

Policy Evaluation

Monte Carlo Evaluation: Temporal Difference Learning

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Temporal Difference Learning

- ▶ "If one had to identify one idea as central and novel to reinforcement learning, it would undoubtedly be temporal-difference (TD) learning." – Sutton and Barto 2017
- ▶ Combination of Monte Carlo & dynamic programming methods
- ▶ Model-free
- ▶ bootstraps and samples
- ▶ Can be used in episodic or infinite-horizon non-episodic settings
- ▶ Immediately updates estimate of V after each (s, a, r, s') tuple

Temporal Difference Learning for Estimating V

- ▶ Aim: estimate $V^\pi(s)$ given episodes generated under policy π
- ▶ $G_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots$ in MDP M under policy π
- ▶ $V^\pi(s) = \mathbb{E}[G_t \mid s_t = s]$

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- ▶ Recall Bellman operator (if known MDP models)

$$B^\pi V(s) = r(s, \pi(s)) + \gamma \sum_{s' \in S} p(s' \mid s, \pi(s)) V(s')$$

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- ▶ Insight: have an estimate of V^π , used to estimate expected return

$$V^\pi(s) = V^\pi(s) + \alpha([r_t + \gamma V^\pi(s_{t+1})] - V^\pi(s))$$

Temporal Difference [TD(0)] Learning

- ▶ Aim: estimate $V^\pi(s)$ given episodes generated under policy π
- ▶ Simplest TD learning: update value towards estimated value

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$$\delta_t = r_t + \gamma V^\pi(s_{t+1}) - V^\pi(s)$$

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- ▶ TD error:

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- ↪ Can immediately update value estimate after (s, a, r, s') tuple
- ↪ Don't need episodic setting

Temporal Difference [TD(0)] Learning Algorithm

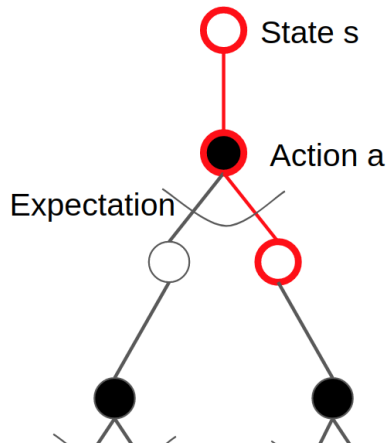
Input: α

Initialize $V^\pi(s) = 0. \forall s \in S$

Loop

- ▶ Sample tuple (s_t, a_t, r_t, s_{t+1})
- ▶ $V^\pi(s) = V^\pi(s) + \alpha(\underbrace{[r_t + \gamma V^\pi(s_{t+1})]}_{\text{TD target}}) - V^\pi(s)$

Temporal Difference [TD(0)] Learning Algorithm



- ▶ TD updates the value estimate using a sample of s_{t+1} to approximate an expectation
- ▶ TD updates the value estimate by bootstrapping, uses estimates of $V(s_{t+1})$