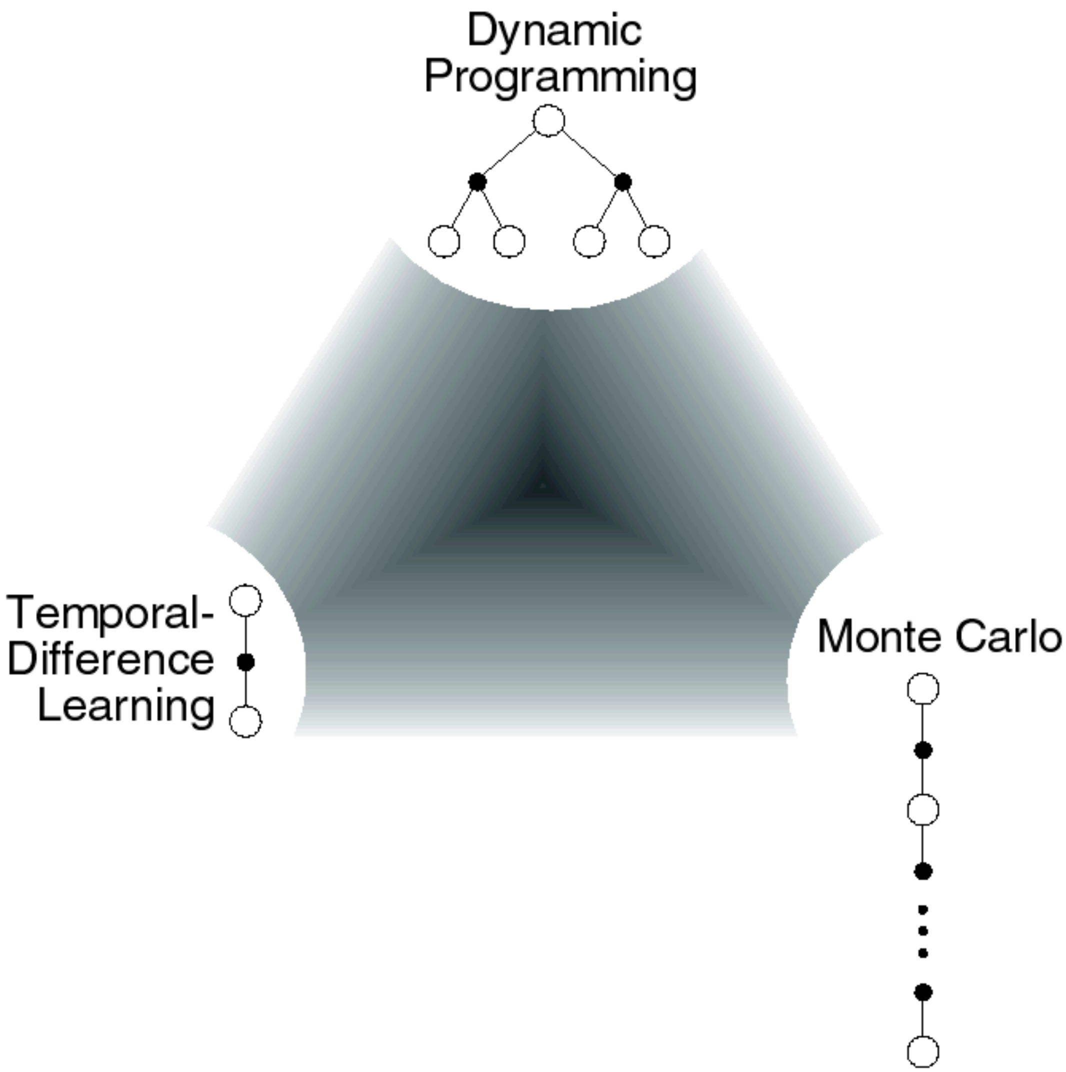
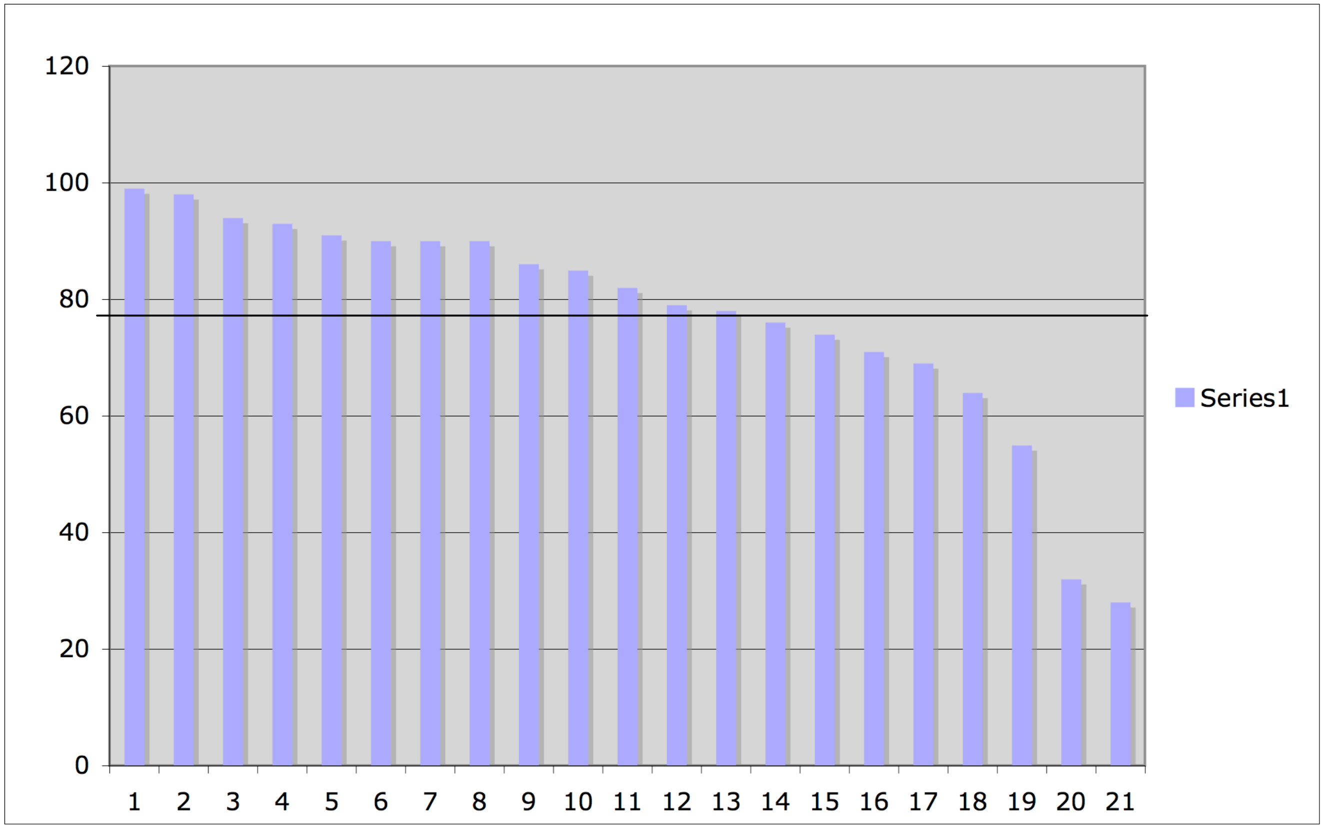
Chapter 7: Eligibility Traces



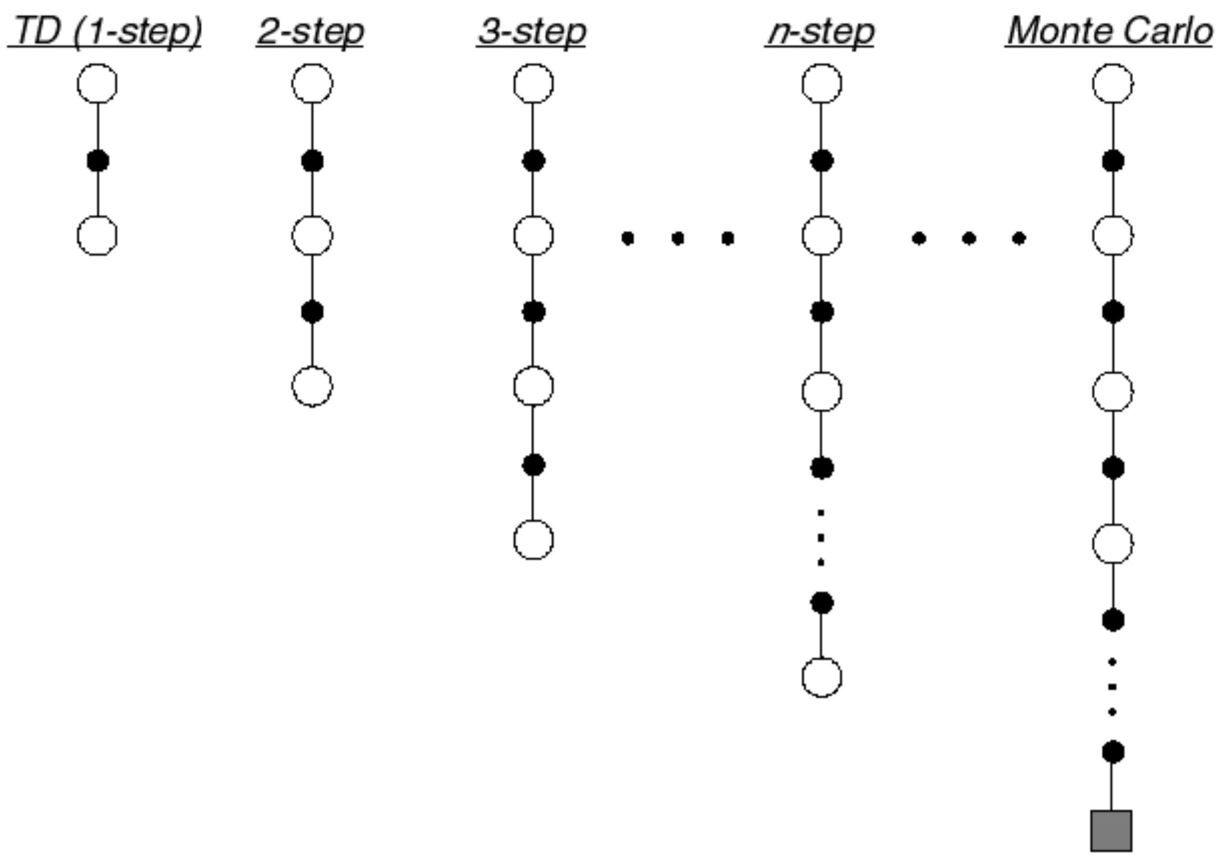
Midterm



Mean = 77.33   Median = 82

N-step TD Prediction

- Idea: Look farther into the future when you do TD backup (1, 2, 3, …, n steps)



Mathematics of N-step TD Prediction

- Monte Carlo: $R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots + \gamma^{T-t-1} r_T$

- TD: $R_t^{(1)} = r_{t+1} + \gamma V_t(s_{t+1})$
  - Use V to estimate remaining return

- n-step TD:
  - 2 step return: $R_t^{(2)} = r_{t+1} + \gamma r_{t+2} + \gamma^2 V_t(s_{t+2})$
  - n-step return: $R_t^{(n)} = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots + \gamma^{n-1} r_{t+n} + \gamma^n V_t(s_{t+n})$

Learning with N-step Backups

- Backup (on-line or off-line):

$$\Delta V_t(s_t) = \alpha\left[R_t^{(n)} - V_t(s_t)\right]$$

- Error reduction property of n-step returns

$$\max_s \left| \underbrace{\underbrace{E_\pi\{R_t^n \mid s_t = s\}}_{\text{n step return}} - V^\pi(s)}_{\text{Maximum error using n-step return}} \right| \le \gamma^n \underbrace{\max_s \left| V(s) - V^\pi(s) \right|}_{\text{Maximum error using V}}$$

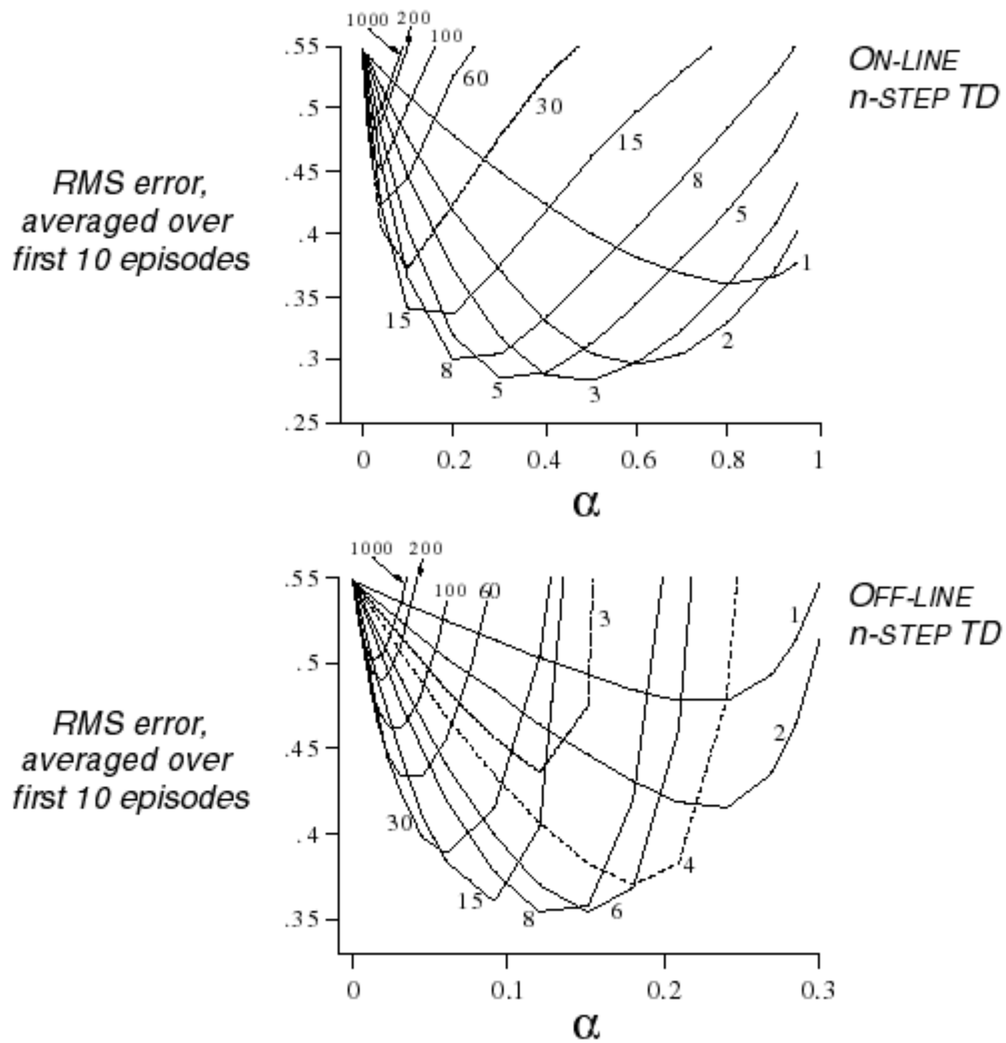
- Using this, you can show that n-step methods converge

Random Walk Examples

- How does 2-step TD work here?
- How about 3-step TD?

A Larger Example

- Task: 19 state random walk
- Do you think there is an optimal n (for everything)?

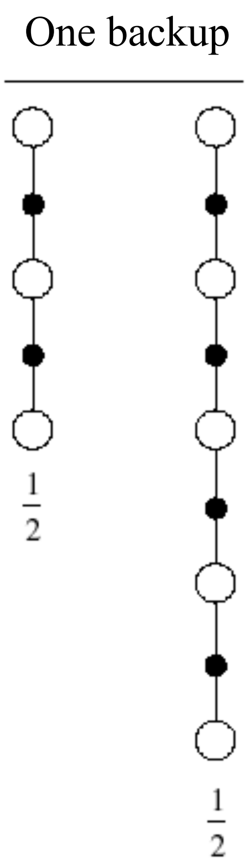


Averaging N-step Returns

- n-step methods were introduced to help with TD(λ) understanding
- Idea: backup an average of several returns
  - e.g. backup half of 2-step and half of 4-step

$$R_t^{avg} = \frac{1}{2} R_t^{(2)} + \frac{1}{2} R_t^{(4)}$$

- Called a complex backup
  - Draw each component
  - Label with the weights for that component



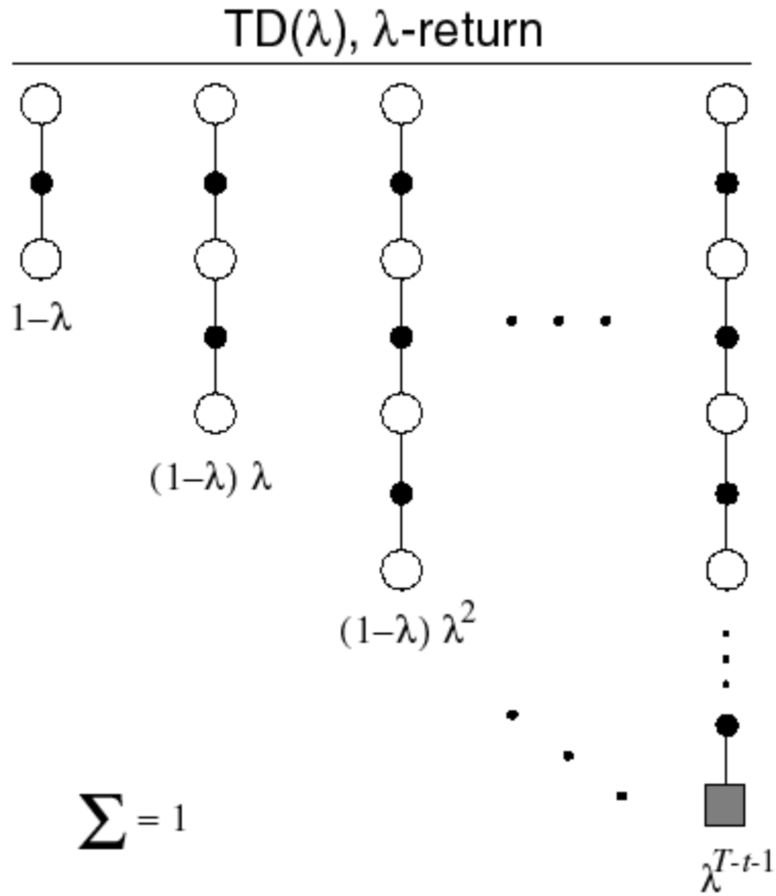
Forward View of TD(λ)

- TD(λ) is a method for averaging all n-step backups
  - weight by λ^{n-1} (time since visitation)
  - λ-return:

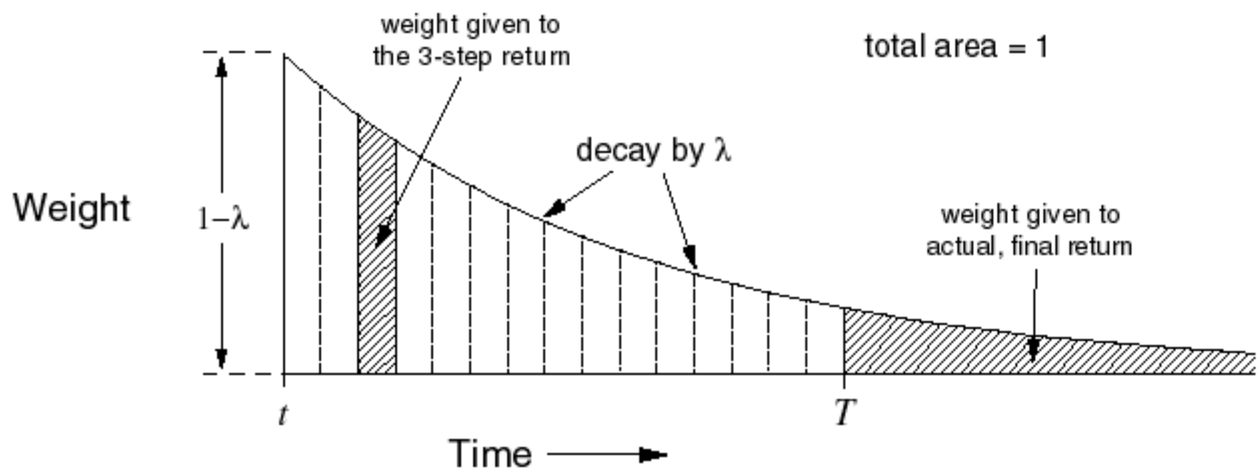
$$R_t^\lambda = (1-\lambda)\sum_{n=1}^{\infty} \lambda^{n-1} R_t^{(n)}$$

- Backup using λ-return:

$$\Delta V_t(s_t) = \alpha\left[R_t^\lambda - V_t(s_t)\right]$$



λ-return Weighting Function



Relation to TD(0) and MC

- λ-return can be rewritten as:

$$R_t^\lambda = \underbrace{(1-\lambda)\sum_{n=1}^{T-t-1}\lambda^{n-1}R_t^{(n)}}_{\text{Until termination}} + \underbrace{\lambda^{T-t-1}R_t}_{\text{After termination}}$$

- If λ = 1, you get MC:

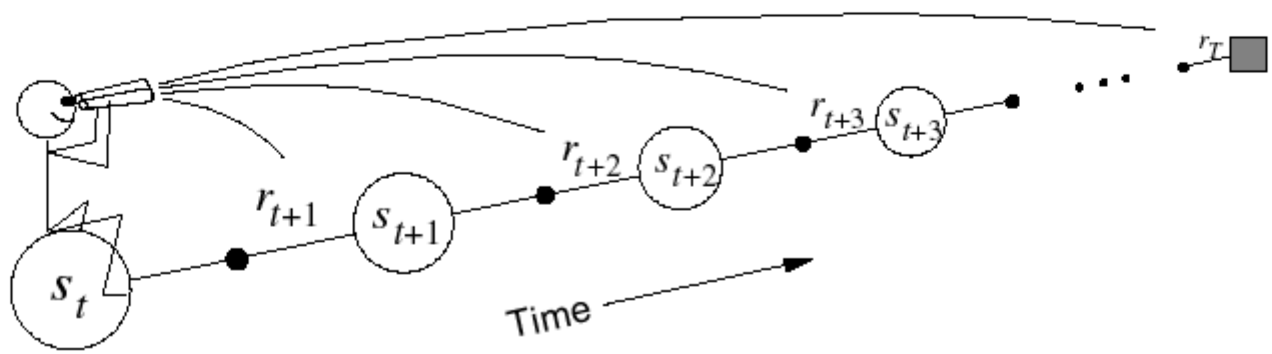
$$R_t^\lambda = (1-1)\sum_{n=1}^{T-t-1}1^{n-1}R_t^{(n)} + 1^{T-t-1}R_t = R_t$$

- If λ = 0, you get TD(0)

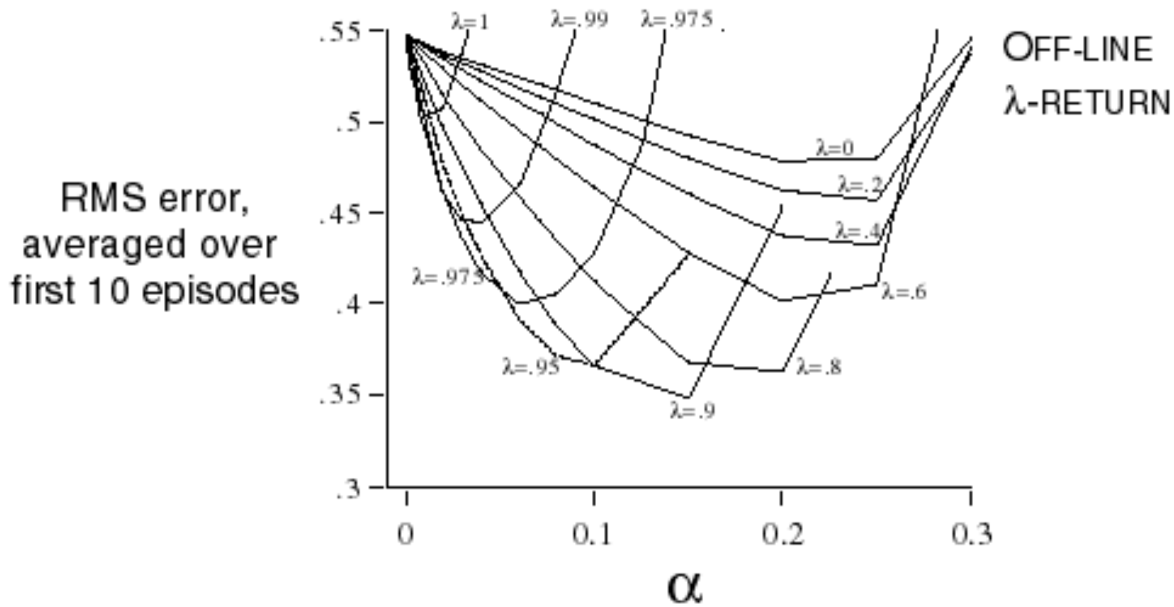
$$R_t^\lambda = (1-0)\sum_{n=1}^{T-t-1}0^{n-1}R_t^{(n)} + 0^{T-t-1}R_t = R_t^{(1)}$$

Forward View of TD(λ) II

- Look forward from each state to determine update from future states and rewards:



λ-return on the Random Walk



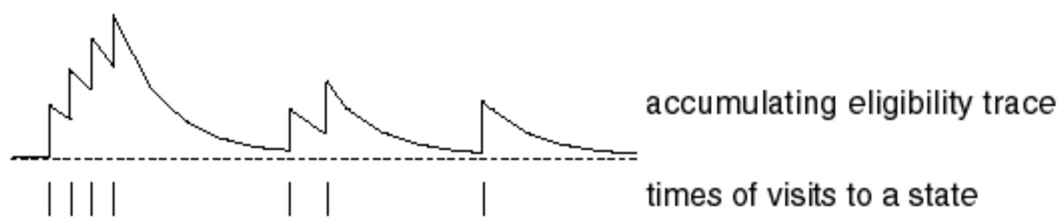
- Same 19 state random walk as before
- Why do you think intermediate values of λ are best?

Backward View of TD(λ)

- The forward view was for theory
- The backward view is for mechanism

- New variable called *eligibility trace* $e_t(s) \in \Re^+$
  - On each step, decay all traces by $\gamma\lambda$ and increment the trace for the current state by 1
  - Accumulating trace

$$e_t(s) = \begin{cases} \gamma\lambda e_{t-1}(s) & \text{if } s \neq s_t \\ \gamma\lambda e_{t-1}(s) + 1 & \text{if } s = s_t \end{cases}$$



On-line Tabular TD(λ)

Initialize $V(s)$ arbitrarily and $e(s) = 0$, for all $s \in S$

Repeat (for each episode) :

  Initialize s

  Repeat (for each step of episode) :

    $a \leftarrow$ action given by π for s

    Take action a, observe reward, r, and next state s'

    $\delta \leftarrow r + \gamma V(s') - V(s)$

    $e(s) \leftarrow e(s) + 1$

    For all s :

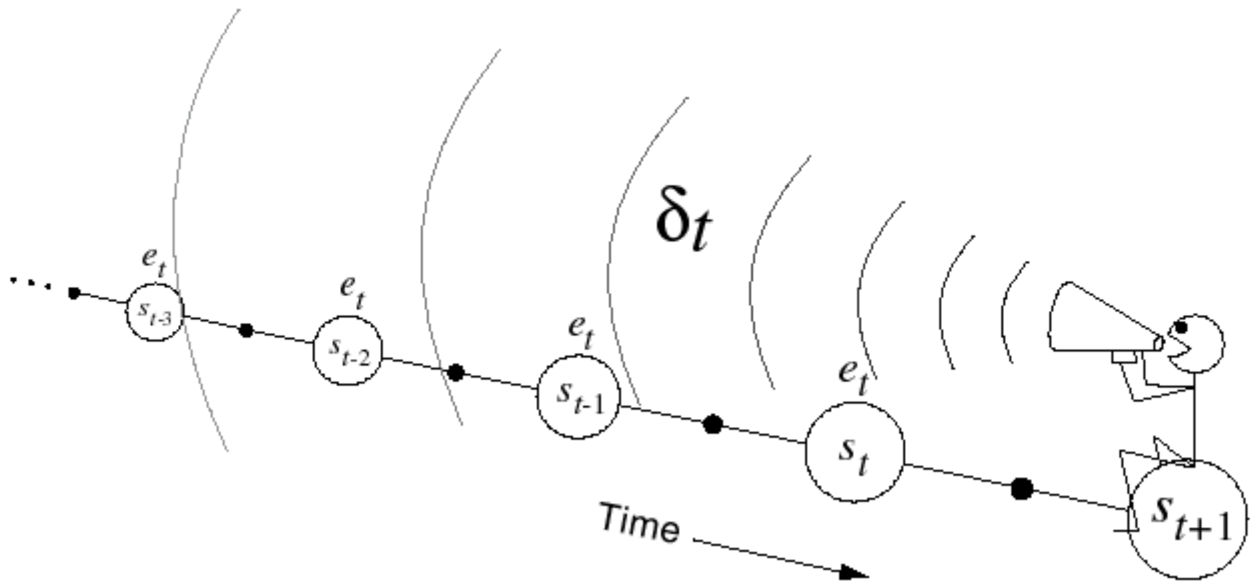
      $V(s) \leftarrow V(s) + \alpha\delta e(s)$

      $e(s) \leftarrow \gamma\lambda e(s)$

    $s \leftarrow s'$

  Until s is terminal

Backward View



$$\delta_t = r_{t+1} + \gamma V_t(s_{t+1}) - V_t(s_t)$$

- Shout δ_t backwards over time
- The strength of your voice decreases with temporal distance by $\gamma\lambda$

Relation of Backwards View to MC & TD(0)

- Using update rule:

$$\Delta V_t(s) = \alpha \delta_t e_t(s)$$

- As before, if you set λ to 0, you get to TD(0)
- If you set λ to 1, you get MC but in a better way
  - Can apply TD(1) to continuing tasks
  - Works incrementally and on-line (instead of waiting to the end of the episode)

Forward View = Backward View

- The forward (theoretical) view of TD(λ) is equivalent to the backward (mechanistic) view for off-line updating
- The book shows:

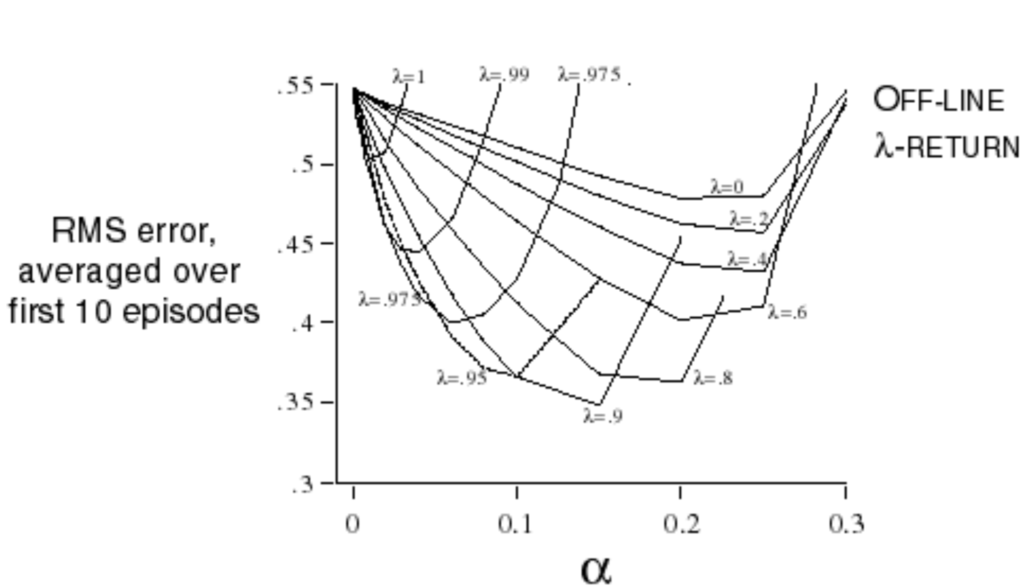
$$\underbrace{\sum_{t=0}^{T-1} \Delta V_t^{TD}(s)}_{\text{Backward updates}} = \underbrace{\sum_{t=0}^{T-1} \Delta V_t^{\lambda}(s_t) I_{ss_t}}_{\text{Forward updates}}$$

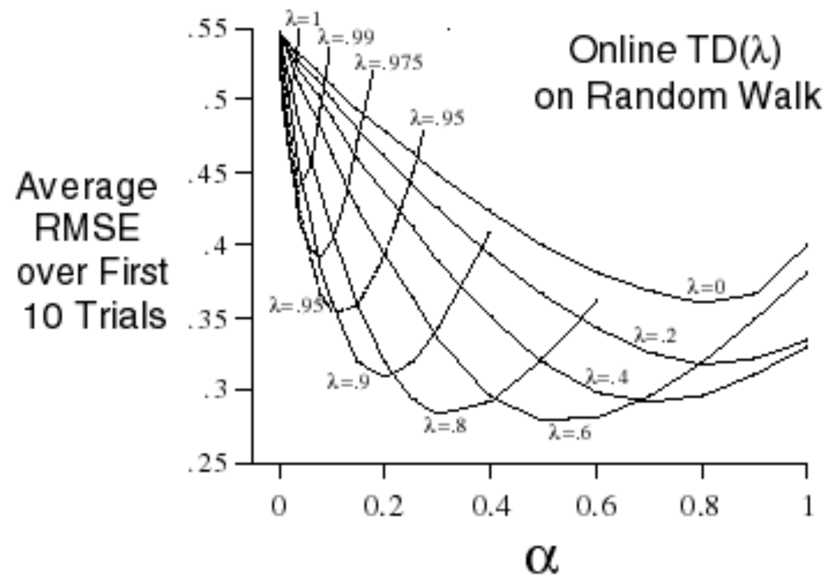
algebra shown in book

$$\sum_{t=0}^{T-1} \Delta V_t^{TD}(s) = \sum_{t=0}^{T-1} \alpha I_{ss_t} \sum_{k=t}^{T-1} (\gamma\lambda)^{k-t} \delta_k \qquad \sum_{t=0}^{T-1} \Delta V_t^{\lambda}(s_t) I_{ss_t} = \sum_{t=0}^{T-1} \alpha I_{ss_t} \sum_{k=t}^{T-1} (\gamma\lambda)^{k-t} \delta_k$$

- On-line updating with small α is similar

On-line versus Off-line on Random Walk





- Same 19 state random walk
- On-line performs better over a broader range of parameters

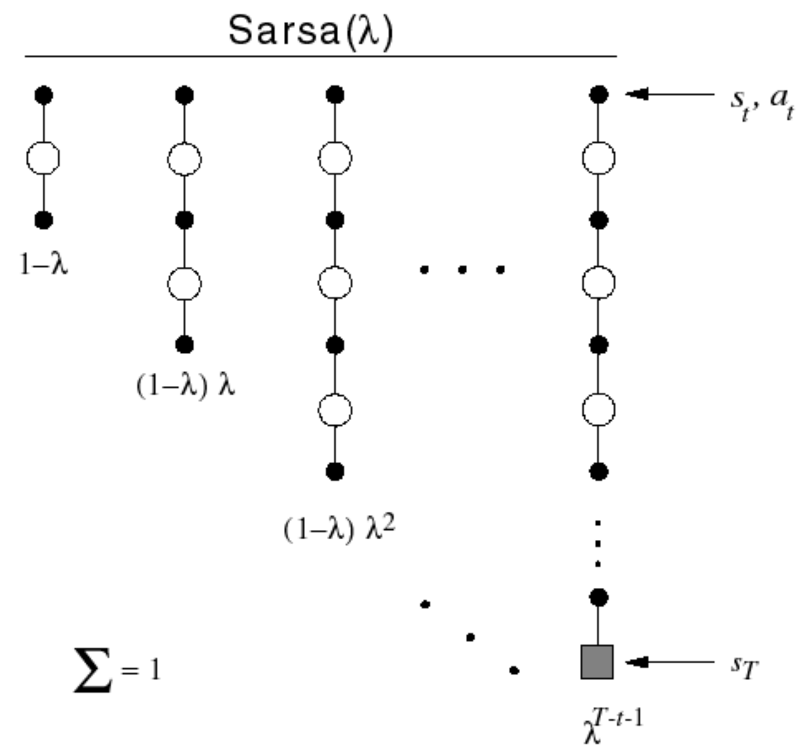
Control: Sarsa(λ)

- Save eligibility for state-action pairs instead of just states

$$e_t(s,a) = \begin{cases} \gamma\lambda e_{t-1}(s,a) + 1 & \text{if } s = s_t \text{ and } a = a_t \\ \gamma\lambda e_{t-1}(s,a) & \text{otherwise} \end{cases}$$

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha\delta_t e_t(s,a)$$

$$\delta_t = r_{t+1} + \gamma Q_t(s_{t+1},a_{t+1}) - Q_t(s_t,a_t)$$



Sarsa(λ) Algorithm

Initialize $Q(s,a)$ arbitrarily and $e(s,a) = 0$, for all s, a

Repeat (for each episode) :

    Initialize s, a

    Repeat (for each step of episode) :

        Take action a, observe r, s'

        Choose a' from s' using policy derived from Q (e.g. ? - greedy)

        $\delta \leftarrow r + \gamma Q(s', a') - Q(s, a)$

        $e(s,a) \leftarrow e(s,a) + 1$

        For all s,a :

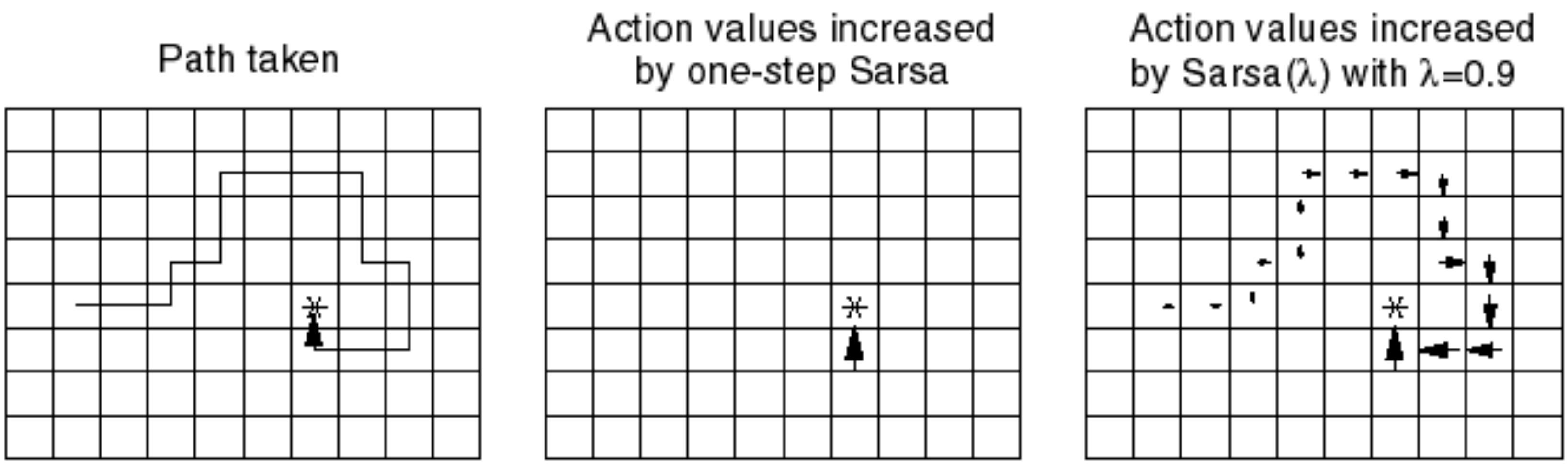
            $Q(s, a) \leftarrow Q(s, a) + \alpha\delta e(s, a)$

            $e(s, a) \leftarrow \gamma\lambda e(s, a)$

        $s \leftarrow s'; a \leftarrow a'$

    Until s is terminal

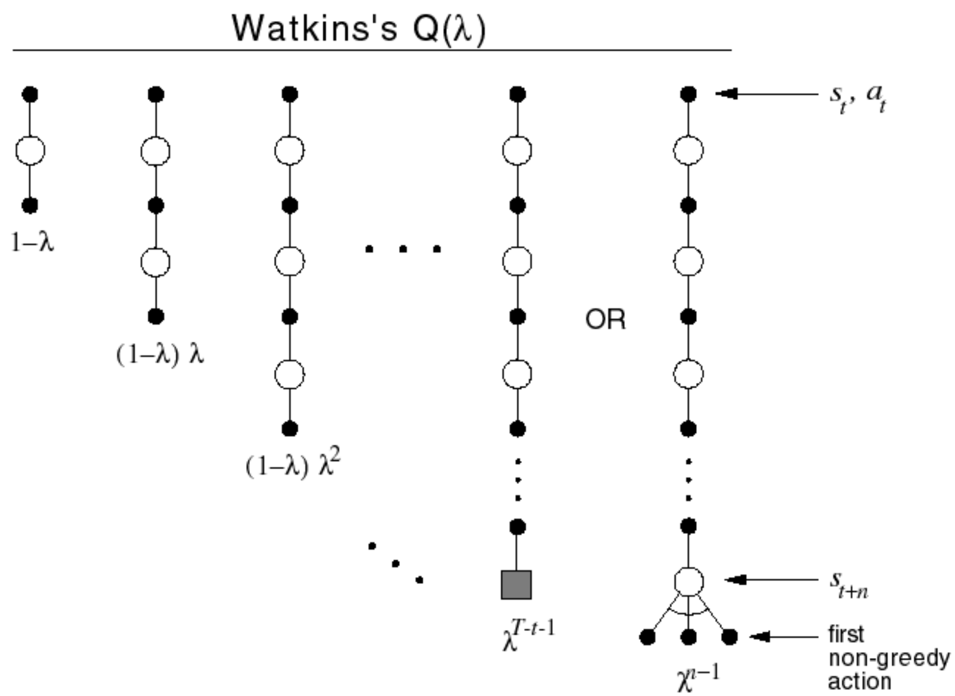
Sarsa(λ) Gridworld Example



- With one trial, the agent has much more information about how to get to the goal
  - not necessarily the *best* way
- Can considerably accelerate learning

Three Approaches to Q(λ)

- How can we extend this to Q-learning?
- If you mark every state action pair as eligible, you backup over non-greedy policy
  - *Watkins*: Zero out eligibility trace after a non-greedy action. Do max when backing up at first non-greedy choice.



$$e_t(s,a) = \begin{cases} 1 + \gamma\lambda e_{t-1}(s,a) & \text{if } s = s_t, a = a_t, Q_{t-1}(s_t,a_t) = \max_a Q_{t-1}(s_t,a) \\ 0 & \text{if } Q_{t-1}(s_t,a_t) \neq \max_a Q_{t-1}(s_t,a) \\ \gamma\lambda e_{t-1}(s,a) & \text{otherwise} \end{cases}$$

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha\delta_t e_t(s,a)$$

$$\delta_t = r_{t+1} + \gamma \max_{a'} Q_t(s_{t+1},a') - Q_t(s_t,a_t)$$

Watkins's Q(λ)

Initialize $Q(s,a)$ arbitrarily and $e(s,a) = 0$, for all s, a

Repeat (for each episode) :

Initialize s, a

Repeat (for each step of episode) :

Take action a, observe r, s'

Choose a' from s' using policy derived from Q (e.g. ? - greedy)

$a^* \leftarrow \arg\max_b Q(s', b)$ (if a ties for the max, then $a^* \leftarrow a'$)

$\delta \leftarrow r + \gamma Q(s', a') - Q(s, a^*)$

$e(s,a) \leftarrow e(s,a) + 1$

For all s,a:

$Q(s,a) \leftarrow Q(s,a) + \alpha \delta e(s,a)$

If $a' = a^*$, then $e(s,a) \leftarrow \gamma \lambda e(s,a)$

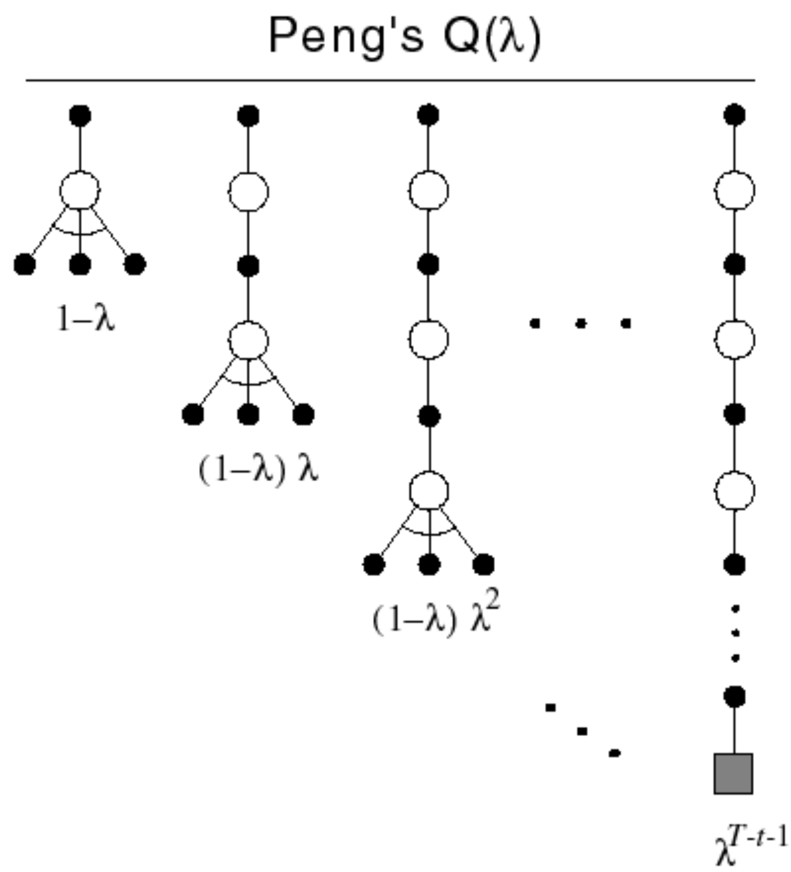
else $e(s,a) \leftarrow 0$

$s \leftarrow s'; a \leftarrow a'$

Until s is terminal

Peng's Q(λ)

- Disadvantage to Watkins's method:
  - Early in learning, the eligibility trace will be "cut" (zeroed out) frequently resulting in little advantage to traces
- Peng:
  - Backup max action except at end
  - Never cut traces
- Disadvantage:
  - Complicated to implement



Naïve Q(λ)

- Idea: is it really a problem to backup exploratory actions?
  - Never zero traces
  - Always backup max at current action (unlike Peng or Watkins's)
- Is this truly naïve?
- Works well is preliminary empirical studies

What is the backup diagram?

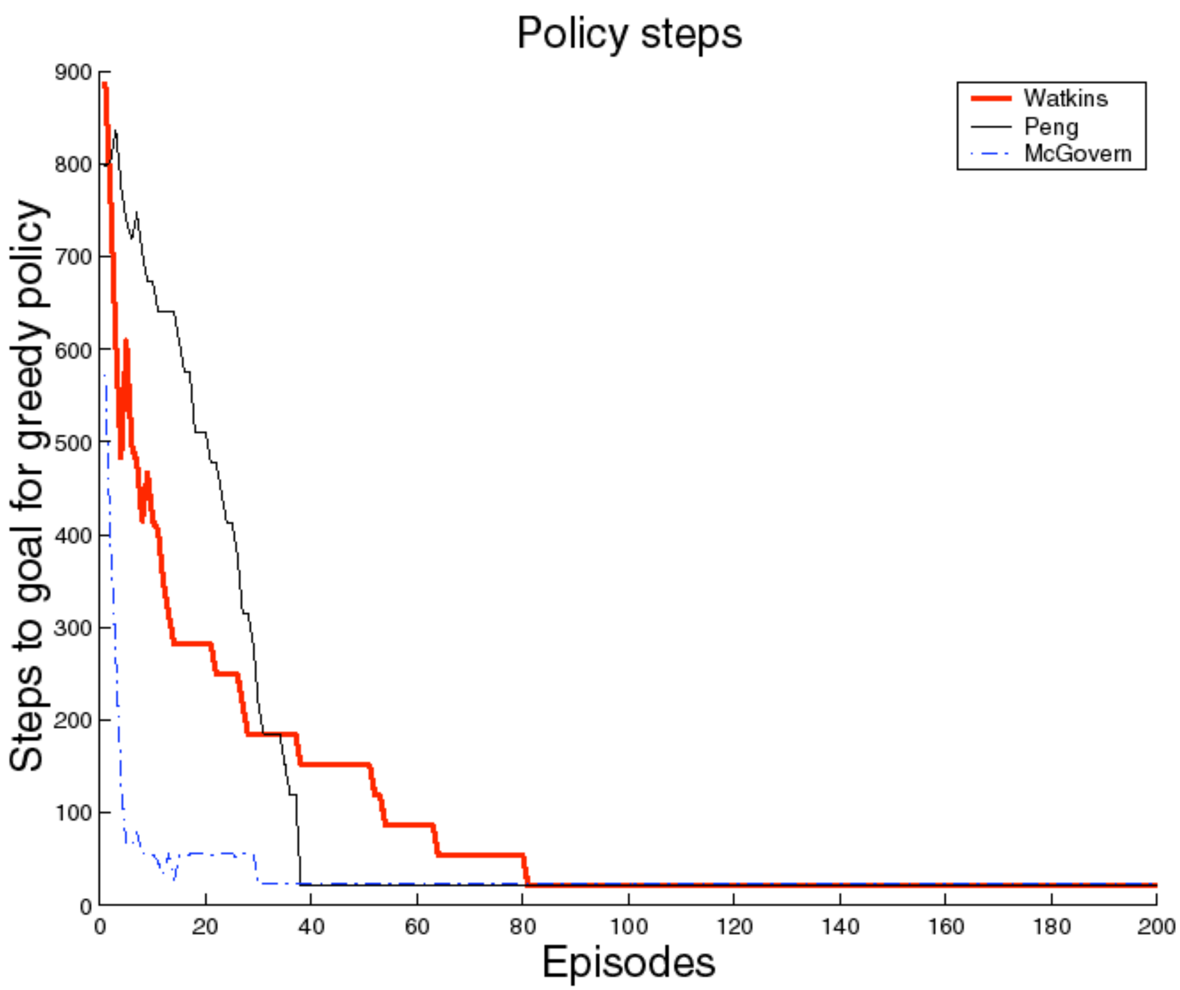
Comparison Task

- Compared Watkins's, Peng's, and Naïve (called McGovern's here) Q(λ) on several tasks.
  - See *McGovern and Sutton (1997). Towards a Better Q(λ)* for other tasks and results (stochastic tasks, continuing tasks, etc)

- Deterministic gridworld with obstacles
  - 10x10 gridworld
  - 25 randomly generated obstacles
  - 30 runs
  - $\alpha = 0.05$, $\gamma = 0.9$, $\lambda = 0.9$, $\varepsilon = 0.05$, accumulating traces

From McGovern and Sutton (1997). Towards a better Q(λ)

Comparison Results



From McGovern and Sutton (1997). Towards a better Q(λ)

Convergence of the Q(λ)'s

- None of the methods are proven to converge.
  - *Much* extra credit if you can prove any of them.
- Watkins's is thought to converge to Q^*
- Peng's is thought to converge to a mixture of Q^π and Q^*
- Naïve - Q^*?

Eligibility Traces for Actor-Critic Methods

- *Critic:* On-policy learning of V^{π}. Use TD(λ) as described before.
- *Actor:* Needs eligibility traces for each state-action pair.
- We change the update equation:

$$p_{t+1}(s,a) = \begin{cases} p_t(s,a) + \alpha\delta_t & \text{if } a = a_t \text{ and } s = s_t \\ p_t(s,a) & \text{otherwise} \end{cases} \quad \text{to} \quad p_{t+1}(s,a) = p_t(s,a) + \alpha\delta_t e_t(s,a)$$

- Can change the other actor-critic update:

$$p_{t+1}(s,a) = \begin{cases} p_t(s,a) + \alpha\delta_t\left[1 - \pi(s,a)\right] & \text{if } a = a_t \text{ and } s = s_t \\ p_t(s,a) & \text{otherwise} \end{cases} \quad \text{to} \quad p_{t+1}(s,a) = p_t(s,a) + \alpha\delta_t e_t(s,a)$$

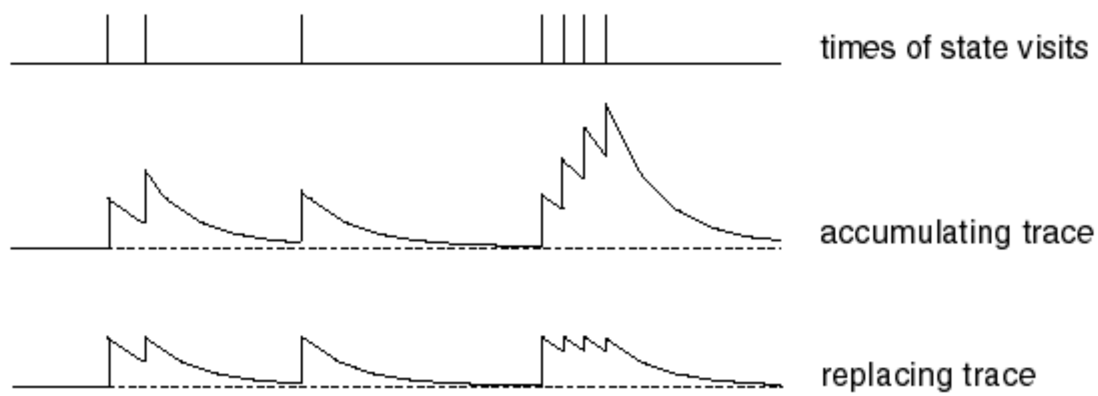
$$\text{where} \qquad e_t(s,a) = \begin{cases} \gamma\lambda e_{t-1}(s,a) + 1 - \pi_t(s_t,a_t) & \text{if } s = s_t \text{ and } a = a_t \\ \gamma\lambda e_{t-1}(s,a) & \text{otherwise} \end{cases}$$

Replacing Traces

- Using accumulating traces, frequently visited states can have eligibilities greater than 1
  - This can be a problem for convergence

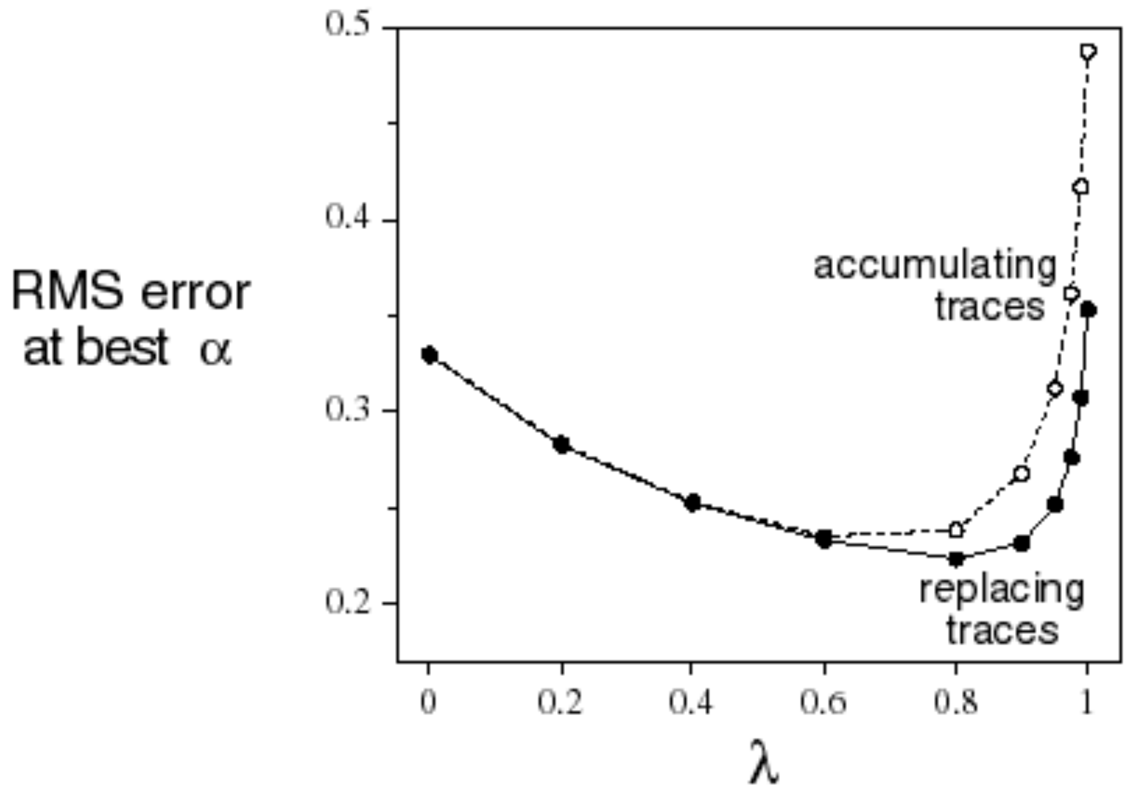
- *Replacing traces:* Instead of adding 1 when you visit a state, set that trace to 1

$$e_t(s) = \begin{cases} \gamma\lambda e_{t-1}(s) & \text{if } s \neq s_t \\ 1 & \text{if } s = s_t \end{cases}$$



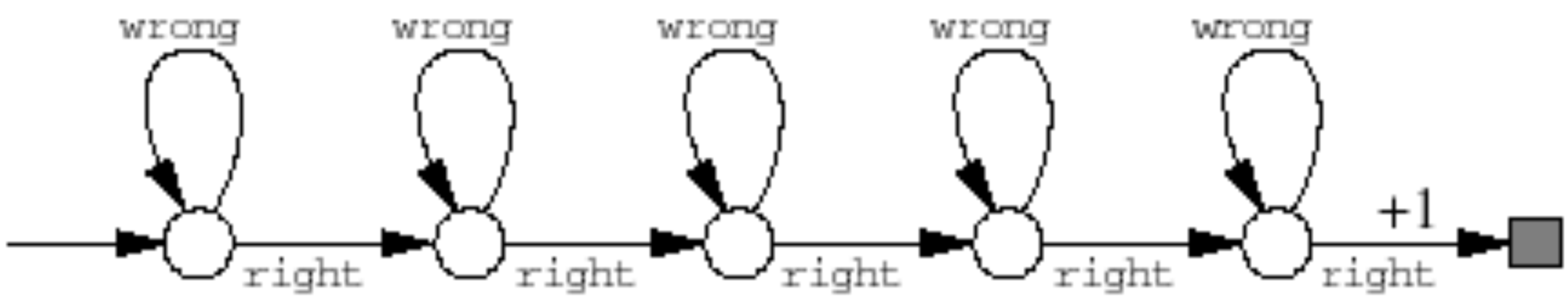
Replacing Traces Example

- Same 19 state random walk task as before
- Replacing traces perform better than accumulating traces over more values of λ



Why Replacing Traces?

- Replacing traces can significantly speed learning
- They can make the system perform well for a broader set of parameters
- Accumulating traces can do poorly on certain types of tasks



Why is this task particularly onerous for accumulating traces?

More Replacing Traces

- Off-line replacing trace TD(1) is identical to first-visit MC

- Extension to action-values:
  - When you revisit a state, what should you do with the traces for the other actions?
  - Singh and Sutton say to set them to zero:

$$e_t(s,a) = \begin{cases} 1 & \text{if } s = s_t \text{ and } a = a_t \\ 0 & \text{if } s = s_t \text{ and } a \neq a_t \\ \gamma\lambda e_{t-1}(s,a) & \text{if } s \neq s_t \end{cases}$$

Implementation Issues

- Could require much more computation
  - But most eligibility traces are VERY close to zero
- If you implement it in Matlab, backup is only one line of code and is very fast (Matlab is optimized for matrices)

Variable λ

- Can generalize to variable λ

$$e_t(s) = \begin{cases} \gamma\lambda_t e_{t-1}(s) & \text{if } s \neq s_t \\ \gamma\lambda_t e_{t-1}(s) + 1 & \text{if } s = s_t \end{cases}$$

- Here λ is a function of time
  - Could define

$$\lambda_t = \lambda(s_t) \text{ or } \lambda_t = \lambda^{t/\tau}$$

Conclusions

- Provides efficient, incremental way to combine MC and TD
  - Includes advantages of MC (can deal with lack of Markov property)
  - Includes advantages of TD (using TD error, bootstrapping)
- Can significantly speed learning
- Does have a cost in computation

Something Here is Not Like the Other