Model-Free
Temporal-Difference (Q-Learning)

Alina Vereshchaka

CSE4/510 Reinforcement Learning
Fall 2019

avereshc@buffalo.edu

September 19, 2019

Overview

1. Recap
2. SARSA
3. Q-Learning

Table of Contents

Recap: Monte Carlo (MC) and Temporal Difference (TD) Learning

- Goal: learn $v_\pi(s)$ from episodes of experience under policy π
- Incremental every-visit Monte-Carlo:
  - Update value $V(S_t)$ toward actual return G_t

$$V(S_t) \leftarrow V(S_t) + \alpha \left(G_t - V(S_t) \right)$$

- Simplest Temporal-Difference learning algorithm: TD(0)
  - Update value $V(S_t)$ toward estimated returns $R_{t+1} + \gamma V(S_{t+1})$

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

- $R_{t+1} + \gamma V(S_{t+1})$ is called the TD target
- $\delta_t = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$ is called the TD error.

TD(0) Method

- Policy Evaluation (the prediction problem):
  - for a given policy π, compute the state-value function v_π

- Remember: Simple every-visit Monte Carlo method:

$$V(S_t) \leftarrow V(S_t) + \alpha \left[G_t - V(S_t) \right]$$

target: the actual return after time *t*

- The simplest Temporal-Difference method TD(0):

$$V(S_t) \leftarrow V(S_t) + \alpha \left[\underbrace{R_{t+1} + \gamma V(S_{t+1})} - V(S_t) \right]$$

target: an estimate of the return

Example: Driving Home

State	*Elapsed Time (minutes)*	*Predicted Time to Go*	*Predicted Total Time*
leaving office, friday at 6	0	30	30
reach car, raining	5	35	40
exiting highway	20	15	35
2ndary road, behind truck	30	10	40
entering home street	40	3	43
arrive home	43	0	43

Example: Driving Home

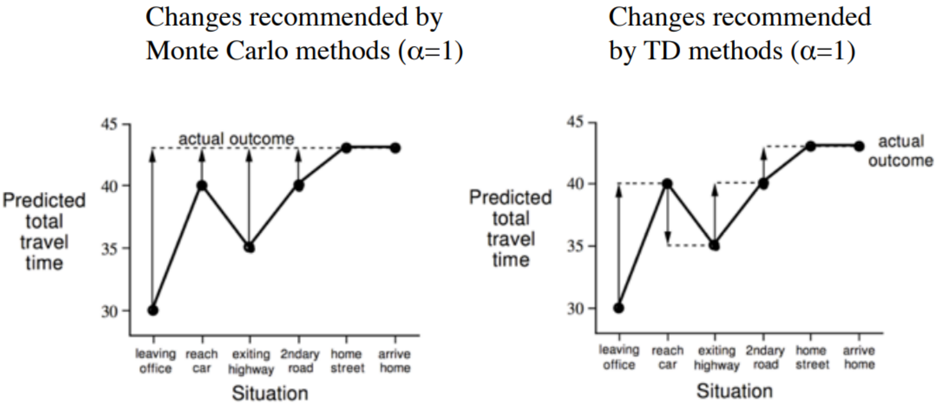
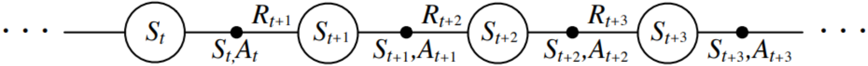


Table of Contents

- Estimate q_π for the current policy π



After every transition from a nonterminal state, S_t, do this:

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

If S_{t+1} is terminal, then define $Q(S_{t+1}, A_{t+1}) = 0$

SARSA

Turn this into a control method by always updating the policy to be **greedy** with respect to the current estimate

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

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize S
  Choose A from S using policy derived from Q (e.g., ε-greedy)
  Loop 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

SARSA

- SARSA is an **on-policy** algorithm which means that while learning the optimal policy it uses the current estimate of the optimal policy to generate the behaviour
- SARSA converges to an **optimal policy** as long as all state-action pairs are visited an infinite number of times and the policy converges in the limit to the greedy policy ($\epsilon = \frac{1}{t}$).

Table of Contents

Q-learning: Off-Policy TD Control

In Q-learning the learned action-value function, Q, directly approximates the optimal action-value function, independent of the policy being followed.

$$Q(s_t, a_t) \leftarrow (s_t, a_t) + \alpha \left(r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right)$$

Q-Learning Algorithm

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

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Take action A, observe R, S'
    $$Q(S, A) \leftarrow Q(S, A) + \alpha\Big[\underbrace{\overbrace{\boxed{\underbrace{R}_{\text{Immediate Reward}} + \gamma \max_a Q(S', a)}}^{\text{Target}} - \overbrace{\boxed{Q(S, A)}}^{\text{Prediction}}}_{\text{loss}}\Big]$$
    $S \leftarrow S'$
  until S is terminal