#### Advanced Topics in Reinforcement Learning Lecture 8: On-Policy Temporal Difference Learning

### Announcements

- Homework 2 due next Thursday @ 9:29 AM
- Project proposals due tonight @ midnight central time!
- Start reading chapter 8 for next week (Models and Planning).



- Finishing Prediction
  - Convergence of TD / Monte Carlo.
  - TD( $\lambda$ )
- On-Policy SARSA for control.
- Q-learning for control.
- Off-Policy SARSA.

## Today



#### Review

- Temporal difference (TD) learning learns from experience and bootstraps
  - Allows immediate learning without a model of the environment.
- In a batch setting, TD-learning converges to the certainty-equivalence estimate.
  - Highlights the connection between TD-learning and dynamic programming.
- TD-learning and Monte Carlo methods sit at either end of a spectrum of n-step return methods.



### Gagan's Presentation

<u>Slides</u>



# Certainty Equivalence Updating

then compute value function for the estimated process.



**True Markov Process** 

Certainty Equivalence Learning: use data to estimate Markov process and





- Same generalized policy iteration scheme from past two weeks.
  - Evaluate  $\pi_k$ .
  - Make  $\pi_{k+1}$  greedy with respect to  $q_k$ .
- Now, use TD(0) to learn action-values:
- Is this update on- or off-policy?
- converge to?

### SARSA

#### $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha [R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)]$

#### • What does generalized policy iteration with TD action-values and $\epsilon$ -greedy exploration



# Q-Learning

- SARSA is essentially policy iteration.
- Can we also use value iteration without a model of the environment? lacksquare
- Q-learning update:

#### $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_t]$

- Is this update on- or off-policy?
  - Off-policy: can follow any policy (e.g.,  $\epsilon$ -greedy) while learning  $q_{\star}$ .
  - "Follow a policy derived from Q" still off-policy!
- What does the Q-learning update converge to?

$$_{t+1} + \gamma \max_{a'} Q(S_{t+1}, a') - Q(S_t, A_t)]$$



# Q-Learning or SARSA?

- Q-learning is off-policy; SARSA is on-policy.
  - Q-learning follows an exploration policy and learns  $q_{\star}$ .
  - SARSA follows an exploration policy,  $\pi$ , and learns  $q_{\pi}$ .
- What if exploration policy is greedy?







# Double Q-Learning

- Q-learning may suffer from maximization bias?
  - What is it?
- Double Q-learning mitigates this bias by learning two action-value functions:
- Is this on- or off-policy?
- What does double Q-learning converge to?









# Off-Policy SARSA

- Can SARSA learn off-policy?
- Yes, with importance sampling!

• 
$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \rho_t [R_{t+1} + \gamma Q(Q_t)]$$
  
• Where  $\rho_t := \frac{\pi(A_t | S_t)}{b(A_t | S_t)}$ .

- What advantage would this have compared to off-policy Monte Carlo? ullet
- What is the off-policy variant of n-step returns?

 $[S_{t+1}, A_{t+1}) - Q(S_t, A_t)]$ 

n the importance weight.



# Expected SARSA

- SARSA samples the final acton A'. How could this be harmful?
  - We know  $\pi$  so we can compute the expected action-value exactly.

• 
$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha [R_{t+1} + \gamma \sum_{a'} \pi(a' | S_{t+1}) Q(S_{t+1}, a') - Q(S_t, A_t)]$$

- How is this update useful? What are its limitations?
  - (+) Lower variance -> more data efficient learning.
  - (-) Computational cost for large or continuous action sets.



### After-States

- In RL, the environment is usually a blackbox.
- But sometimes we have intermediate state changes that are available immediately after an action is taken.
- Such knowledge can be built into RL algorithms to help generalize learning.





# Summary

- TD-learning can be integrated into generalized policy iteration in several ways.
  - SARSA uses on-policy TD-learning.
  - Q-learning learns  $q_{\star}$  while acting off-policy.
  - Expected SARSA generalizes Q-learning and usually improves upon SARSA.
- These methods enable fully incremental, online, model-free learning.



### Action Items

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- Project proposal due midnight tonight.
- Begin reading Chapter 8.

