

Control With Gradient TD Methods + The Nonlinear Case

COMP 767

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Overview

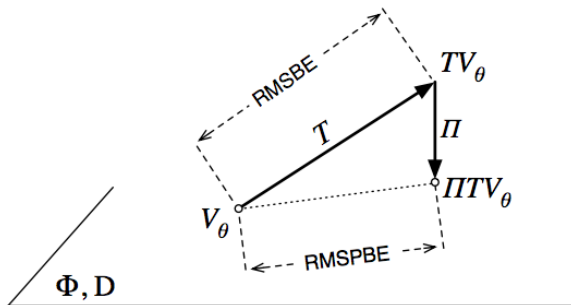
Gradient TD

Control With Gradient TD Methods

This slide is just to add slides.

The part we've covered:

- This Picture:

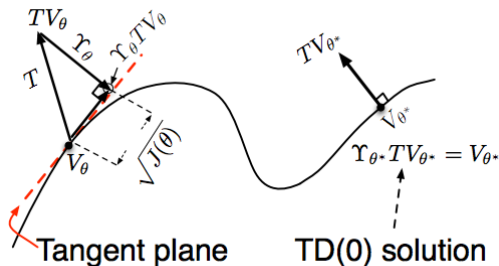


►

$$\begin{aligned}MSPBE &= \|(\Pi_\theta TV_\theta - V_\theta)\|_D^2 \\ -1/2 \nabla MSPBE &= -\mathbb{E}[\delta\phi] - \gamma \mathbb{E}[\phi' \phi^\top] w \\ w &= \mathbb{E}[\phi \phi^\top]^{-1} \mathbb{E}[\delta\phi]\end{aligned}$$

The part we haven't:

- This Picture:



- MSPBE now projects onto the tangent space of the nonlinear function which we assume to be smooth enough to be locally linear.

$$\begin{aligned}MSPBE &= ||\Pi_\theta(TV_\theta - V_\theta)||_D^2 \\ -1/2 \nabla MSPBE &= -\mathbb{E}[\delta\phi] - \gamma \mathbb{E}[\phi' \phi^\top] w + h(\theta, w) \\ w &= \mathbb{E}[\phi \phi^\top]^{-1} \mathbb{E}[\delta\phi]\end{aligned}$$

The part we haven't:

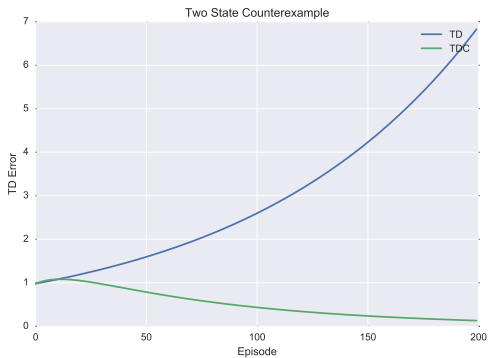
- Update rules are much the same but now there are second order terms.

$$\theta_{k+1} = \Gamma \left[\theta_k + \alpha_k \{ \delta_k \phi_k - \gamma \phi'_k (\phi_k^\top w_k) - h_k \} \right]$$

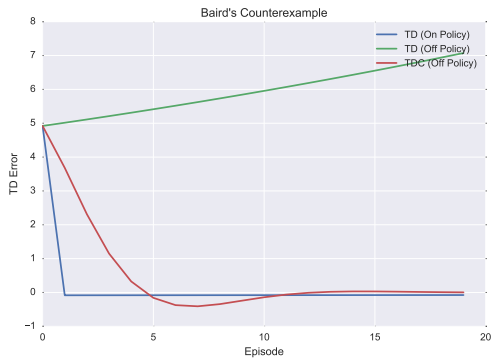
$$h_k = \delta_k - (\phi_k^\top w_k) \delta^2 V_\theta(s_k) w_k$$

- note that now $\phi_k = \nabla V_\theta(s_k)$
- Also, Lee and Anderson, 2014 do this + control with small neural nets

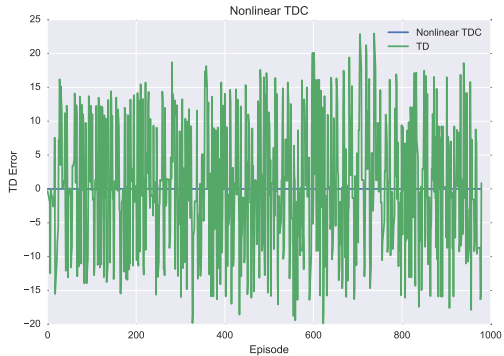
Quick Results



Quick Results



Quick Results



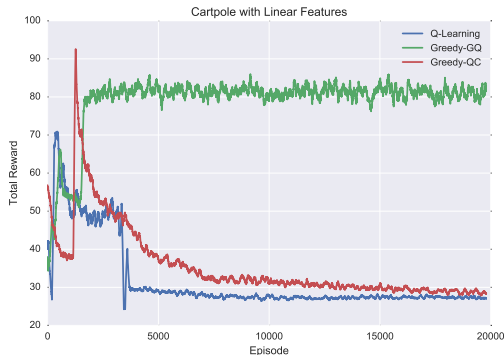
Control With Gradient TD Methods

```
 $\theta \sim \text{random}$   
 $s \sim \text{initial state}$  while not terminal do  
  Choose  $a$  from  $\epsilon$ -Greedy on  $Q_\theta(s, a)$   
  Observe  $(s', r)$   
  Choose  $a' = \max_i (Q_\theta(s', i))$   
  update  $Q_\theta$  according to  $\text{TDC}(\theta, s, a, r, s', a')$   
   $s = s'$   
end
```

Algorithm 1: Greedy-QC

Simply Plug TDC or GTD2 into SARSA or Q-learning!

This is in the original feature space!



Simply Plug TDC or GTD2 into SARSA or Q-learning!

This is in the original feature space!

