Improving Off-Policy Hierarchical Reinforcement Learning in Soar

Mitchell Keith Bloch

University of Michigan
2260 Hayward Street
Ann Arbor, MI. 48109-2121
bazald@umich.edu

June 15-17, 2011

Outline

Reinforcement Learning

- The Reinforcement Learning (RL) problem – learn to maximize the expected discounted return from any reachable state
  - More simply – learn the optimal choice of action from each state
- Environment models can help, but are not always desirable
- SARSA(λ) and Q(λ) are popular model-free RL algorithms

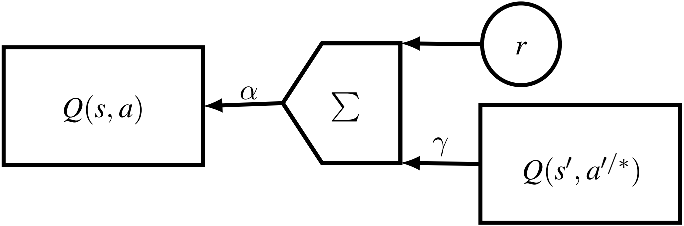


Figure: Temporal Difference (TD) Backup for a Q-Value

On/Off-Policy Temporal Difference (TD) Learning

- SARSA(λ) is on-policy – learning about policy being followed
  - Incorporates expected return of selected next action
  - Optimizing the current policy
- Q(λ) is off-policy – not learning about policy being followed
  - Incorporates expected return of best available next action
  - Optimizing the optimal policy
- In context of HRL – learning off-policy enables all-goals updating
  - Learn about multiple goals concurrently

On/Off-Policy Cliff-Walking Domain

Exploration requires choosing non-greedy actions
(occasionally going off the edge of the cliff)

On-Policy converges indirectly to the ultimately optimal policy

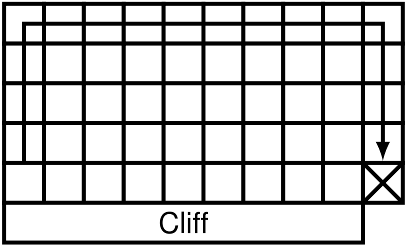


Figure: An on-policy agent with high exploration steers clear of the cliff

On/Off-Policy Cliff-Walking Domain

Exploration requires choosing non-greedy actions
(occasionally going off the edge of the cliff)

On-Policy converges indirectly to the ultimately optimal policy

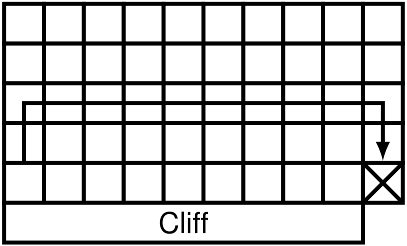


Figure: An on-policy agent with moderate exploration stays closer to the cliff

On/Off-Policy Cliff-Walking Domain

Exploration requires choosing non-greedy actions
(occasionally going off the edge of the cliff)

On-Policy converges indirectly to the ultimately optimal policy

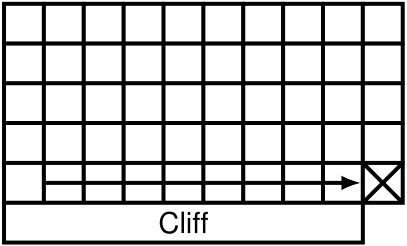


Figure: An on-policy agent with low exploration stays adjacent to the cliff

On/Off-Policy Cliff-Walking Domain

Exploration requires choosing non-greedy actions
(occasionally going off the edge of the cliff)

Off-policy converges directly to the ultimately optimal policy

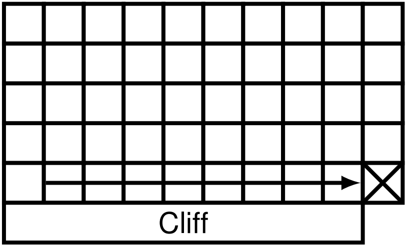
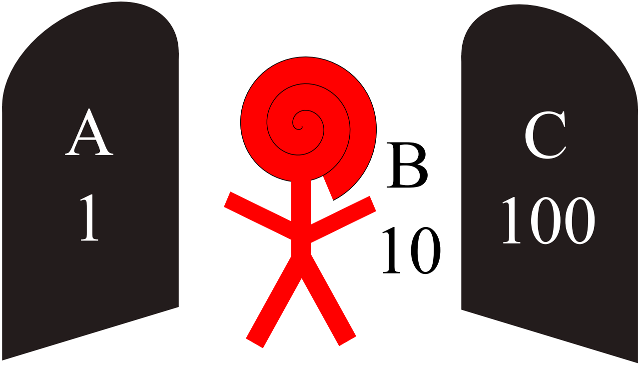


Figure: An off-policy agent stays adjacent to the cliff regardless of exploration

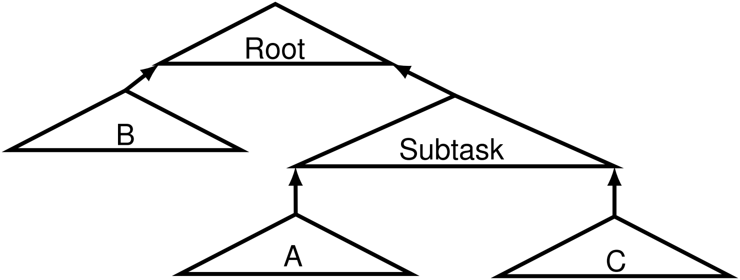
Outline

Bandit Task of Interest



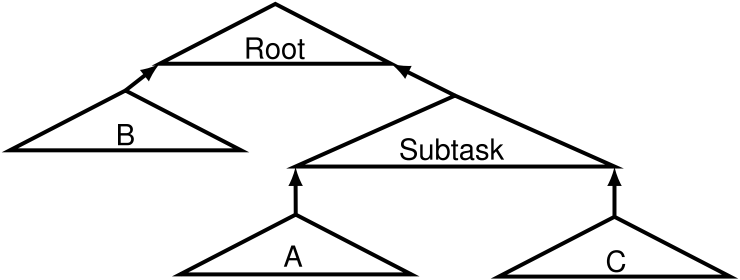
- A – Reward 1 – Escape into tunnel with dragon
- B – Reward 10 – Fight less dangerous monster (depicted)
- C – Reward 100 – Escape into tunnel with treasure

Hierarchical RL (HRL)



- Large or complex problems involving separable goals can be broken down hierarchically
- Decouples the problem of deciding which goal to achieve next from the problem of how to achieve it
- Enables state abstraction and goal reuse

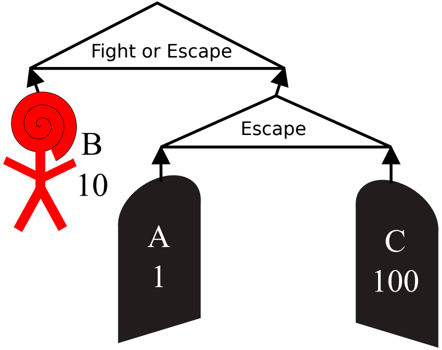
Exploration and Learning



- Can explore non-greedy actions within a goal
  - Must learn correctly in supergoals regardless
- Can explore subgoals with no chance of success
  - Must learn correctly in subgoals regardless

Exploring Non-Greedy Actions - The Setup

Why are non-greedy actions in subgoals problematic?



Group actions A and C in a subtask, “Escape”. The decision procedure becomes:

1. Fight (B) or Escape?
2. If Escape, then (A) or (C)?

Exploring Non-Greedy Actions - The Mistake

1. The true value of Escape is 100, once Escape is learned
2. Exploration, required by convergence proofs, causes Escape to yield only 1 reward
3. The initial decision can learn that Escape is worth only 1

Point 3 is true even when learning with Q(λ).

The Mistake - Visualized

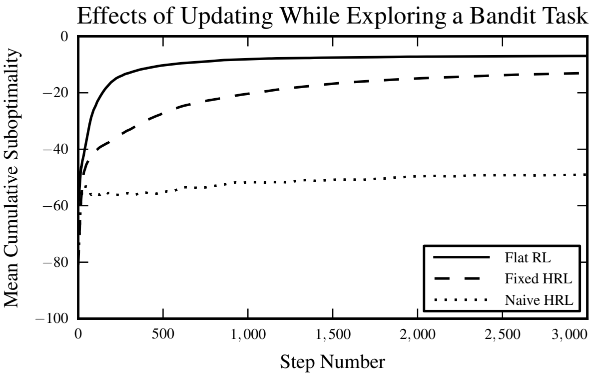


Figure: Mean cumulative suboptimality for Naive RL asymptotes at approximately -50 reward in the limit, regardless of cooling strategy. Fixed HRL achieves an optimal policy but does worse than Flat RL due to higher persistent exploration: $(1-\varepsilon)^2 < 1-\varepsilon$

Exploring Non-Greedy Actions - The Mistake

1. The true value of Escape is 100, once Escape is learned
2. Exploration, required by convergence proofs, causes Escape to yield only 1 reward
3. The initial decision can learn that Escape is worth only 1

Point 3 is true even when learning with Q(λ).

This is not what we expect when learning off-policy!

Exploring Non-Greedy Actions - The Mistake

1. The true value of Escape is 100, once Escape is learned
2. Exploration, required by convergence proofs, causes Escape to yield only 1 reward
3. The initial decision can learn that Escape is worth only 1

Point 3 is true even when learning with Q(λ).

This is not what we expect when learning off-policy!

Conclusion: Learning must be blocked by exploration in subgoals.

Hierarchical Credit Assignment

When does a goal bear responsibility for reward received?

- On-Policy? – Goal is attainable when selected by supergoals
- Off-Policy? – Additionally, all subgoals choose greedily

Outline

Soar-RL

- Implements RL using numeric preferences and the RL link
  - Actually, one RL link per goal for correct hierarchical credit assignment
- Supports both SARSA(λ) and Q(λ) [Nason and Laird, 2004; Derbinsky *et al.*, 2009]
- Implements HRL using operator no-change impasses and multiple RL links

Recommendation 1: Exploration in Subgoals

When learning off-policy, TD updates must be blocked and eligibility traces must be cleared.

Intra-option learning [Sutton and Precup, 1998] and (G)TSDT [Bloch, 2011b,a] can improve this situation somewhat.

Recommendation 1.5: Intra-Option Learning

It is necessary to pursue a goal until success or failure for Soar-RL to learn in the context of HRL, but this commitment is not integral to Soar.

Supporting intra-option learning [Sutton and Precup, 1998] and (G)TSDT [Bloch, 2011b,a] would enable learning in cases where this commitment is not desired.

Recommendation 2: Operator No-Change Impasses

Learning on-policy or off-policy, terminal reward should be backed up as a goal retracts **iff** the impasse resolves normally.

A supergoal retracting should prevent TD updates.

Outline

Nuggets and Coal

Nuggets:

- Identified conditions under which HRL fails to work as expected
- Modified HSMQ [Dietterich, 2000] and Intra-option learning [Sutton and Precup, 1998], resulting in what I believe to be the first off-policy TD methods to converge reliably in model-free HRL systems
- Created new traces to improve performance over HSMQ and Intra-option learning [Bloch, 2011b,a] given the new constraints

Coal:

- No formal convergence proofs provided
- Not formally addressed function approximation (yet)

Outline

Mitchell Keith Bloch. Off-Policy hierarchical reinforcement learning. arXiv:cs.LG/1104.5059, 2011.

Mitchell Keith Bloch. Temporal second difference traces. arXiv:cs.LG/1104.4664, 2011.

Nate Derbinsky, Nick Gorski, John Edwin Laird, Bob Marinier, and Yongjia Wang. *Soar-RL Manual*, 2009. Version 1.0.1.

Thomas G. Dietterich. An overview of MAXQ hierarchical reinforcement learning. In *SARA*, pages 26–44, 2000.

Shelley Nason and John E. Laird. Soar-rl: Integrating reinforcement learning with soar. In *Cognitive Systems Research*, pages 51–59, 2004.

Richard S. Sutton and Doina Precup. Intra-option learning about temporally abstract actions. In *Proceedings of the Fifteenth International Conference on Machine Learning*, pages 556–564. Morgan Kaufman, 1998.