OPTION-VALUE LEARNING ALGORITHMS

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OVERVIEW

- Comparison of algorithms to estimate option-values.
 - SMDP Q-Learning
 - Intra-option Q-Learning
 - Combined SMDP/intra-option Q-Learning
 - Combined SMDP/intra-option SARSA

OPTIONS

- Temporally-abstract actions.
- An option is a triple:
 - states from which the option can be selected
 - policy to follow after the option is selected
 - probability of terminating in each state

SMDP Q-LEARNING

- Execute option o until termination.
 - Keep track of discounted reward r and number of timesteps k.
 - When option finished, update q-val for option:
 - s: state in which option was chosen; s': state in which option finished

$$Q(s,o) \leftarrow Q(s,o) + \alpha \left[r + \gamma^k \max_{o' \in \mathcal{O}_{s'}} Q(s',o') - Q(s,o) \right]$$

Propagates value back to option start state.

INTRA-OPTION Q-LEARNING

- After each primitive action taken (during an option):
 - Update all options o that could have taken that action.

$$Q(s_t, o) \leftarrow Q(s_t, o) + \alpha [(r_{t+1} + \gamma U(s_{t+1}, o)) - Q(s_t, o)]$$

where

$$U(s,o) = (1 - \beta(s))Q(s,o) + \beta(s) \max_{o' \in \mathcal{O}} Q(s,o').$$

More efficient use of trajectories (more updates).

COMBINED SMDP/INTRA-OPTION Q-LEARNING

- Combine two update rules of SMDP and Intra-option.
 - When option terminates: use SMDP Q update rule.
 - At all times: use intra-option Q update rule.

• From Stolle's thesis (2004).

COMBINED SMDP/INTRA-OPTION SARSA

- Same as previous but:
 - Fix choice of next option o_{t+1}.
 - Use SARSA update rules:
 - SMDP:

$$Q(s, o) \leftarrow Q(s, o) + \alpha[r + \gamma^{k}Q(s', o_{t+1}) - Q(s, o)]$$

Intra-option:

$$Q(s_t, o) \leftarrow Q(s_t, o) + \alpha[(r_{t+1} + \gamma U(s_{t+1}, o)) - Q(s_t, o)]$$

where
$$U(s, o) = (1 - \beta(s)) Q(s, o) + \beta(s) Q(s, o_{t+1})$$

IMPLEMENTATION

- Uses Gridworld RL framework from UC Berkeley Al course
 - http://ai.berkeley.edu/reinforcement.html
- Extension to options.

METHOD

- Gridworld "rooms example" used for experiments.
 - 4 rooms connected by single-tile hallway.
 - · Goal in one room.
 - 4 single-movement primitive options (available everywhere).
 - 4 "hallway options" per room:
 - Two per hallway: takes shortest distance to that hallway.
 - One prefers horizontal movement, one prefers vertical.

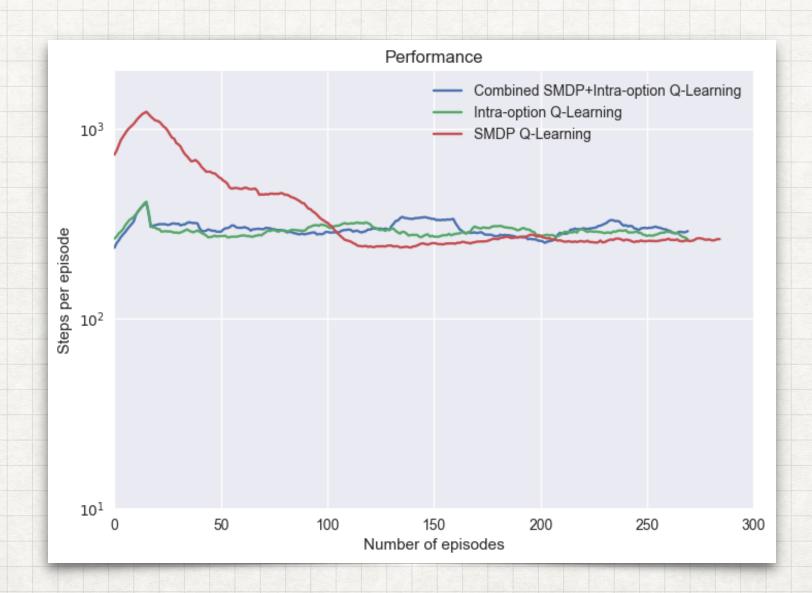
ROOMS EXAMPLE

ROOMS EXAMPLE

0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
	0.00					0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00				0.00		
0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00

METHOD

TIME COMPARISON



Q-LEARNING VS SARSA

- Same as earlier rooms example, except:
 - Noise in actions: 1/3 chance to move in wrong direction.
 - Middle corners of rooms are terminal states (negative reward).
 - Goal in left-most hallway.

SCARY ROOMS EXAMPLE

Q-LEARNING VS SARSA: AVG. TOTAL RETURN



CODE

Available at course GitHub repo:

https://github.com/rllabmcgill/rlcourse-march-10-campbelljc