

Temporal Difference Methods

for Control

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Difference between prediction and control in pseudocode

tabular TD(0) for q_{π} : $Q(S_t, A_t) \leftarrow Q(S_t, A_t)$

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 $s \in S^+$, $a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$ Loop for each episode: Initialize SChoose 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) $Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma Q(S',A') - Q(S,A) \right]$ $S \leftarrow S'; A \leftarrow A';$ until S is terminal

What would you modify in the above to get the pseudo code for TD(0)?

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

Q-learning and on-policy vs. off-policy

SARSA: $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + a$

Q-learning: $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha$

Notice what the target of the update represents and whether the underlying policy of that matches the behavior policy

 $V^{MC}(S_t) \leftarrow V^{MC}$ **On-policy constant-** α **MC:**

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

$$C(S_t) + \alpha \begin{bmatrix} G_t & -V^{MC}(S_t) \\ target \end{bmatrix}$$

Off-policy constant- α **MC**: $V^{MC}(S_t) \leftarrow V^{MC}(S_t) + \alpha \left[\rho_{t:T-1} G_t - V^{MC}(S_t) \right]$

Difference between Q-learning and SARSA in pseudocode

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 $s \in S^+$, $a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$ Loop for each episode: Initialize SChoose 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) $Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma Q(S',A') - Q(S,A) \right]$ $S \leftarrow S'; A \leftarrow A';$ until S is terminal

t = 0

choose action

Take action & observe

choose action

Time $t \rightarrow$

Where would you put SARSA updates?

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 $s \in S^+$, $a \in A(s)$, 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' $Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma \max_{a} Q(S',a) - Q(S,A) \right]$

 $S \leftarrow S'$

until S is terminal

Take action & observe

choose action

Take action & observe

Where would you put Q-learning updates?

What happens if we switch the time of update for both?

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

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Algorithm parameters: step size \alpha \in (0,1], small \varepsilon > 0
Initialize Q(s, a), for all s \in S^+, a \in 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., \varepsilon-greedy)
Loop for each step of episode:
Take action A, observe R, S'
Choose A' from S' using policy derived from Q (e.g., \varepsilon-greedy)
Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma Q(S', A') - Q(S, A)]
S \leftarrow S'; A \leftarrow A';
until S is terminal
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Say we make the SARSA update after taking the next action. Is it still same or correct?

Say we make the Q-learning update before taking action. Is it still same or correct?

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 $s \in S^+$, $a \in A(s)$, 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'

$$Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma \max_{a} Q(S',a) - Q(S,A) \right]$$

until S is terminal

 $S \leftarrow S'$

Modify the Q-learning Pseudocode minimally to get SARSA

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

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$ Loop for each episode: Initialize SLoop for each step of episode: Choose A from S using policy derived from Q (e.g., ε -greedy) Take action A, observe R, S' $Q(S, A) \leftarrow Q(S, A) + \alpha \left[R + \gamma \max_{a} Q(S', a) - Q(S, A) \right]$ $S \leftarrow S'$ until S is terminal

Initialize Q(s, a), for all $s \in S^+$, $a \in A(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

The equivalence of two SARSA algorithms breaks in the real world

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 $s \in S^+$, $a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$ Loop for each episode: Initialize SChoose 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) $Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma Q(S',A') - Q(S,A) \right]$ $S \leftarrow S'; A \leftarrow A';$ until S is terminal



What will be an off-policy TD(0) update for q_{π} ?