Bootstrapping Skills

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Outline

Motivation

Skills

Algorithm Learning Skills via Bootstrapping (LSB)

Convergence Guarantee and Analysis

Experiments

1 Motivation

2 Skills

3 Algorithm Learning Skills via Bootstrapping (LSB)

4 Convergence Guarantee and Analysis

5 Experiments

Monolithic Policy

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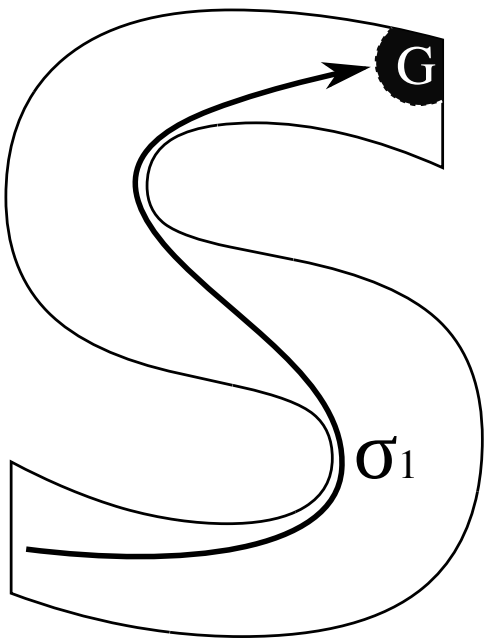
Convergence Guarantee and Analysis

Experiments

- One policy
- Big and Complex
- No attempt to decompose



Example: Monolithic Policy

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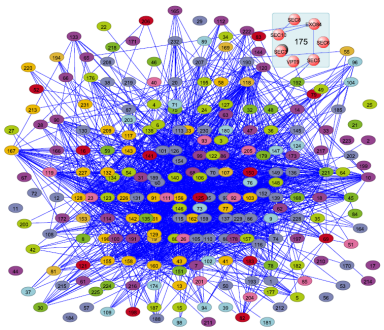
Experiments

- Task: Leave the room
- Skill to Learn: Walk to door, grasp door knob, open the door and walk through door opening



Skills

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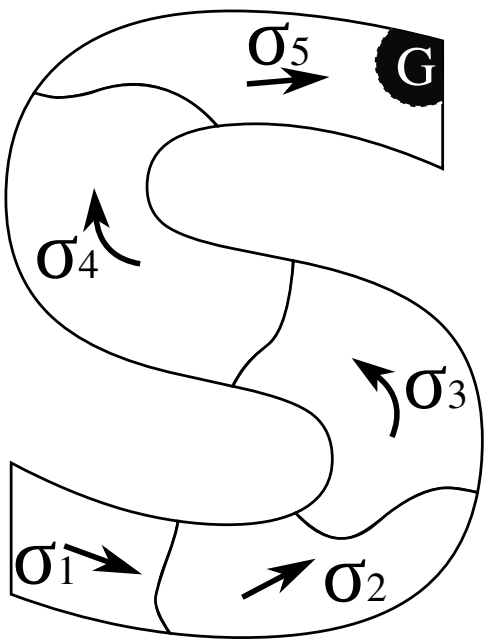
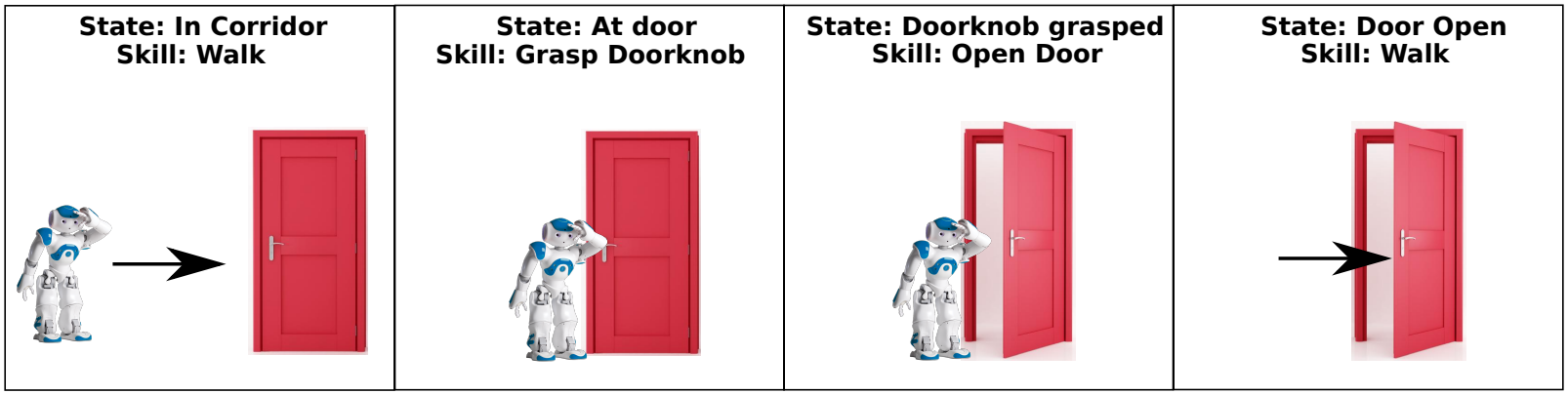
Experiments

- Accomplish a subgoal (decompose)
- Can be applied in different contexts (reusable)
- Special form of an option [1]



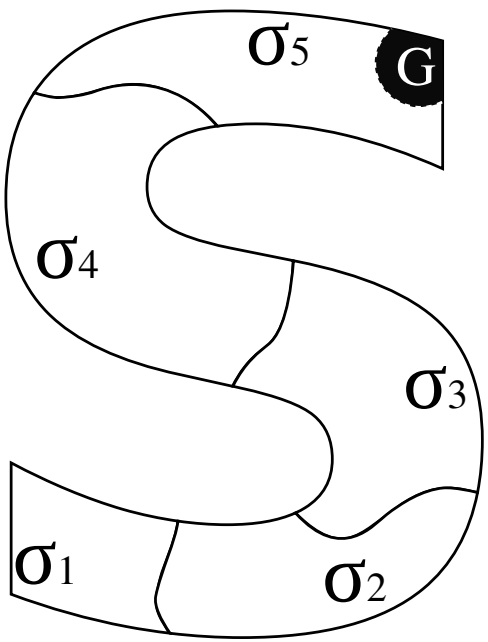
Example: Skills

- Task: Leave the room
- *Skills* to Learn:
  - Walk
  - Grasp door knob
  - Open the door

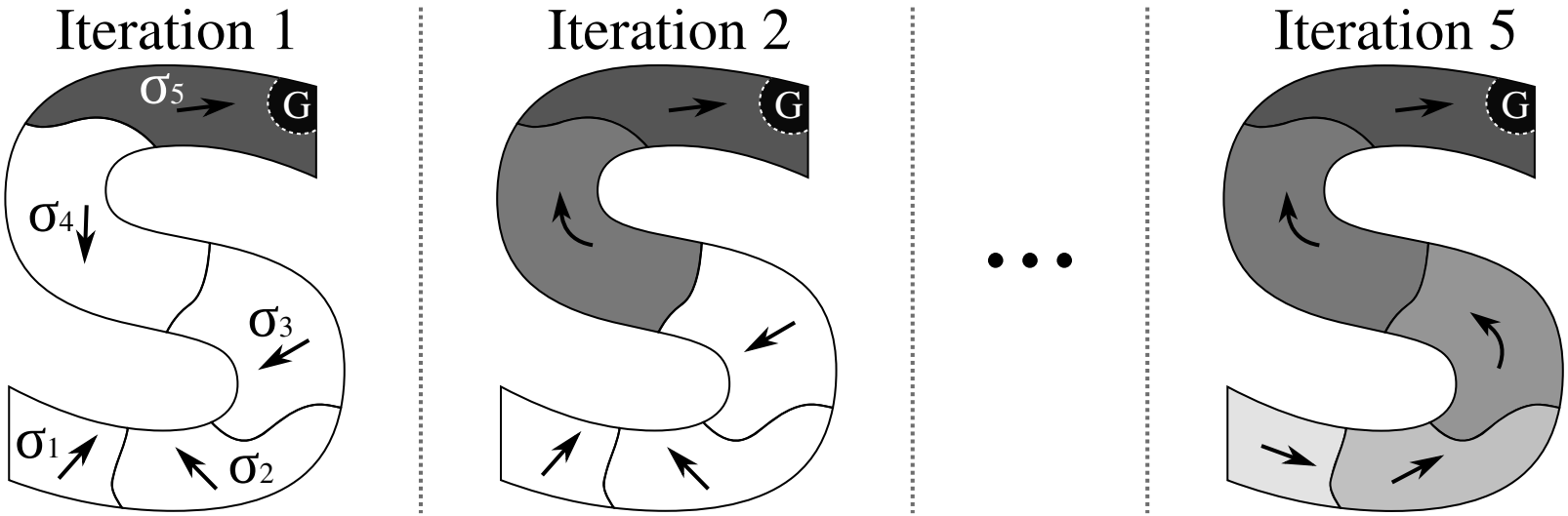


Learning Skills

- Given a partition of states
- Find the best 'local' policy
- Inspired by Skill Chaining [2]

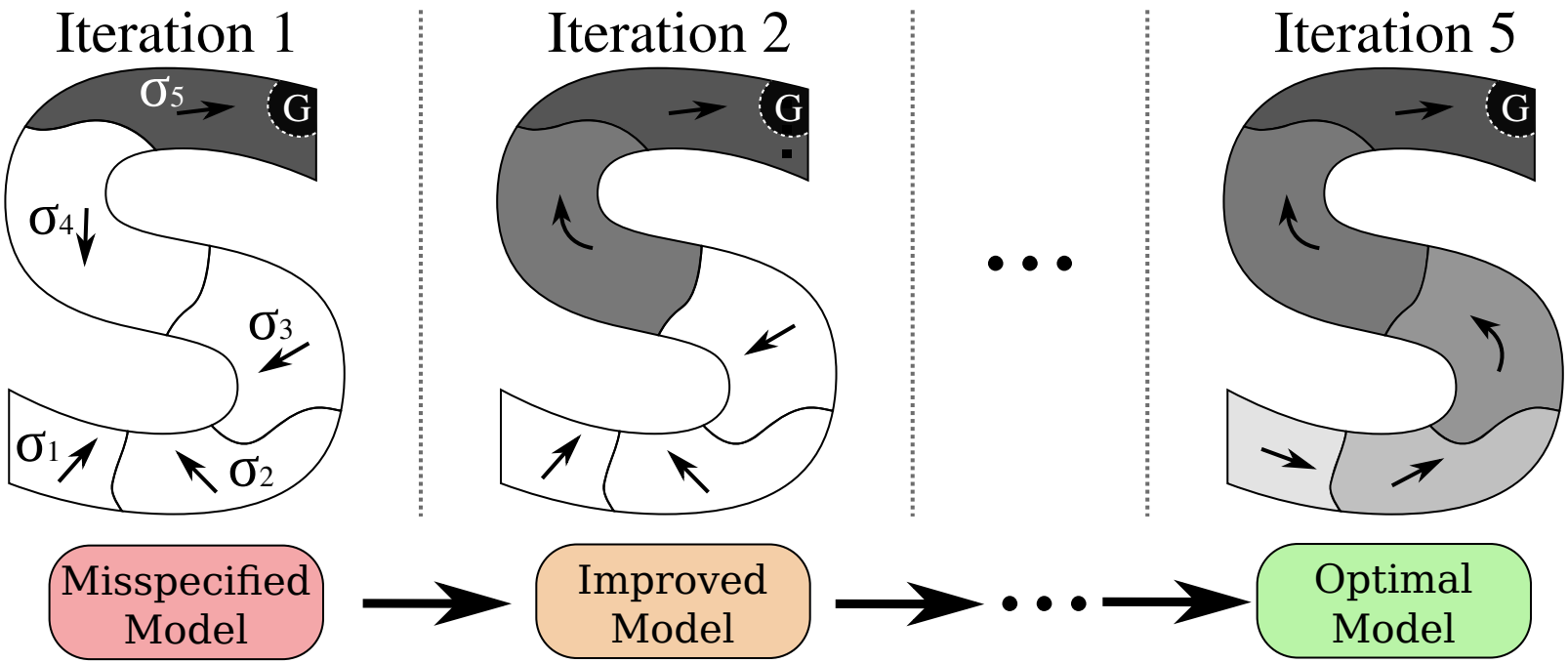


Learning Skills via Bootstrapping (LSB)



- First theoretical convergence guarantees for iteratively learning skills in a continuous state MDP

Model Iteration



Main Theorem

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Theorem

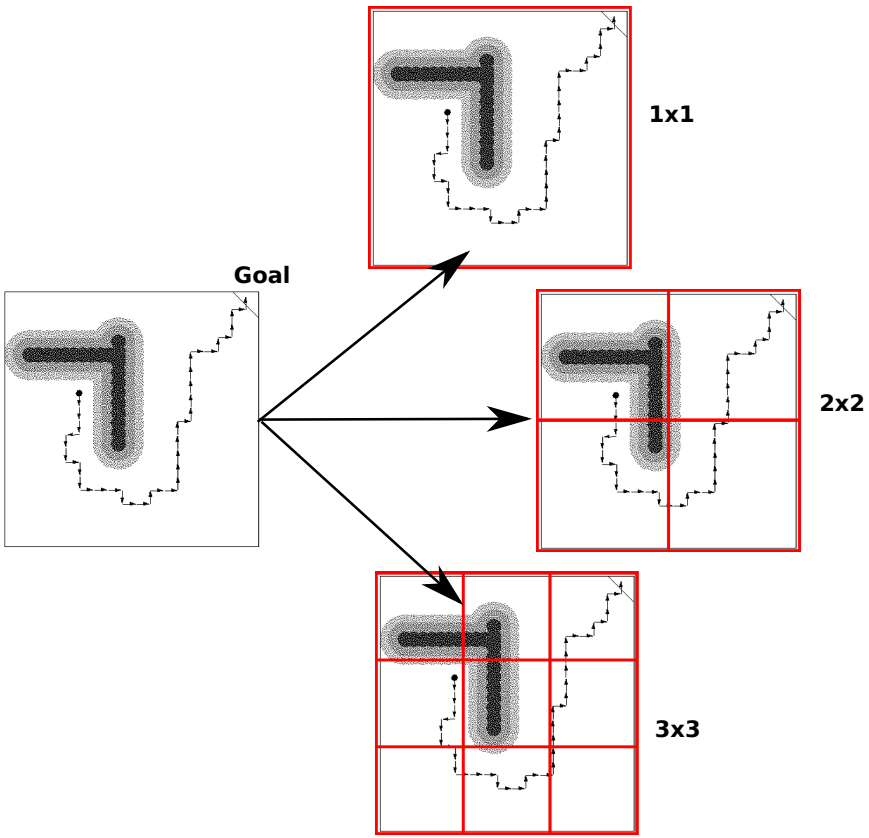
Let $\varepsilon > 0$. If we run LSB with partition $\mathcal{P}$ for $K \geq \log_\gamma(\varepsilon(1-\gamma))$ iterations, then the algorithm returns policy $\varphi = \langle \mu, \Sigma \rangle$ such that

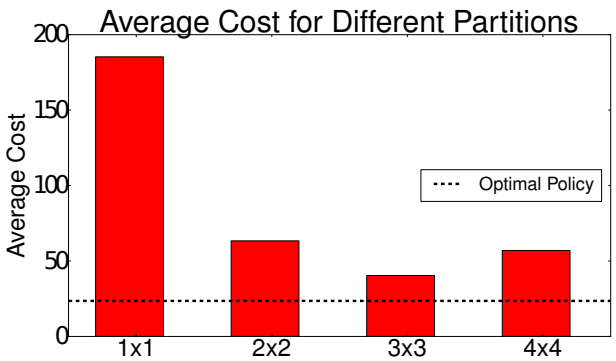
$$\|V_M^* - V_M^\varphi\|_\infty \leq \frac{m\eta_\mathcal{P}}{(1-\gamma)^2} + \varepsilon \ , \tag{1}$$

where m is the number of classes in $\mathcal{P}$.

- LSB learns a near-optimal policy

Experiment: Puddle World





Experiments: Puddle World

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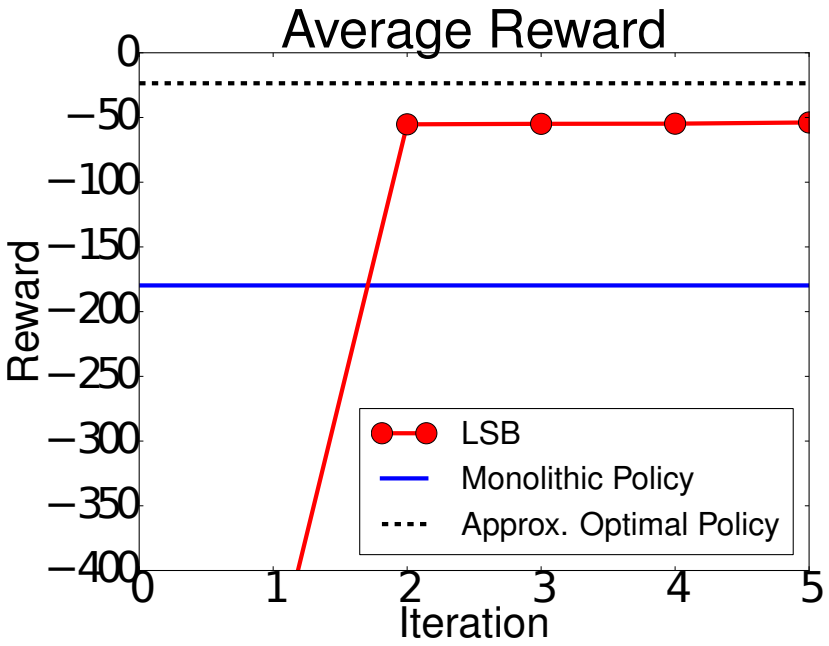
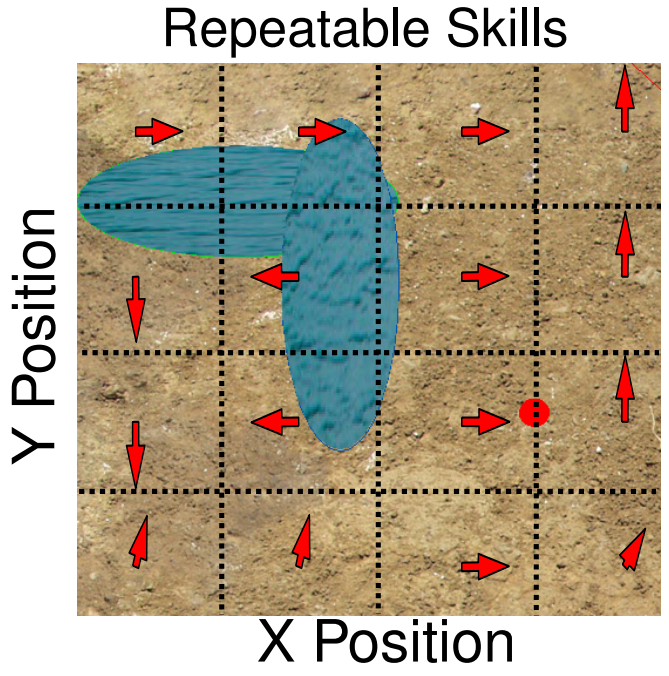
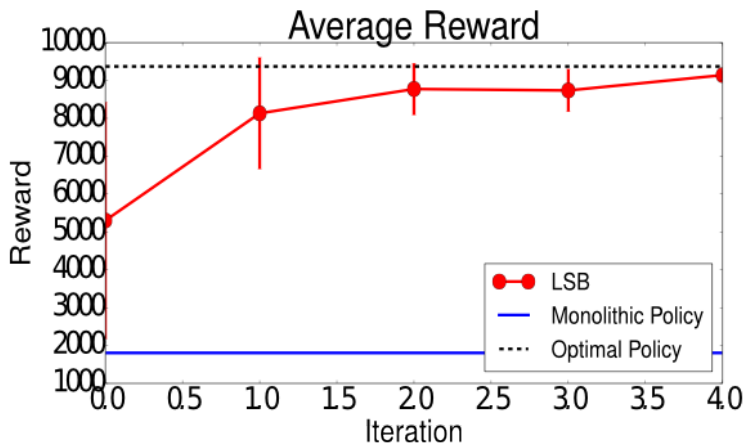
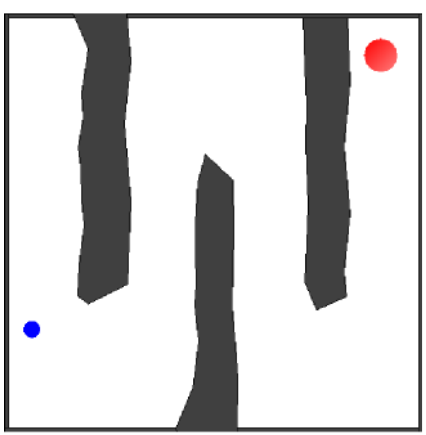


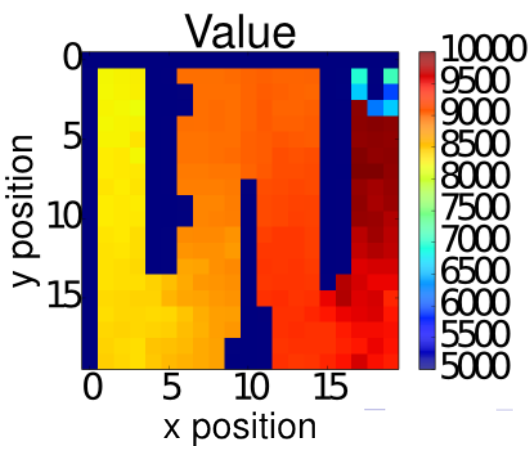


Experiments: Pinball

- Maze-world
- More complex dynamics
- 4 dimensional state space

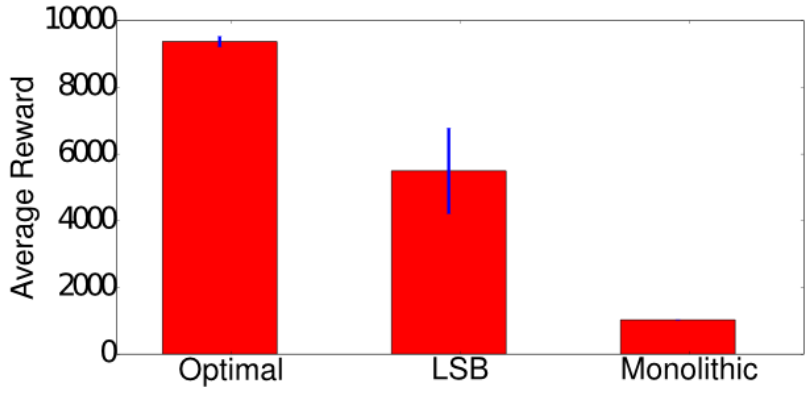


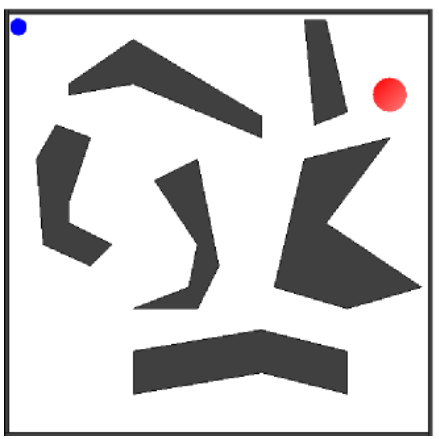


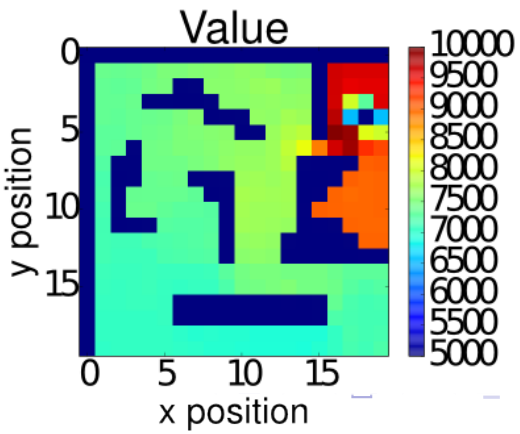


Experiments: Pinball

- Pinball-world
- Sharp obstacles, non-linear dynamics at obstacle edges
- 4 dimensional state space







Conclusion

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- Monolithic Approach is not feasible for many real-world problems
- Decomposing the task and iteratively learning skills allows us to scale
- **We provide the first theoretical convergence guarantees for skill learning in a continuous state environment**
  - Skills **work together**
  - Skill learning requires **iterative improvements**

Acknowledgements

The research leading to these results has received funding from the European Research Council under the European Unions Seventh Framework Programme (FP/2007-2013) / ERC Grant Agreement n.306638.

For Further Reading I

R. Sutton, D. Precup,S. Singh.
Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning.
Journal Artificial Intelligence, vol. 112, no. 1, 1999.

G. Konidaris, A. Barto.
Skill Discovery in Continuous Reinforcement Learning Domains using Skill Chaining
Advances in Neural Information Processing Systems, 2009.