OPTION-VALUE LEARNIG 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.

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

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 AI 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.

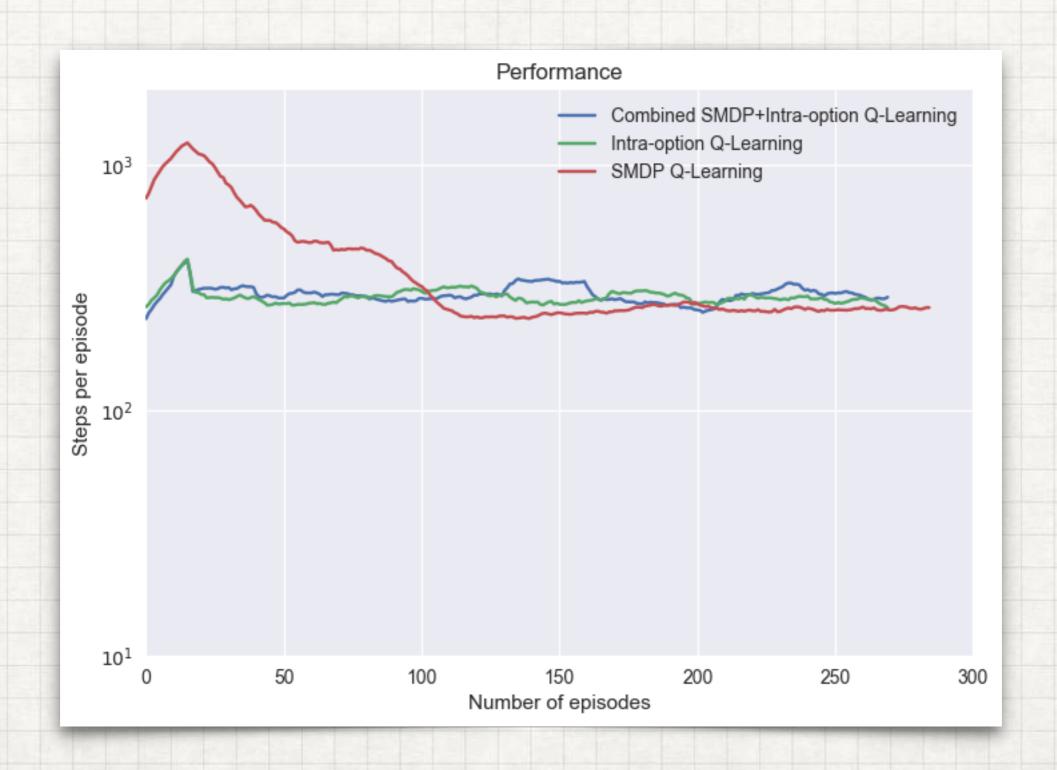
ROOMS EXAMPLE

ROOMS EXAMPLE

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METHOD

TIME COMPARISON



COMPARISON ANALYSIS

- SMDP takes longer to converge to optimal.
 - Low % of primitive options contributes to this difference.
 - (SMDP == Intra-option when all opts. primitive)
- No difference between intra-option and combined:
 - Environment may be too simple to show meaningful difference.

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 right-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