

Lecture 4: Model-Free Prediction

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Outline

- 1 Introduction
- 2 Monte-Carlo Learning
- 3 Temporal-Difference Learning
- 4 $TD(\lambda)$

Model-Free Reinforcement Learning

- Last lecture:
 - Planning by dynamic programming
 - Solve a *known* MDP
- This lecture:
 - Model-free prediction
 - Estimate the value function of an *unknown* MDP
- Next lecture:
 - Model-free control
 - Optimise the value function of an *unknown* MDP

Monte-Carlo Reinforcement Learning

- MC methods learn directly from episodes of experience
- MC is *model-free*: no knowledge of MDP transitions / rewards
- MC learns from *complete* episodes: no bootstrapping
- MC uses the simplest possible idea: value = mean return
- Caveat: can only apply MC to *episodic* MDPs
 - All episodes must terminate

Monte-Carlo Policy Evaluation

- Goal: learn v_π from episodes of experience under policy π

$$S_1, A_1, R_2, \dots, S_k \sim \pi$$

- Recall that the *return* is the total discounted reward:

$$G_t = R_{t+1} + \gamma R_{t+2} + \dots + \gamma^{T-1} R_T$$

- Recall that the value function is the expected return:

$$v_\pi(s) = \mathbb{E}_\pi [G_t \mid S_t = s]$$

- Monte-Carlo policy evaluation uses *empirical mean* return instead of *expected* return

First-Visit Monte-Carlo Policy Evaluation

- To evaluate state s
- The **first** time-step t that state s is visited in an episode,
- Increment counter $N(s) \leftarrow N(s) + 1$
- Increment total return $S(s) \leftarrow S(s) + G_t$
- Value is estimated by mean return $V(s) = S(s)/N(s)$
- By law of large numbers, $V(s) \rightarrow v_\pi(s)$ as $N(s) \rightarrow \infty$

Every-Visit Monte-Carlo Policy Evaluation

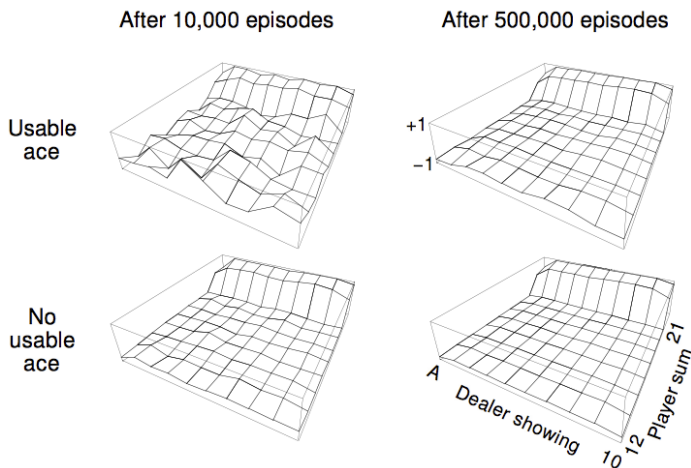
- To evaluate state s
- **Every** time-step t that state s is visited in an episode,
- Increment counter $N(s) \leftarrow N(s) + 1$
- Increment total return $S(s) \leftarrow S(s) + G_t$
- Value is estimated by mean return $V(s) = S(s)/N(s)$
- Again, $V(s) \rightarrow v_{\pi}(s)$ as $N(s) \rightarrow \infty$

Blackjack Example

- States (200 of them):
 - Current sum (12-21)
 - Dealer's showing card (ace-10)
 - Do I have a "useable" ace? (yes-no)
- Action **stick**: Stop receiving cards (and terminate)
- Action **twist**: Take another card (no replacement)
- Reward for **stick**:
 - +1 if sum of cards $>$ sum of dealer cards
 - 0 if sum of cards = sum of dealer cards
 - -1 if sum of cards $<$ sum of dealer cards
- Reward for **twist**:
 - -1 if sum of cards $>$ 21 (and terminate)
 - 0 otherwise
- Transitions: automatically **twist** if sum of cards $<$ 12



Blackjack Value Function after Monte-Carlo Learning



Policy: **stick** if sum of cards ≥ 20 , otherwise **twist**

Incremental Mean

The mean μ_1, μ_2, \dots of a sequence x_1, x_2, \dots can be computed incrementally,

$$\begin{aligned}\mu_k &= \frac{1}{k} \sum_{j=1}^k x_j \\ &= \frac{1}{k} \left(x_k + \sum_{j=1}^{k-1} x_j \right) \\ &= \frac{1}{k} (x_k + (k-1)\mu_{k-1}) \\ &= \mu_{k-1} + \frac{1}{k} (x_k - \mu_{k-1})\end{aligned}$$

Incremental Monte-Carlo Updates

- Update $V(s)$ incrementally after episode $S_1, A_1, R_2, \dots, S_T$
- For each state S_t with return G_t

$$N(S_t) \leftarrow N(S_t) + 1$$

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

- In non-stationary problems, it can be useful to track a running mean, i.e. forget old episodes.

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

Temporal-Difference Learning

- TD methods learn directly from episodes of experience
- TD is *model-free*: no knowledge of MDP transitions / rewards
- TD learns from *incomplete* episodes, by *bootstrapping*
- TD updates a guess towards a guess

MC and TD

- Goal: learn v_π online from experience under policy π
- Incremental every-visit Monte-Carlo
 - Update value $V(S_t)$ toward *actual* return G_t

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

- Simplest temporal-difference learning algorithm: TD(0)
 - Update value $V(S_t)$ toward *estimated* return $R_{t+1} + \gamma V(S_{t+1})$

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

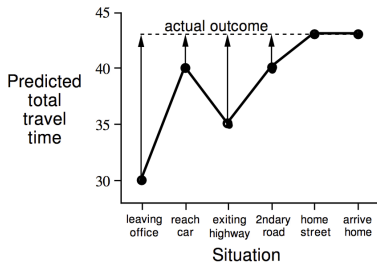
- $R_{t+1} + \gamma V(S_{t+1})$ is called the *TD target*
- $\delta_t = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$ is called the *TD error*

Driving Home Example

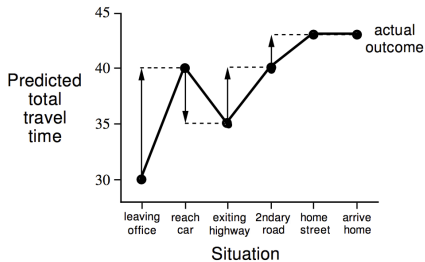
State	Elapsed Time (minutes)	Predicted Time to Go	Predicted Total Time
leaving office	0	30	30
reach car, raining	5	35	40
exit highway	20	15	35
behind truck	30	10	40
home street	40	3	43
arrive home	43	0	43

Driving Home Example: MC vs. TD

Changes recommended by
Monte Carlo methods ($\alpha=1$)



Changes recommended
by TD methods ($\alpha=1$)



Advantages and Disadvantages of MC vs. TD

- TD can learn *before* knowing the final outcome
 - TD can learn online after every step
 - MC must wait until end of episode before return is known
- TD can learn *without* the final outcome
 - TD can learn from incomplete sequences
 - MC can only learn from complete sequences
 - TD works in continuing (non-terminating) environments
 - MC only works for episodic (terminating) environments

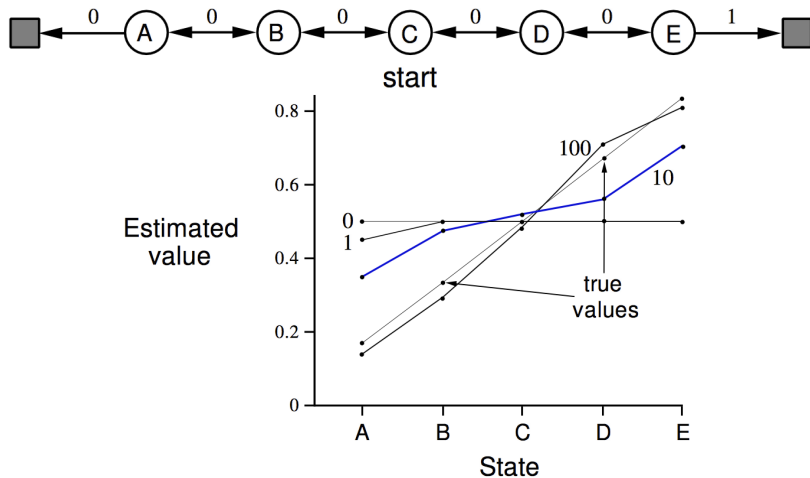
Bias/Variance Trade-Off

- Return $G_t = R_{t+1} + \gamma R_{t+2} + \dots + \gamma^{T-1} R_T$ is *unbiased* estimate of $v_\pi(S_t)$
- True TD target $R_{t+1} + \gamma v_\pi(S_{t+1})$ is *unbiased* estimate of $v_\pi(S_t)$
- TD target $R_{t+1} + \gamma V(S_{t+1})$ is *biased* estimate of $v_\pi(S_t)$
- TD target is much lower variance than the return:
 - Return depends on *many* random actions, transitions, rewards
 - TD target depends on *one* random action, transition, reward

Advantages and Disadvantages of MC vs. TD (2)

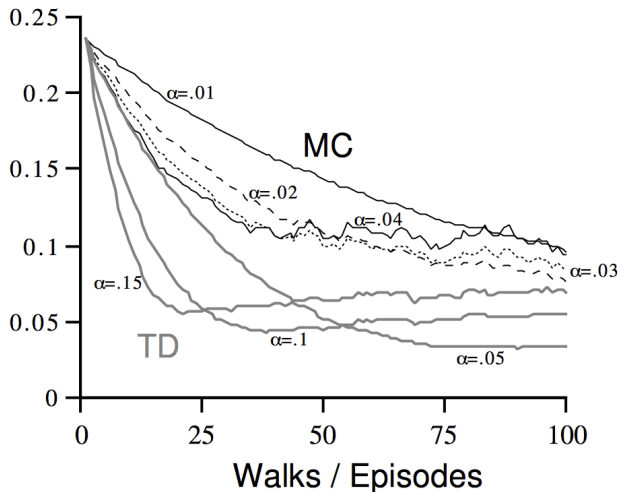
- MC has high variance, zero bias
 - Good convergence properties
 - (even with function approximation)
 - Not very sensitive to initial value
 - Very simple to understand and use
- TD has low variance, some bias
 - Usually more efficient than MC
 - TD(0) converges to $v_{\pi}(s)$
 - (but not always with function approximation)
 - More sensitive to initial value

Random Walk Example



Random Walk: MC vs. TD

RMS error,
averaged
over states



Batch MC and TD

- MC and TD converge: $V(s) \rightarrow v_{\pi}(s)$ as experience $\rightarrow \infty$
- But what about batch solution for finite experience?

$$\begin{array}{c} s_1^1, a_1^1, r_2^1, \dots, s_{T_1}^1 \\ \vdots \\ s_1^K, a_1^K, r_2^K, \dots, s_{T_K}^K \end{array}$$

- e.g. Repeatedly sample episode $k \in [1, K]$
- Apply MC or TD(0) to episode k

AB Example

Two states A, B ; no discounting; 8 episodes of experience

$A, 0, B, 0$

$B, 1$

$B, 1$

$B, 1$

$B, 1$

$B, 1$

$B, 1$

$B, 0$

What is $V(A)$, $V(B)$?

AB Example

Two states A, B ; no discounting; 8 episodes of experience

$A, 0, B, 0$

$B, 1$

$B, 1$

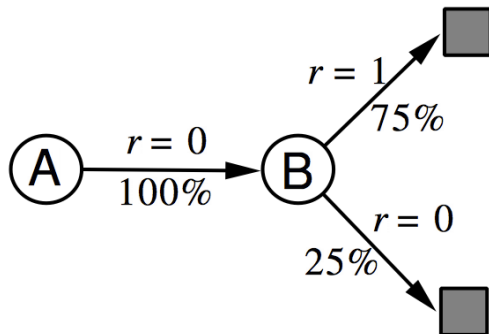
$B, 1$

$B, 1$

$B, 1$

$B, 1$

$B, 0$



What is $V(A), V(B)$?

Certainty Equivalence

- MC converges to solution with minimum mean-squared error
 - Best fit to the observed returns

$$\sum_{k=1}^K \sum_{t=1}^{T_k} (G_t^k - V(s_t^k))^2$$

- In the AB example, $V(A) = 0$
- TD(0) converges to solution of max likelihood Markov model
 - Solution to the MDP $\langle \mathcal{S}, \mathcal{A}, \hat{\mathcal{P}}, \hat{\mathcal{R}}, \gamma \rangle$ that best fits the data

$$\hat{\mathcal{P}}_{s,s'}^a = \frac{1}{N(s,a)} \sum_{k=1}^K \sum_{t=1}^{T_k} \mathbf{1}(s_t^k, a_t^k, s_{t+1}^k = s, a, s')$$

$$\hat{\mathcal{R}}_s^a = \frac{1}{N(s,a)} \sum_{k=1}^K \sum_{t=1}^{T_k} \mathbf{1}(s_t^k, a_t^k = s, a) r_t^k$$

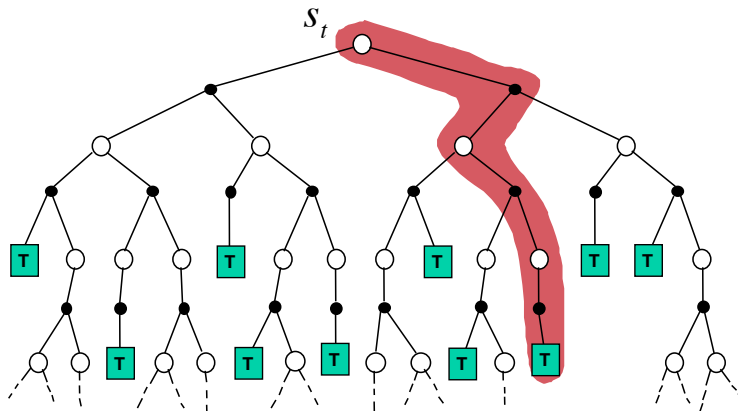
- In the AB example, $V(A) = 0.75$

Advantages and Disadvantages of MC vs. TD (3)

- TD exploits Markov property
 - Usually more efficient in Markov environments
- MC does not exploit Markov property
 - Usually more effective in non-Markov environments

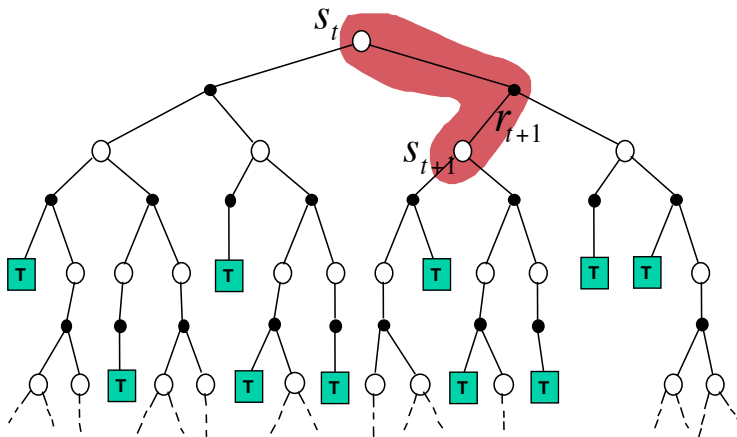
Monte-Carlo Backup

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



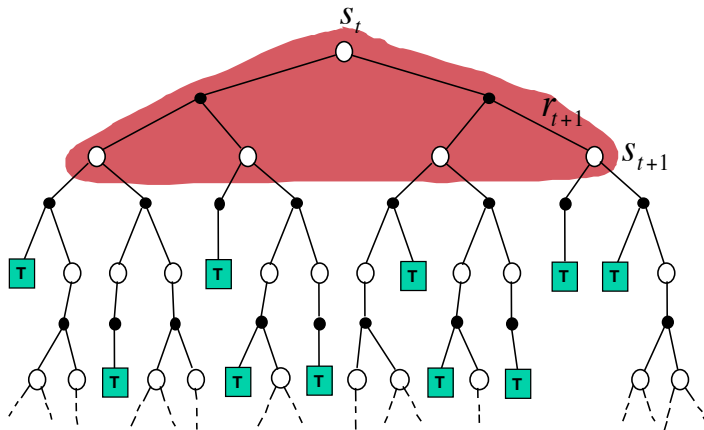
Temporal-Difference Backup

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



Dynamic Programming Backup

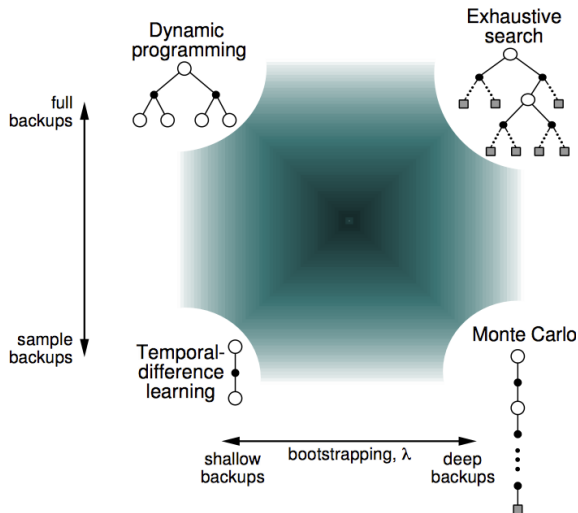
$$V(S_t) \leftarrow \mathbb{E}_{\pi} [R_{t+1} + \gamma V(S_{t+1})]$$



Bootstrapping and Sampling

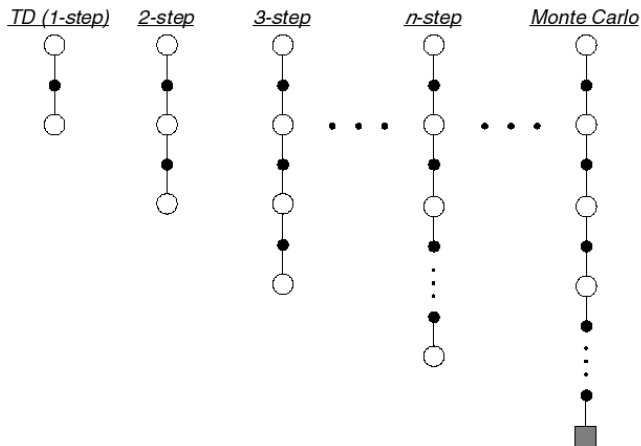
- **Bootstrapping**: update involves an estimate
 - MC does not bootstrap
 - DP bootstraps
 - TD bootstraps
- **Sampling**: update samples an expectation
 - MC samples
 - DP does not sample
 - TD samples

Unified View of Reinforcement Learning



n -Step Prediction

- Let TD target look n steps into the future



n -Step Return

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

$$n = 1 \quad (TD) \quad G_t^{(1)} = R_{t+1} + \gamma V(S_{t+1})$$

$$n = 2 \quad G_t^{(2)} = R_{t+1} + \gamma R_{t+2} + \gamma^2 V(S_{t+2})$$

$$\vdots \quad \vdots$$

$$n = \infty \quad (MC) \quad G_t^{(\infty)} = R_{t+1} + \gamma R_{t+2} + \dots + \gamma^{T-1} R_T$$

- Define the n -step return

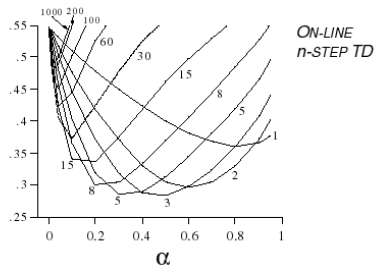
$$G_t^{(n)} = R_{t+1} + \gamma R_{t+2} + \dots + \gamma^{n-1} R_{t+n} + \gamma^n V(S_{t+n})$$

- n -step temporal-difference learning

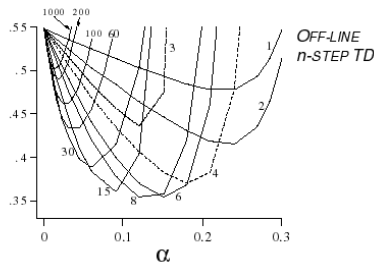
$$V(S_t) \leftarrow V(S_t) + \alpha \left(G_t^{(n)} - V(S_t) \right)$$

Large Random Walk Example

*RMS error,
averaged over
first 10 episodes*



*RMS error,
averaged over
first 10 episodes*



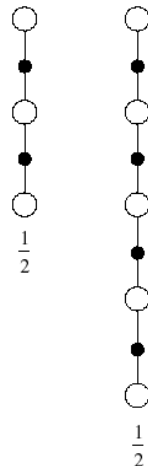
Averaging n -Step Returns

- We can average n -step returns over different n
- e.g. average the 2-step and 4-step returns

$$\frac{1}{2}G^{(2)} + \frac{1}{2}G^{(4)}$$

- Combines information from two different time-steps
- Can we efficiently combine information from all time-steps?

One backup



λ -return

TD(λ), λ -return

- The λ -return G_t^λ combines all n -step returns $G_t^{(n)}$
- Using weight $(1-\lambda)\lambda^{n-1}$

$$G_t^\lambda = (1-\lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_t^{(n)}$$

- Forward-view TD(λ)

$$V(S_t) \leftarrow V(S_t) + \alpha (G_t^\lambda - V(S_t))$$

TD(λ) Weighting Function

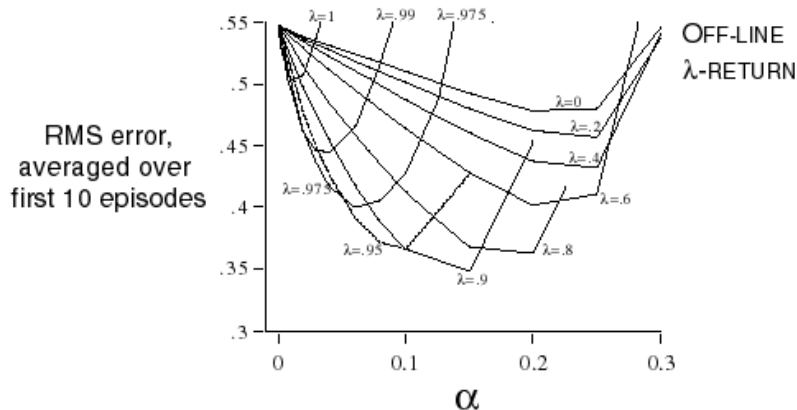


$$G_t^\lambda = (1 - \lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_t^{(n)}$$

Forward-view TD(λ)



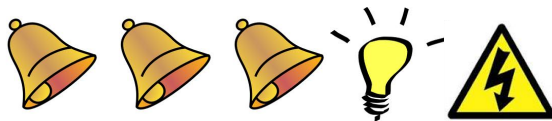
- Update value function towards the λ -return
- Forward-view looks into the future to compute G_t^λ
- Like MC, can only be computed from complete episodes

Forward-View TD(λ) on Large Random Walk

Backward View TD(λ)

- Forward view provides theory
- Backward view provides mechanism
- Update online, every step, from incomplete sequences

Eligibility Traces



- Credit assignment problem: did bell or light cause shock?
- **Frequency heuristic**: assign credit to most frequent states
- **Recency heuristic**: assign credit to most recent states
- *Eligibility traces* combine both heuristics

$$E_0(s) = 0$$

$$E_t(s) = \gamma\lambda E_{t-1}(s) + \mathbf{1}(S_t = s)$$

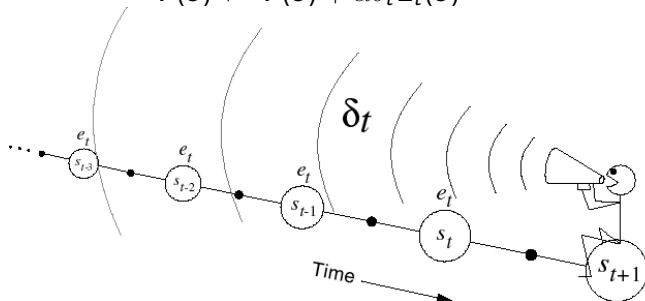


Backward View TD(λ)

- Keep an eligibility trace for every state s
- Update value $V(s)$ for every state s
- In proportion to TD-error δ_t and eligibility trace $E_t(s)$

$$\delta_t = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$$

$$V(s) \leftarrow V(s) + \alpha \delta_t E_t(s)$$



TD(λ) and TD(0)

- When $\lambda = 0$, only current state is updated

$$E_t(s) = \mathbf{1}(S_t = s)$$
$$V(s) \leftarrow V(s) + \alpha \delta_t E_t(s)$$

- This is exactly equivalent to TD(0) update

$$V(S_t) \leftarrow V(S_t) + \alpha \delta_t$$

TD(λ) and MC

- When $\lambda = 1$, credit is deferred until end of episode
- Consider episodic environments with offline updates
- Over the course of an episode, total update for TD(1) is the same as total update for MC

Theorem

The sum of offline updates is identical for forward-view and backward-view TD(λ)

$$\sum_{t=1}^T \alpha \delta_t E_t(s) = \sum_{t=1}^T \alpha \left(G_t^\lambda - V(S_t) \right) \mathbf{1}(S_t = s)$$

MC and TD(1)

- Consider an episode where s is visited once at time-step k ,
- TD(1) eligibility trace discounts time since visit,

$$\begin{aligned} E_t(s) &= \gamma E_{t-1}(s) + \mathbf{1}(S_t = s) \\ &= \begin{cases} 0 & \text{if } t < k \\ \gamma^{t-k} & \text{if } t \geq k \end{cases} \end{aligned}$$

- TD(1) updates accumulate error *online*

$$\sum_{t=1}^{T-1} \alpha \delta_t E_t(s) = \alpha \sum_{t=k}^{T-1} \gamma^{t-k} \delta_t = \alpha (G_k - V(S_k))$$

- By end of episode it accumulates total error

$$\delta_k + \gamma \delta_{k+1} + \gamma^2 \delta_{k+2} + \dots + \gamma^{T-1-k} \delta_{T-1}$$

Telescoping in TD(1)

When $\lambda = 1$, sum of TD errors telescopes into MC error,

$$\begin{aligned}
 & \delta_t + \gamma\delta_{t+1} + \gamma^2\delta_{t+2} + \dots + \gamma^{T-1-t}\delta_{T-1} \\
 &= R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \\
 &+ \gamma R_{t+2} + \gamma^2 V(S_{t+2}) - \gamma V(S_{t+1}) \\
 &+ \gamma^2 R_{t+3} + \gamma^3 V(S_{t+3}) - \gamma^2 V(S_{t+2}) \\
 &\quad \vdots \\
 &+ \gamma^{T-1-t} R_T + \gamma^{T-t} V(S_T) - \gamma^{T-1-t} V(S_{T-1}) \\
 &= R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} \dots + \gamma^{T-1-t} R_T - V(S_t) \\
 &= G_t - V(S_t)
 \end{aligned}$$

TD(λ) and TD(1)

- TD(1) is roughly equivalent to every-visit Monte-Carlo
- Error is accumulated online, step-by-step
- If value function is only updated offline at end of episode
- Then total update is exactly the same as MC

Telescoping in TD(λ)

For general λ , TD errors also telescope to λ -error, $G_t^\lambda - V(S_t)$

$$\begin{aligned}
 G_t^\lambda - V(S_t) &= -V(S_t) + (1-\lambda)\lambda^0 (R_{t+1} + \gamma V(S_{t+1})) \\
 &\quad + (1-\lambda)\lambda^1 (R_{t+1} + \gamma R_{t+2} + \gamma^2 V(S_{t+2})) \\
 &\quad + (1-\lambda)\lambda^2 (R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 V(S_{t+3})) \\
 &\quad + \dots \\
 &= -V(S_t) + (\gamma\lambda)^0 (R_{t+1} + \gamma V(S_{t+1}) - \gamma\lambda V(S_{t+1})) \\
 &\quad + (\gamma\lambda)^1 (R_{t+2} + \gamma V(S_{t+2}) - \gamma\lambda V(S_{t+2})) \\
 &\quad + (\gamma\lambda)^2 (R_{t+3} + \gamma V(S_{t+3}) - \gamma\lambda V(S_{t+3})) \\
 &\quad + \dots \\
 &= (\gamma\lambda)^0 (R_{t+1} + \gamma V(S_{t+1}) - V(S_t)) \\
 &\quad + (\gamma\lambda)^1 (R_{t+2} + \gamma V(S_{t+2}) - V(S_{t+1})) \\
 &\quad + (\gamma\lambda)^2 (R_{t+3} + \gamma V(S_{t+3}) - V(S_{t+2})) \\
 &\quad + \dots \\
 &= \delta_t + \gamma\lambda\delta_{t+1} + (\gamma\lambda)^2\delta_{t+2} + \dots
 \end{aligned}$$

Forwards and Backwards TD(λ)

- Consider an episode where s is visited once at time-step k ,
- TD(λ) eligibility trace discounts time since visit,

$$\begin{aligned} E_t(s) &= \gamma\lambda E_{t-1}(s) + \mathbf{1}(S_t = s) \\ &= \begin{cases} 0 & \text{if } t < k \\ (\gamma\lambda)^{t-k} & \text{if } t \geq k \end{cases} \end{aligned}$$

- Backward TD(λ) updates accumulate error *online*

$$\sum_{t=1}^T \alpha \delta_t E_t(s) = \alpha \sum_{t=k}^T (\gamma\lambda)^{t-k} \delta_t = \alpha \left(G_k^\lambda - V(S_k) \right)$$

- By end of episode it accumulates total error for λ -return
- For multiple visits to s , $E_t(s)$ accumulates many errors

Offline Equivalence of Forward and Backward TD

Offline updates

- Updates are accumulated within episode
- but applied in batch at the end of episode

Online Equivalence of Forward and Backward TD

Online updates

- TD(λ) updates are applied online at each step within episode
- Forward and backward-view TD(λ) are slightly different
- **NEW**: Exact online TD(λ) achieves perfect equivalence
- By using a slightly different form of eligibility trace
- Sutton and von Seijen, ICML 2014

Summary of Forward and Backward TD(λ)

Offline updates	$\lambda = 0$	$\lambda \in (0, 1)$	$\lambda = 1$
Backward view	TD(0) 	TD(λ) 	TD(1)
Forward view	TD(0)	Forward TD(λ)	MC
Online updates	$\lambda = 0$	$\lambda \in (0, 1)$	$\lambda = 1$
Backward view	TD(0) 	TD(λ) ≠	TD(1) ≠
Forward view	TD(0) 	Forward TD(λ) 	MC
Exact Online	TD(0)	Exact Online TD(λ)	Exact Online TD(1)

= here indicates equivalence in total update at end of episode.