Multiple-Step Greedy Policies in Online and Approximate Reinforcement Learning

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Multiple-step lookahead policies in RL give state-of-the-art-performance.

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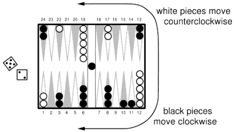
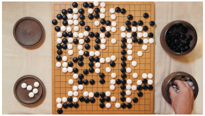
- **Monte Carlo Tree Search (MCTS) in RL** Tesauro and Galperin (1997); Baxter et al. (1999); Sheppard (2002); Veness et al. (2009); Lai (2015); Silver et al. (2017); Amos et al. (2018), and many more...





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Here: Extend to online and approximate RL.

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Optimal *first* action in h-horizon γ-discounted Markov Decision Process,
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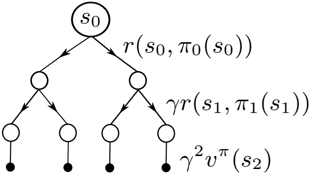

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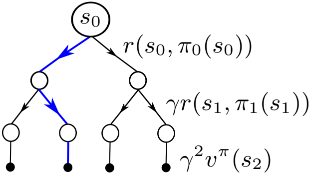
Path with
max. total reward



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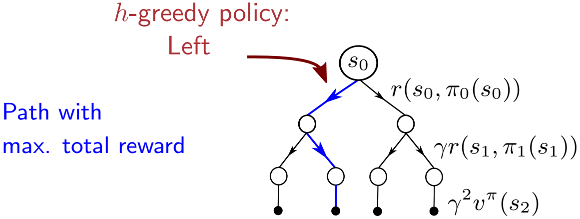

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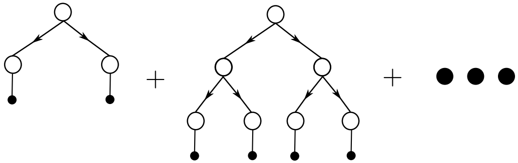

1-Step Greedy Policies and Soft Updates

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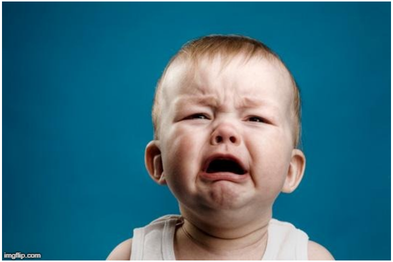
Important fact in:

Two-timescale online PI (Konda and Borkar (1999)),
Conservative PI (Kakade and Langford (2002)),
TRPO (Schulman et al. (2015)), and many more...

Negative Result on Multiple-Step Greedy Policies

Soft update using a multiple-step greedy policy **does not** necessarily improves policy.



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- $(1-\alpha)\pi + \alpha\pi_{\mathcal{G}_\kappa}$ *is always better than* π *iff* $\alpha \geq \kappa$.

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Open Problem:

More techniques to circumvent the problem.

Take Home Messages

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- Multiple-step PI has *theoretical* benefits (more discussion at the poster session).
- Further study should be devoted.

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