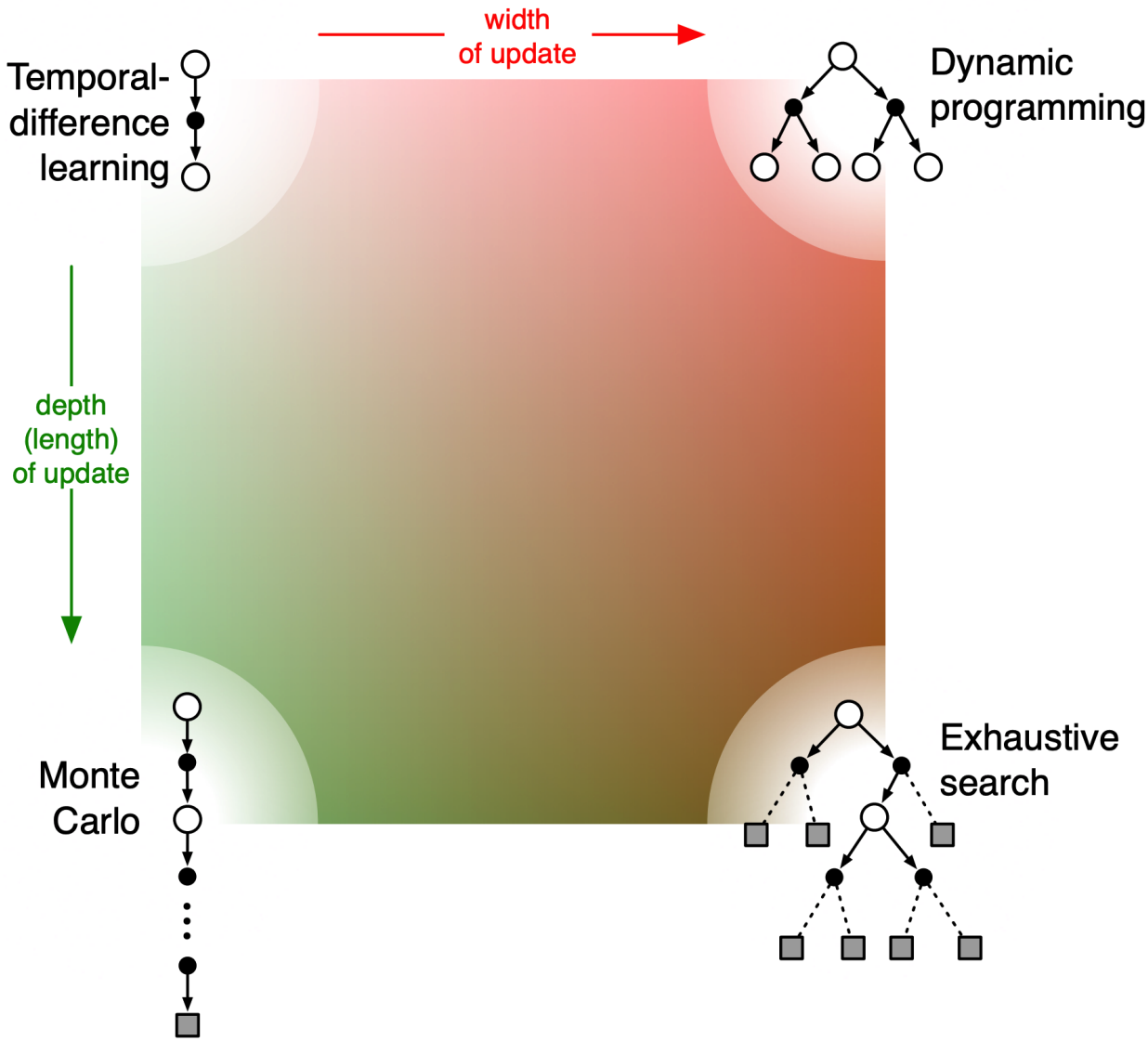
On-line performance of Q-learning is worse than that of Sarsa

Summary of DP and TD

Expected Update (DP)	**Sample Update (TD)**
Iterative Policy Evaluation $V(s) \leftarrow \mathbb{E}[R + \gamma V(S')\|s]$	TD Learning $V(S) \leftarrow^{\alpha} R + \gamma V(S')$
Q-Policy Iteration $Q(S, A) \leftarrow \mathbb{E}[R + \gamma Q(S', A')\|s, a]$	Sarsa $Q(S, A) \leftarrow^{\alpha} R + \gamma Q(S', A')$
Q-Value Iteration $Q(S, A) \leftarrow \mathbb{E}[R + \gamma \max_{a' \in \mathcal{A}} Q(S', A')\|s, a]$	Q-Learning $Q(S, A) \leftarrow^{\alpha} R + \gamma \max_{a' \in \mathcal{A}} Q(S', a')$

where $x \leftarrow^{\alpha} y$ is defined as $x \leftarrow x + \alpha(y - x)$

Unified View of Reinforcement Learning



Sarsa and Q-Learning Example

https://github.com/cuhkrlcourse/RLexample/tree/master/modelfree

Summary

1. Model-free prediction in MDP
2. Model-free control in MDP

End

1. Course proposal due by the end of this week
2. Homework 1 due by the end of next Tuesday
3. Next week:
    1. Off-policy learning and importance sampling
    2. Reinforcement Learning and Optimal control