Advising and Instructing Reinforcement Learning Agents with LTL and Automata

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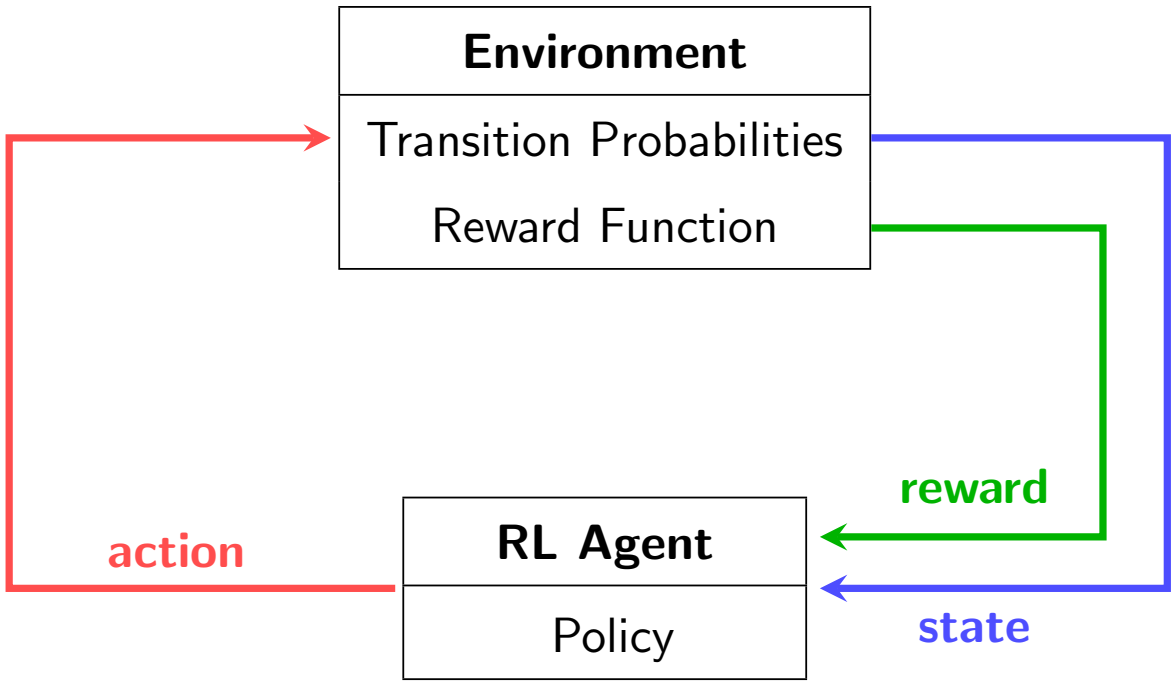
Papers appearing at

- Canadian AI (Toro Icarte et al., 2018b),
- AAMAS 2018 (Toro Icarte et al., 2018a),
- and ICML 2018 (Toro Icarte et al., 2018c)

Outline

1. Reinforcement Learning (RL):
    - What is RL?
    - Two difficulties in applying RL
2. Instructions for Reinforcement Learning
    - LTL formulas
    - Reward Machines
3. Advice for Reinforcement Learning
4. Summary

How does Reinforcement Learning work?



Based on diagram from Sutton and Barto (1998, Figure 3.1)

Two difficulties in applying RL

- **Reward specification**: It is really hard to define proper reward functions for complex tasks.
- **Sample efficiency**: RL agents might require billions of interactions with the environment to learn good policies.

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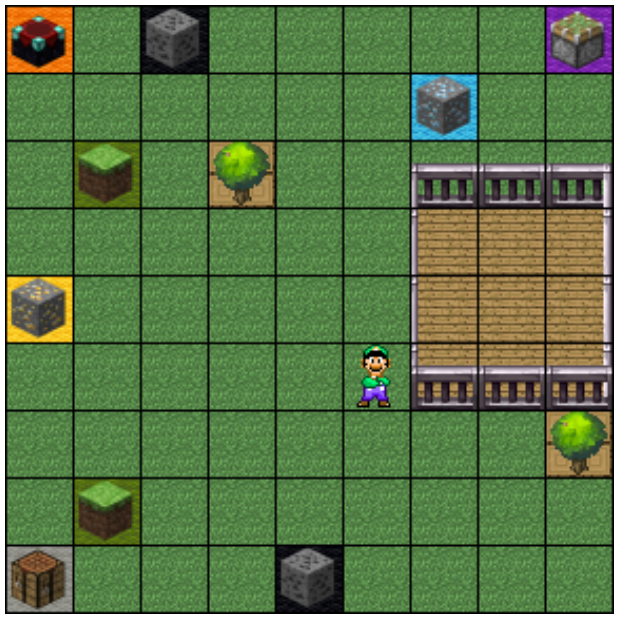

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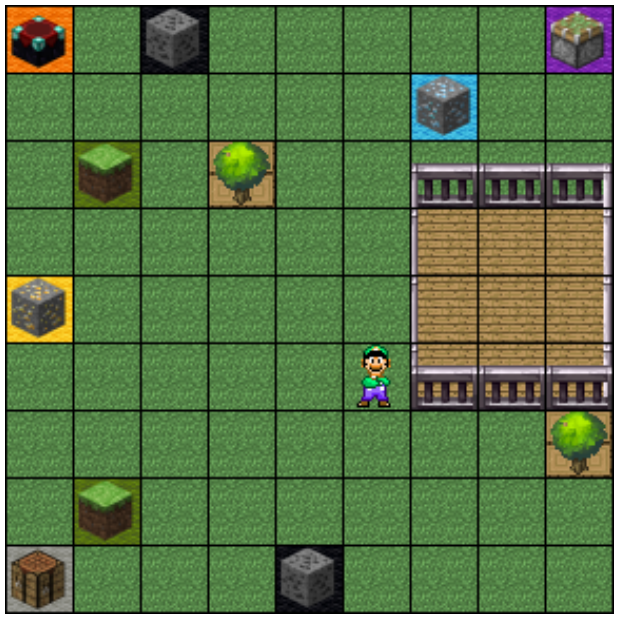


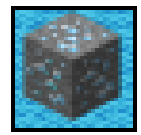
Luigi can collect raw materials:


wood


grass


iron


gold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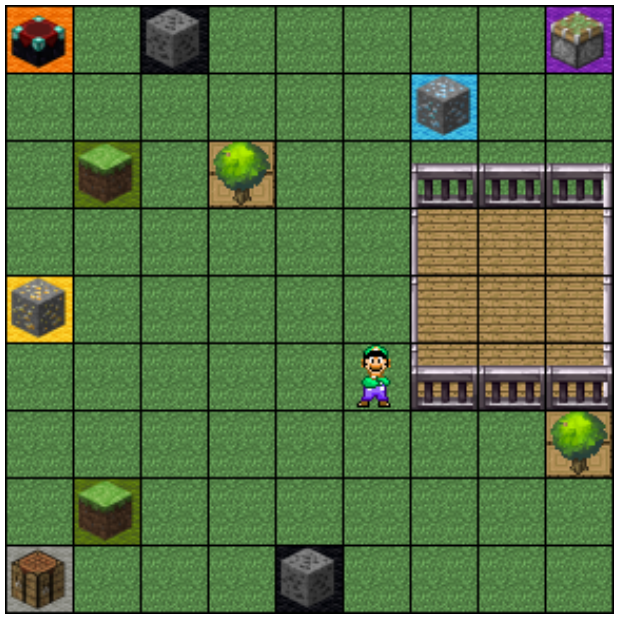

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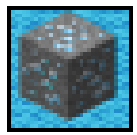
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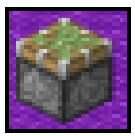
... and make new objects in:


factory


toolshed


workbench

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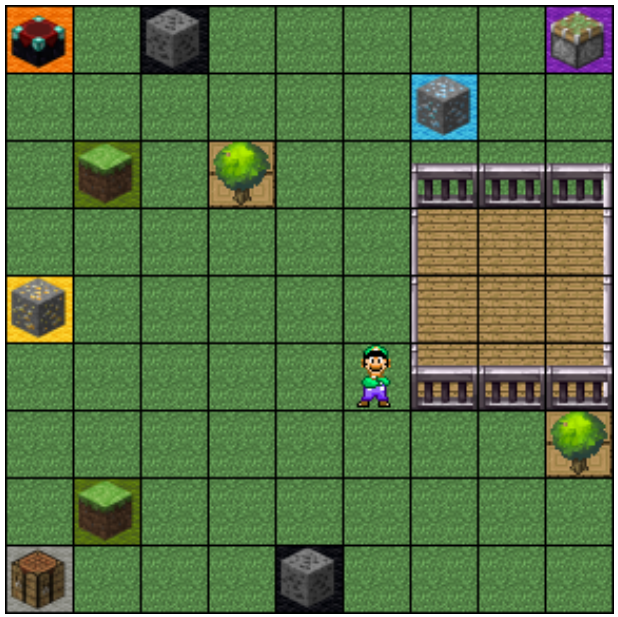

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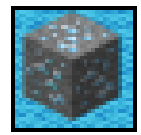
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Make a bridge: get wood, iron, and use the factory

Linear Temporal Logic (LTL) (Pnueli, 1977)

LTL augments propositional logic with the **temporal** operators $\bigcirc$ (*next*), $\Diamond$ (*eventually*), and U (*until*):

$$\varphi ::= p \mid \neg\varphi \mid \varphi_1 \wedge \varphi_2 \mid \bigcirc\varphi \mid \Diamond\varphi \mid \varphi_1 \,\mathsf{U}\, \varphi_2$$

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Examples:

$$\Diamond \texttt{got\_wood} \tag{1}$$

$$\Diamond(\texttt{got\_grass} \wedge \Diamond \texttt{used\_factory}) \tag{2}$$

$$\Diamond \texttt{got\_wood} \vee \Diamond \texttt{got\_iron} \tag{3}$$

$$\Diamond \texttt{got\_grass} \wedge \Diamond \texttt{got\_iron} \tag{4}$$

$$(\texttt{is\_night} \rightarrow \texttt{at\_shelter})\,\mathsf{U}\,\texttt{got\_wood} \tag{5}$$

Instructing RL agents with co-safe LTL

General idea:

- Reward the agent when it satisfies the formula.
- Therefore, an optimal policy would satisfy the formula **as soon as possible**.

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Main advantage:

- **Standard RL**: The reward function is a black box.
- **RL with LTL**: The LTL formula exposes the task's structure to the agent.

Example

Consider telling the agent to learn a policy for the following task:

$$\varphi = \Diamond(\texttt{got\_iron} \wedge \Diamond\texttt{used\_factory}) \wedge \Diamond\texttt{got\_gold}$$

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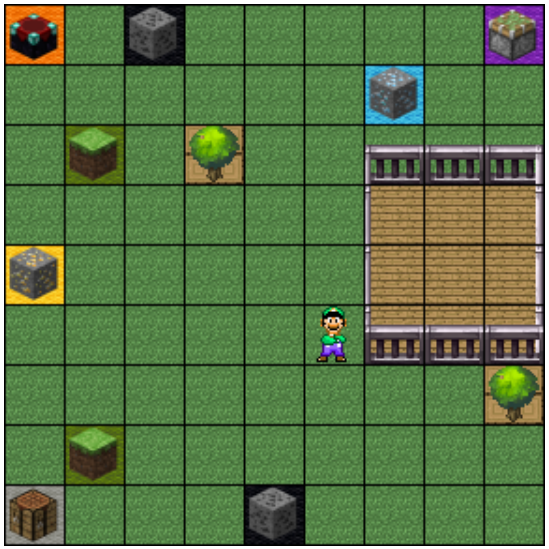
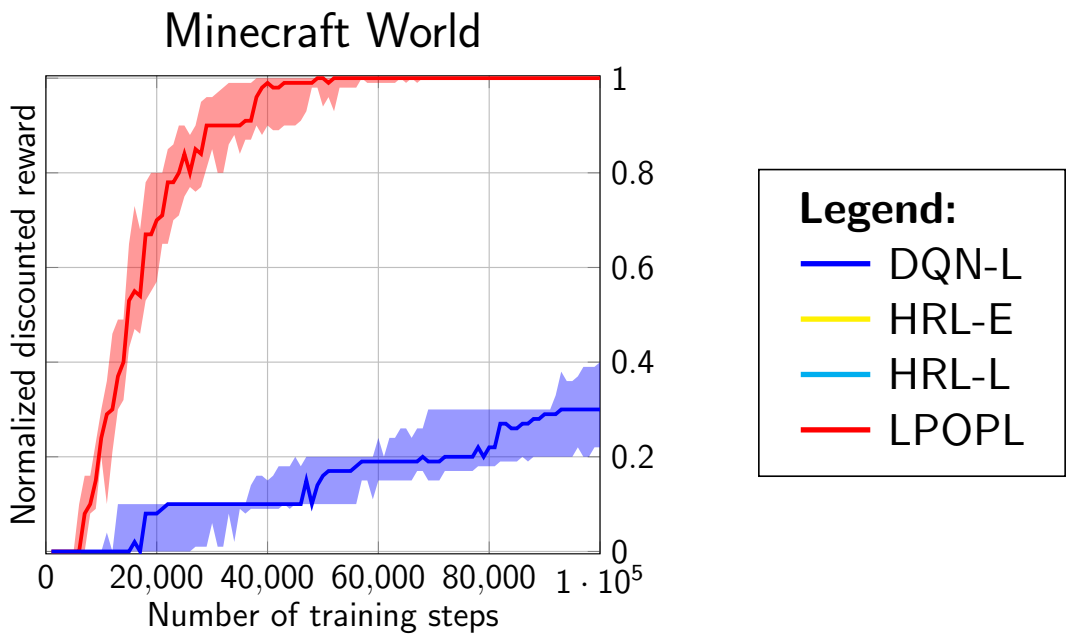
We proposed to combine this knowledge with off-policy (deep) RL to learn optimal policies for the task and each subtask in parallel.

Results





Our approach (red curve) finds better policies faster than standard DRL (blue curve)

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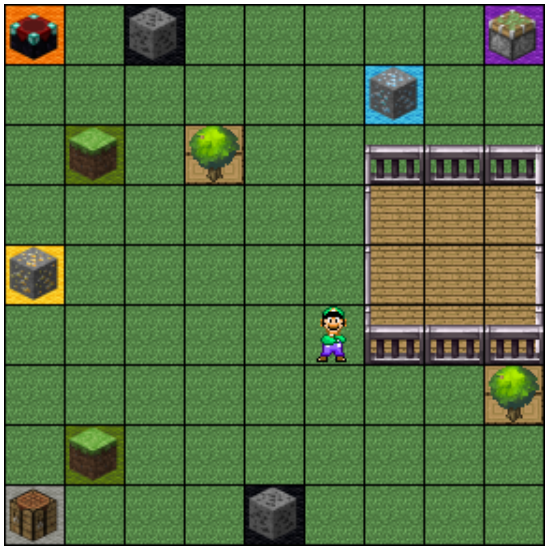

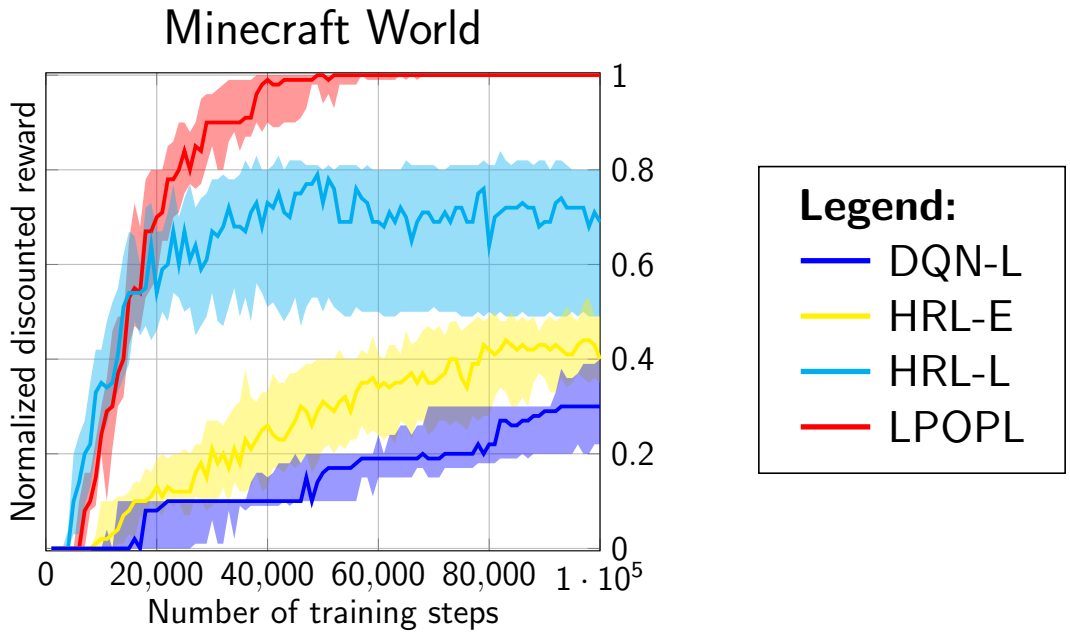

Our approach (red curve) finds better policies faster than standard DRL (blue curve) and Hierarchical DRL (yellow and cyan curves).

Paper: "Teaching Multiple Tasks to an RL Agent using LTL"
Code: `https://bitbucket.org/RToroIcarte/lpopl`

Instructing RL agents with automata

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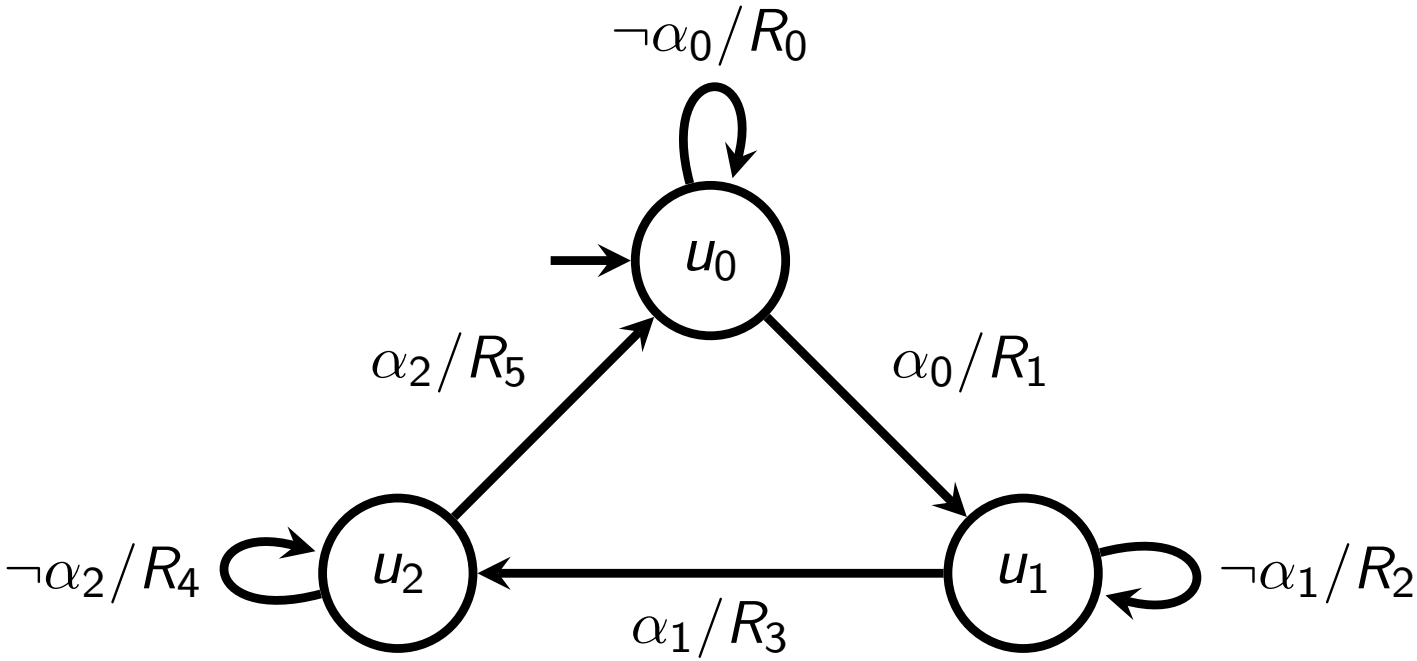

Figure: A **reward machine**

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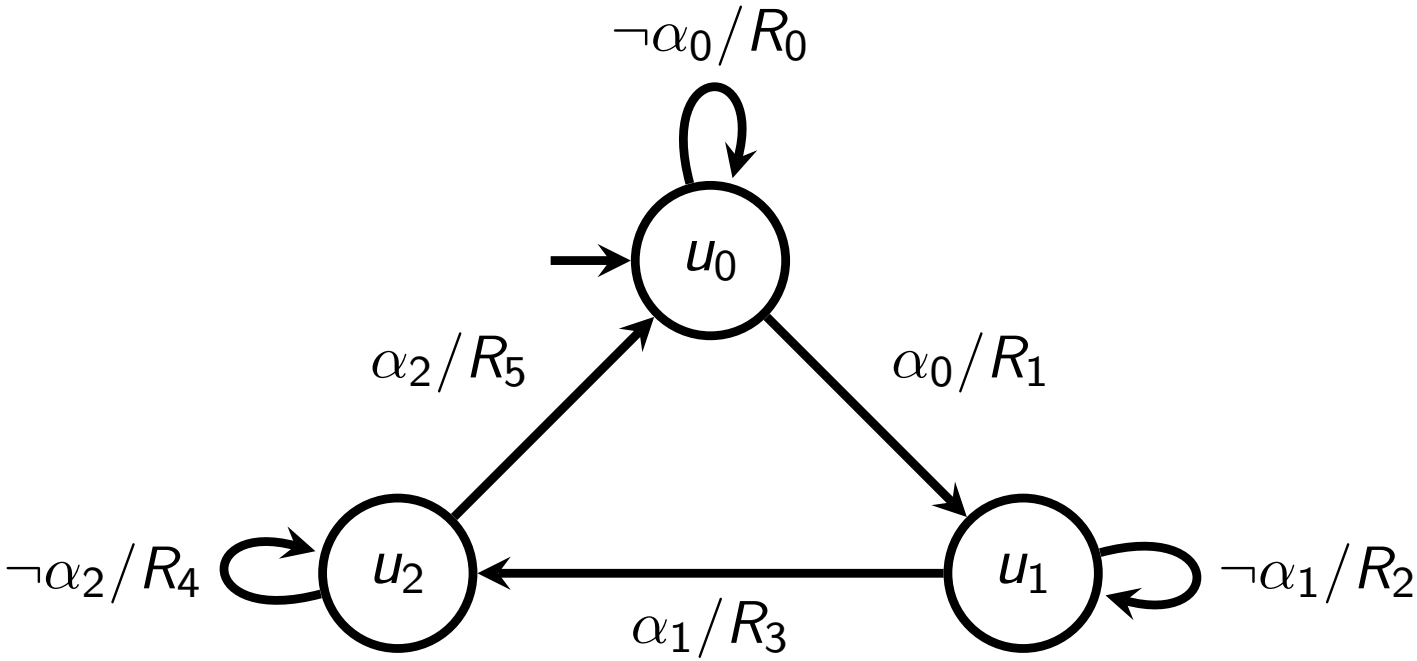
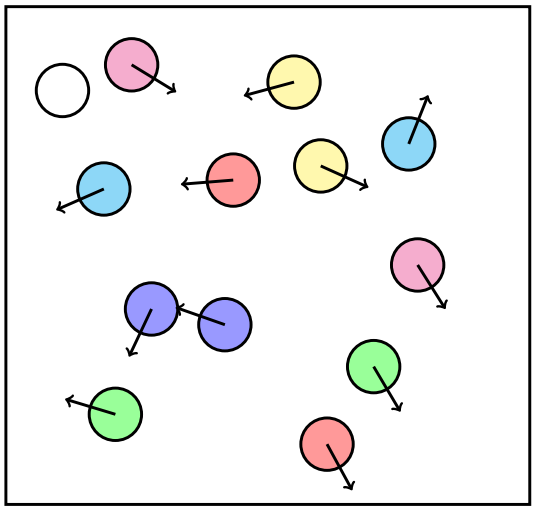
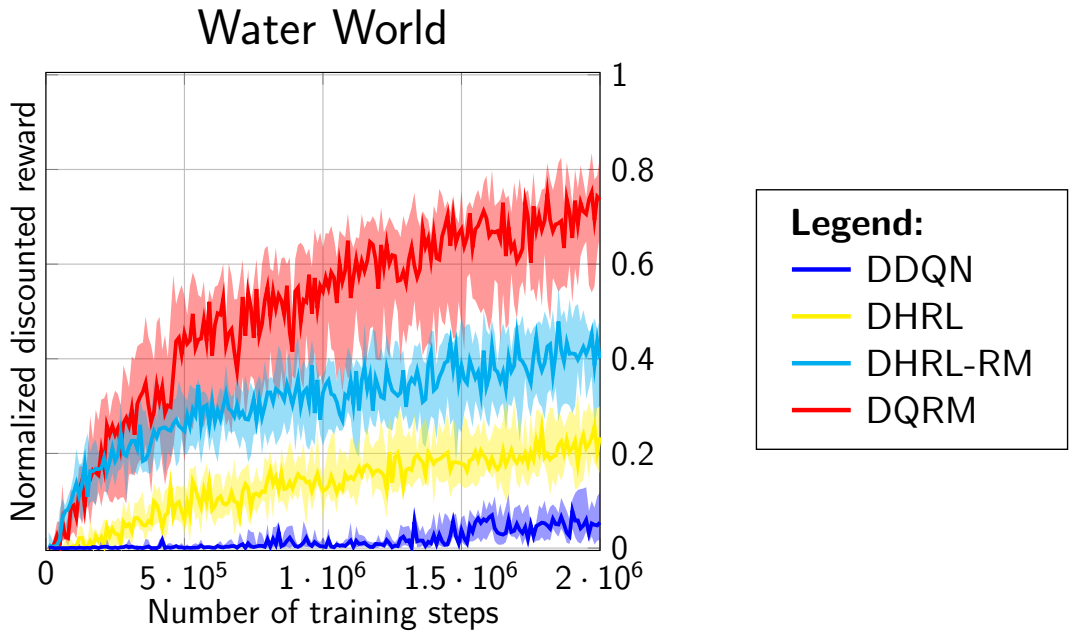


Figure: A **reward machine**

In this case, our approach learns one policy for each node.

More results





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Paper: "Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning"
Code: `https://bitbucket.org/RToroIcarte/qrm`

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LTL as an advice language

Advice suggests how to achieve rewards, but does not define the rewards.

Idea:

- Use a **model-based** RL algorithm.
- Guide the exploration with a **heuristic** estimating what actions will make progress towards satisfying the (finite) LTL advice.
  - Good advice can reduce the amount of exploration required to learn a good policy,
  - Bad advice will eventually be recovered from.

Paper: "Advice-Based Exploration in Model-Based Reinforcement Learning"

Summary

Instructions:

- "Teaching Multiple Tasks to an RL Agent using LTL" (AAMAS 2018)
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Advice:

- "Advice-Based Exploration in Model-Based Reinforcement Learning" (Canadian AI 2018)

References

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