



Cliffwalking with Eligibility Trace

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Outline



- Eligibility traces
- Accumulating, Dutch, and Replacing Traces
- Simulation:
 - Simulation settings
 - Simulation results for different cases

Eligibility traces



- Another way of combining Monte Carlo and Temporal Difference methods
- λ return is now:
$$G_t^\lambda \doteq (1 - \lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_t^{(n)}$$
- Depending on choice of λ . It can be MC ($\lambda=1$) and TD ($\lambda=0$).
- It can be interpreted as average of n-step returns

Eligibility traces



- According to the incrementing strategy, there are mainly three eligibility traces.
- Accumulating trace [1]:

$$\begin{aligned} \mathbf{e}_0 &\doteq \mathbf{0}, \\ \mathbf{e}_t &\doteq \nabla \hat{v}(S_t, \boldsymbol{\theta}_t) + \gamma \lambda \mathbf{e}_{t-1} \end{aligned}$$

Eligibility traces



- Replacing trace[1]:

$$e_{i,t} \doteq \begin{cases} 1 & \text{if } \phi_{i,t} = 1 \\ \gamma \lambda e_{i,t-1} & \text{otherwise.} \end{cases}$$

- Suitable for task with binary features.

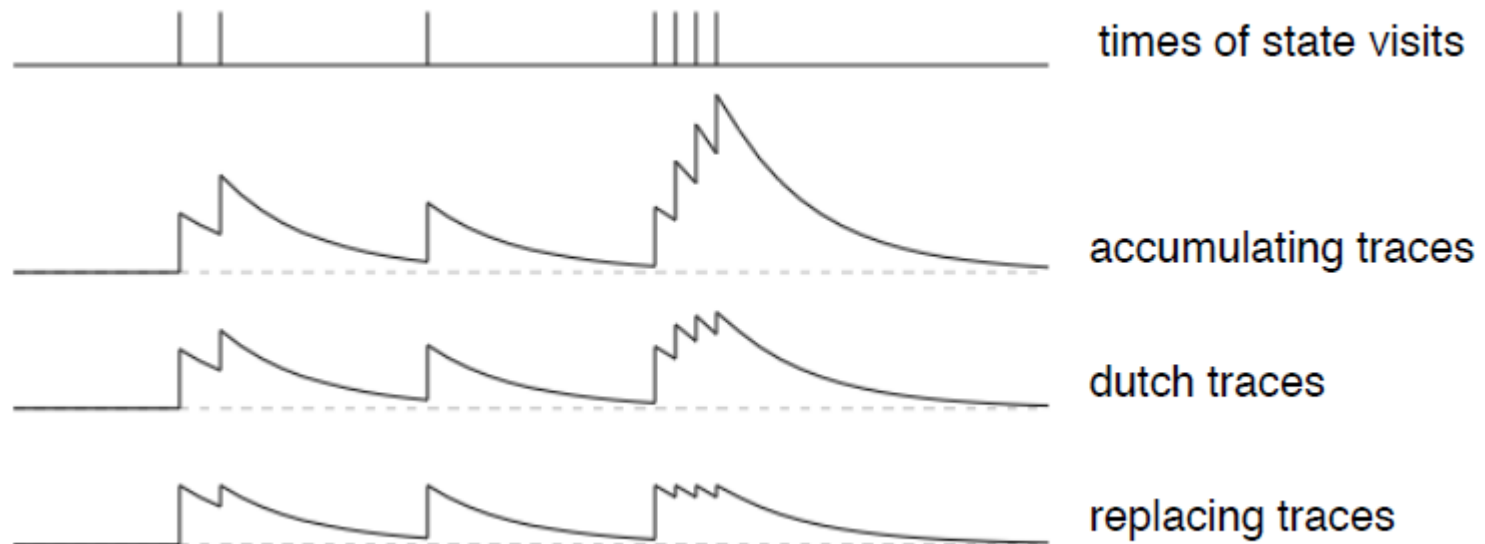
- Dutch trace[2][3]:

$$\mathbf{e}_t \doteq \gamma \lambda \mathbf{e}_{t-1} + \left(1 - \alpha \gamma \lambda \mathbf{e}_{t-1}^\top \boldsymbol{\phi}_t\right) \boldsymbol{\phi}_t.$$

Eligibility traces



- Three traces are different in incrementing



This graph is from Sutton's
RL course slide

Pseudo code for Sarsa(λ)



■ Sarsa(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., ϵ -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

This is from Sutton's RL
book website

Pseudo code for $Q(\lambda)$



■ $Q(\lambda)$:

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., ε -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

This is from Sutton's RL
book website

Simulation results description

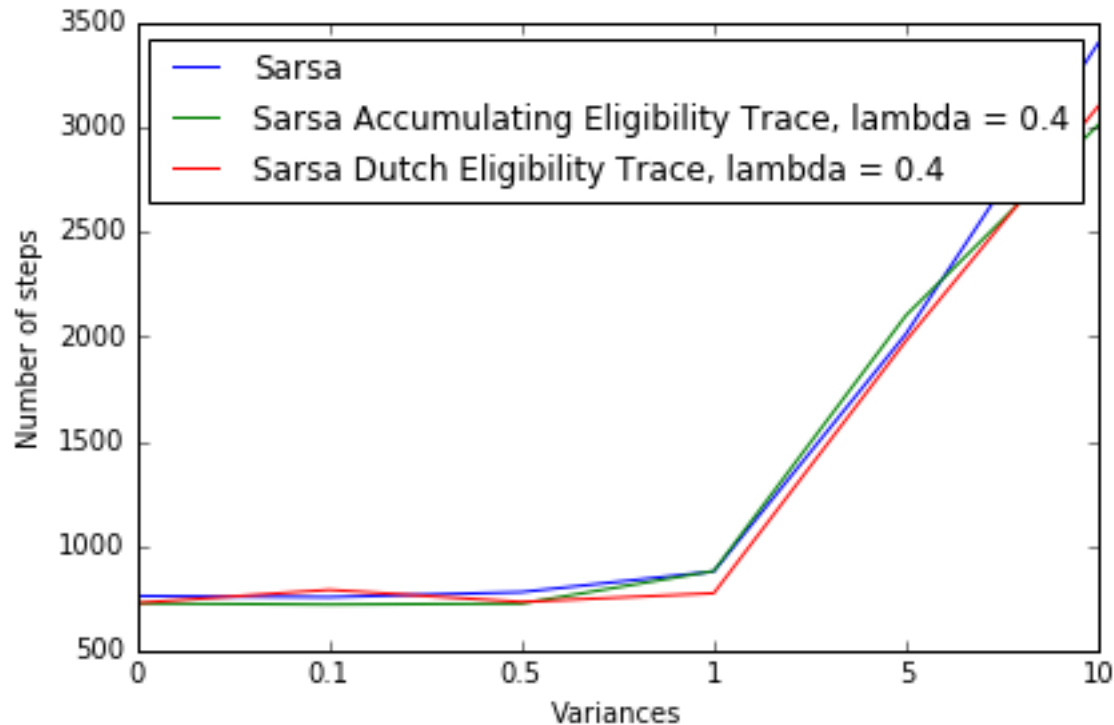


- I use the Weiwei Zhang's implementation (Sarsa) on CliffWalking as baselines.
- I implemented the following algorithms:
 - Sarsa with Dutch trace
 - Sarsa with Accumulating trace
 - Q Learning with Accumulating trace
 - Q Learning with Dutch trace

Simulation Results



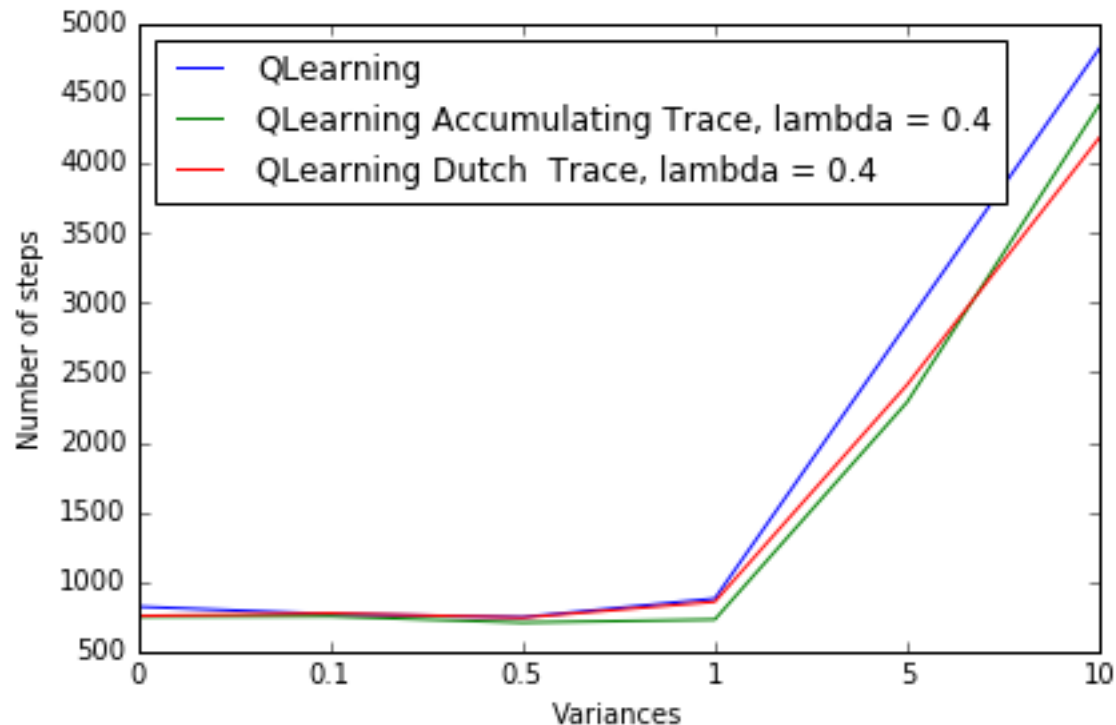
- Simulation results for Sarsa with dutch trace and accumulating trace



Simulation Results



- Simulation results for Q Learning with dutch trace and accumulating trace



Reference



- [1] Milan, Stephanie, et al. "The impact of physical maltreatment history on the adolescent mother–infant relationship: Mediating and moderating effects during the transition to early parenthood." *Journal of Abnormal Child Psychology* 32.3 (2004): 249-261.
- [2] van Seijen, Harm, and Richard S. Sutton. "True Online TD (λ)." ICML. Vol. 14. 2014.
- [3] Van Seijen, Harm, et al. "True online temporal-difference learning." *Journal of Machine Learning Research* 17.145 (2016): 1-40.



Thanks!