The Utility of Temporal Abstraction in Reinforcement Learning

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Outline

1. Motivation: Hierarchical Reinforcement Learning
2. Experimental Results
   - Learning with Options
   - Options and Random Exploration
   - Other Applications of Options

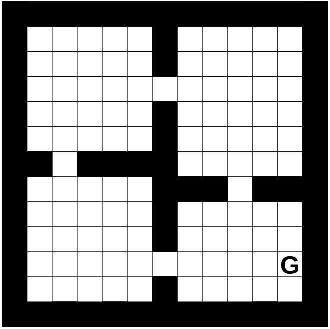
Goal: Learn Agent Behaviors Autonomously

Reinforcement learning algorithms:

- Given experience with an unknown environment
- Estimates the value of states
- Learns a policy

Problem

How to learn more efficiently?



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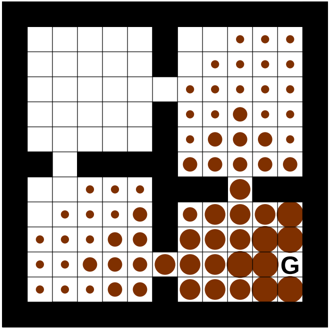

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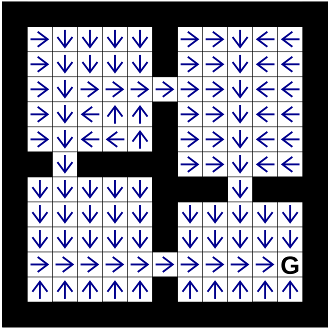

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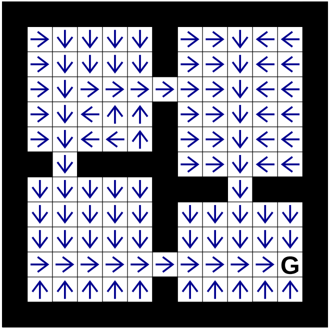

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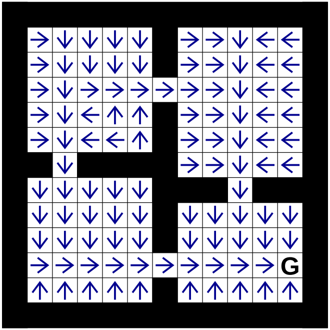
Intuition: Decompose Tasks into Subtasks

- Standard RL assumes flat state and action spaces.
- Real-world applications have hierarchical structure.
- Abstract actions
  - Represent sequences of primitive actions
  - Achieve subgoals



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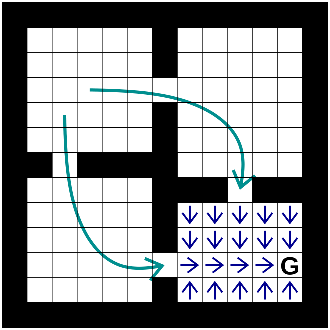
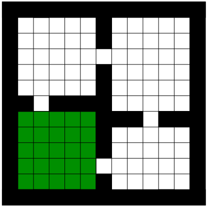


The Most Popular Framework for Hierarchical RL



- Options: analogous to macro-operators
  - Initiation set (precondition)
  - Termination function (postcondition)
  - Option policy (implementation)
- Typically used to augment an action space
- Can be treated simply as temporally extended actions

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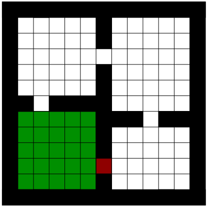

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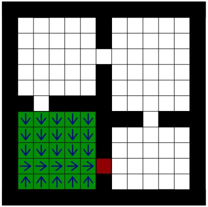

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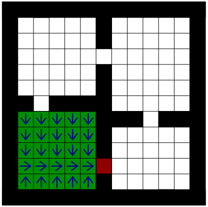

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The Benefits of Options

- Prior work: options are good
- Future work: where do the options come from?

Key Question

How precisely does the addition of options affect learning?

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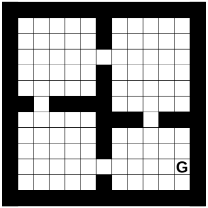
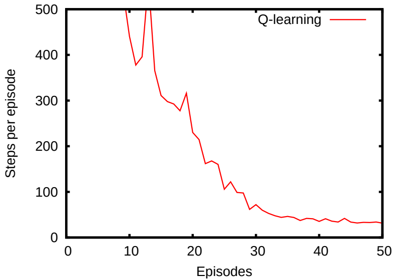
Replicating Results in Option Discovery

- Apply standard Q-learning with ϵ-greedy exploration
- Introduce options after 20 episodes
  - One option for each of four given subgoals
  - Option policies learned from experience replay
  - Initiation set: states that can reach subgoal



One of four options



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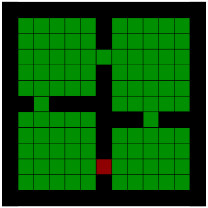

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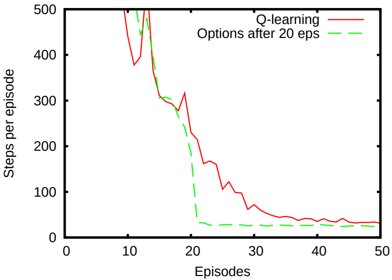
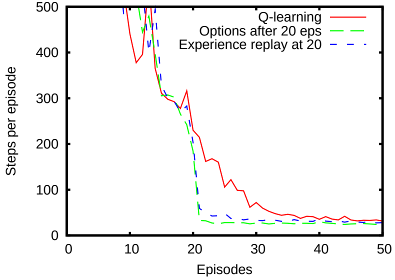


Hierarchical Reasoning or Additional Computation?

Observation

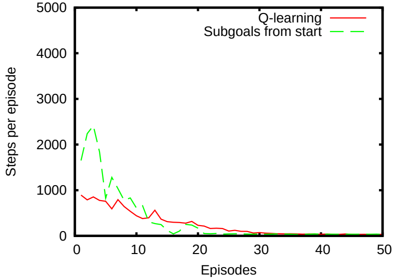
The technique used to obtain the option policy can also be used to improve the value function without using options at all!



- Better baseline: just experience replay after 20 episodes

Options Can Degrade Learning Performance

- Isolating the effect of hierarchy
  - Give only subgoals (at start)
  - Learn option policies online
- Subgoals can degrade performance initially.
- Correct options can severely degrade performance!



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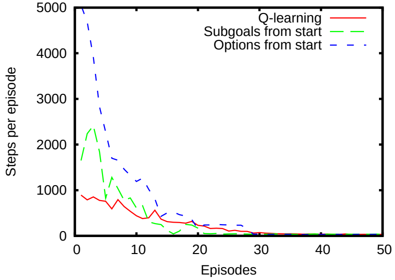

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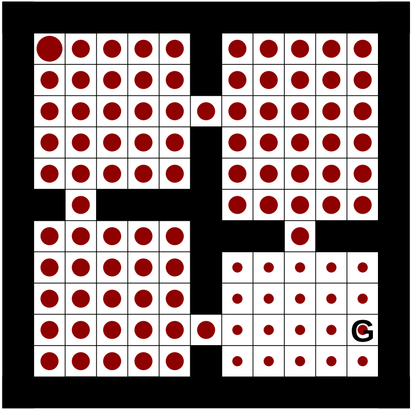
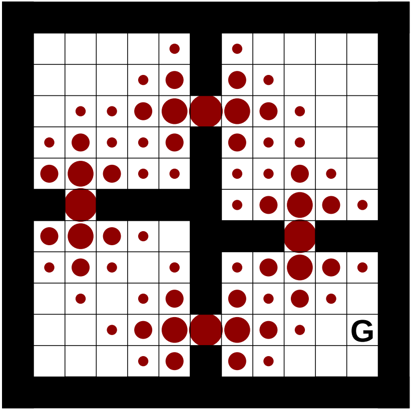
Options Change the Environment Structure



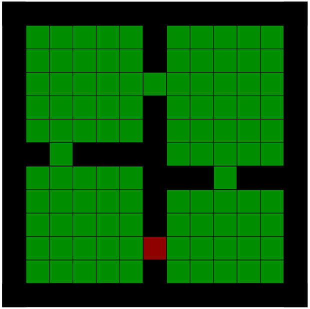
Random walk in original environment



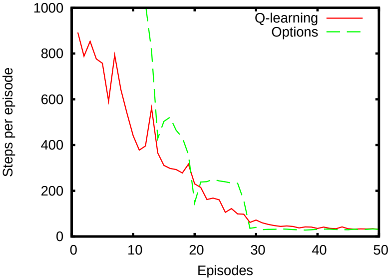
Random walk in augmented environment

Restricting the Initiation Set

- Idea: Limit options to certain states
- Requires domain expertise



Initiation set of one option



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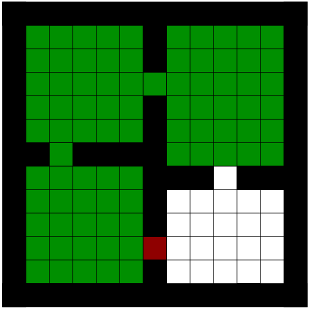

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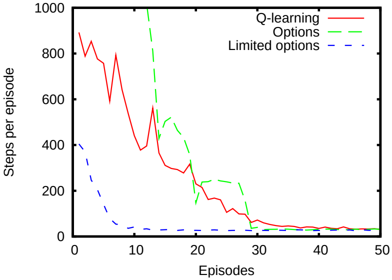

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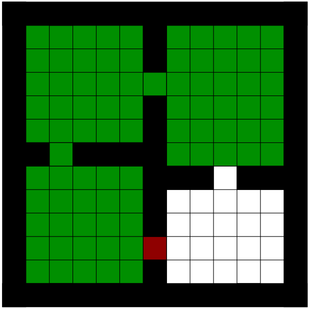

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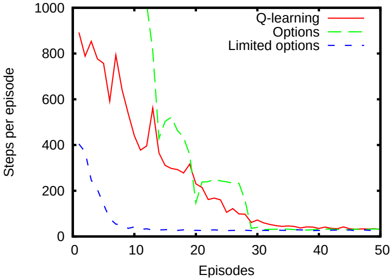
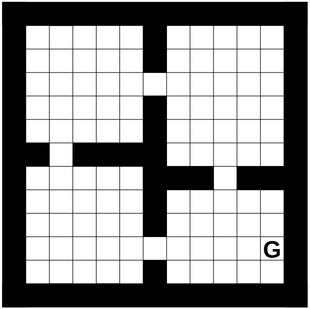
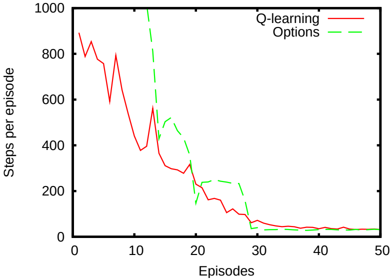


Delaying Option Deployment

- Idea: wait until value function partially learned
- Somewhat brittle



Value function on option deployment



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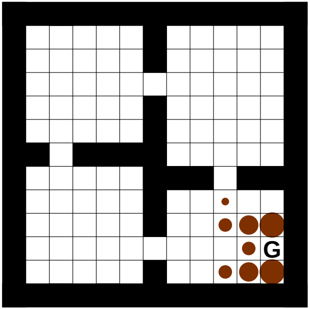

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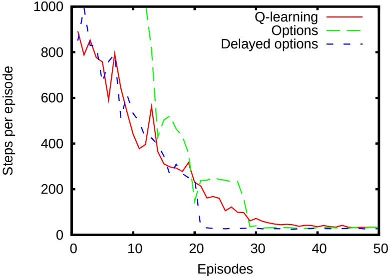

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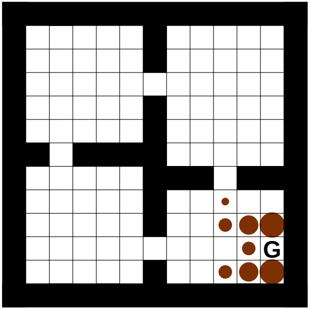

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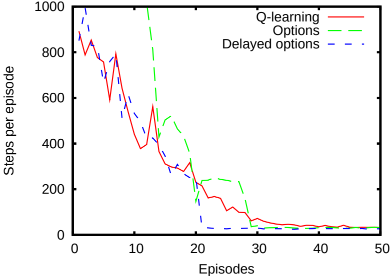

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Options and Optimistic Exploration

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We can blame some of the performance degradation on random exploration.

- Alternative: optimism in the face of uncertainty
- Optimism offers solid theoretical benefits.
- Heuristic implementation: optimistic initialization of the value function

Thorough exploration eliminates the impact of options!

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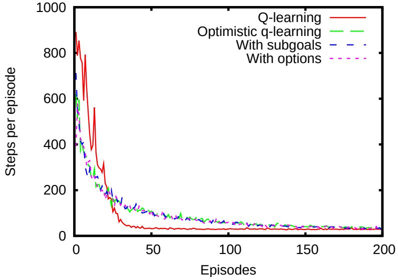

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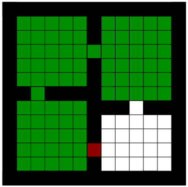
Options that Abstract Instead of Augment

- Remove primitive actions superceded by options.



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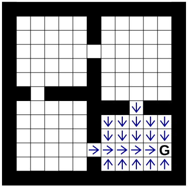
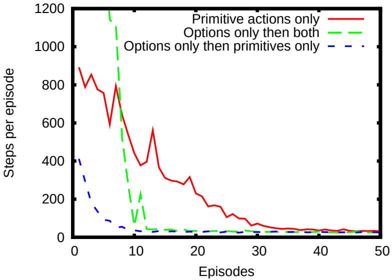


Availability of primitive actions



Temporal Abstraction in Other Algorithms

Observation

Q-learning may not be the best baseline algorithm for studying hierarchy.

- Q-learning uses each piece of experience exactly once.
- It therefore confounds data acquisition (exploration) with computatation (planning).

See also

In ICML 2008: Jong and Stone, “Hierarchical Model-Based Reinforcement Learning: R-MAX + MAXQ”

Summary

- Options do not always help reinforcement learning; in some cases, they can severely hinder learning.
- Hierarchical methods impact learning by biasing or constraining exploration.