Suboptimality in Hierarchical RL

March 6th, 2013 CS394R Reinforcement Learning Ruohan Zhang

Outline

Source of suboptimality in

 Recursively optimal policy
 Hierarchically optimal policy

• Solutions have been developed

Recall: Recursively vs. hierarchically optimal policy

- *Hierarchical optimality*: the final policy is the best policy consistent with given hierarchy.
- *Recursive optimality*: the final policy is optimal *given* the policies learned by its children.
- Source of suboptimality for each type?

Domain (Dietterich)



- Grid world, start in the room on the left side, the Goal is located in the upper right corner.
- Actions: $\rightarrow \psi \uparrow$
- 2 doors
- Each action costs -1, goal gives reward 0.

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- "exit by the nearest door?"
- What is the optimal policy,

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- From the optimal policies of our subtask, we achieve this final policy.
- Is it recursively optimal?
- Is it hierarchically optimal?
- Is it globally optimal?



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- Is it recursively optimal?
- Is it hierarchically optimal?
- Is it optimal?
- This is a *recursively* optimal policy, but not *hierarchically* optimal nor *globally* optimal.



- What would be a hierarchically optimal policy?
- We can always exit by upper

door.

- Is it recursively optimal?
- Is it globally optimal?



• One question we may ask is, is hierarchically optimal policy always optimal? What about in our example?

- One question we may ask is, is hierarchically optimal policy always optimal? What about in our example?
- If we put a "landmark" at the lower door, and we always exit by the lower door.
- The result is clearly hierarchically optimal, but not globally optimal.

Summary: source of suboptimality

• *Hierarchical optimality*: the imposed hierarchy constrains our policy.

• *Recursive optimality*: the policies learned from the subtasks are locally optimal, but we may have better policies for parent task.

Next...

- How do we deal with this problem?
 - Ideas?
 - There are helpful thoughts from our readings.

Solutions

• How do we deal with this problem?

- Approaches
 - Extend option set *O* to include *A* (primitive actions)
 - Redefine the reward of completing subtasks
 - Non-hierarchical execution

1. Extending O to include A

- Introduce primitive actions as special cases of options
 - Recall the hallway example and experimental results

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- What is the cost?
 - Could it be even slower than non-hierarchical learning?

2. Redefine the subtasks

- What is the difference between subtask and option?
 - Option: <I, π , β >
 - Subtask: <I, R, β >
 - R: pseudo reward function.



2. Dynamically redefine the subtasks

- Denote the subgoal states for task i as B(i)
- Initialize V'(s) for all states in B(i)
- Repeat:
 - Define a Pseudo-reward functions
 - R'(s) = V'(s), for s that are in B(i)
 - 0, elsewhere
 - Apply hierarchical SMDP learning method to learn recursive optimal policy
 - Update V'(s)

3. Non-hierarchical execution

- $Q^{\pi}(s,a)$: function Q for learned hierarchical policy π , *a* is an option.
- At each time step, compute $a = argmax_a Q^{\pi}(s,a)$, then execute one primitive action according to a.
- We might terminate an option early.
- Similar to policy improvement in policy iteration, it always improves the policy.

3. Non-hierarchical execution

• An extreme case: what if we interrupt at every step (polling execution)? Do we still have advantage over non-hierarchical algorithms?

Thank you!