# LTL and Beyond:

Formal Languages for Reward Function Specification in Reinforcement Learning



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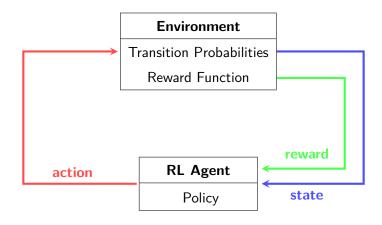
Richard Valenzano



Sheila A. McIlraith

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### Reinforcement learning (RL)

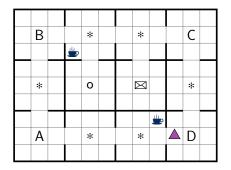


### **Takeaway points**

• Reward machines (RMs) are a form of automaton that are a way of representing (temporally extended) reward functions.

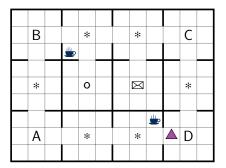
• Formulas in many temporal languages (e.g.,  $LTL_f$ ) can be **translated** into RMs.

 Once a reward function is represented as an RM, its structure can be exploited by various RM-specific algorithms for more efficient reinforcement learning.



Symbol	Meaning
	Agent
*	Decoration
1	Coffee machine
$\bowtie$	Mail room
0	Office
A,B,C,D	Marked locations

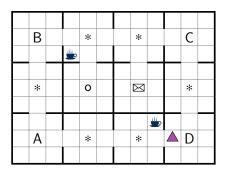
 $\textbf{Task} \colon \mathsf{Patrol}\ \mathsf{A},\ \mathsf{B},\ \mathsf{C},\ \mathsf{and}\ \mathsf{D}.$ 



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Task: Patrol A, B, C, and D.

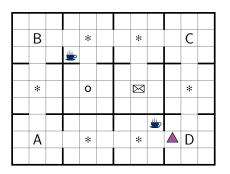
- For RL, the task has to be specified in terms of a reward function
  - which might be derived from a formula in Linear Temporal Logic (LTL) or some other formal language, or programmed directly.



```
m = 0 # global variable
def get_reward(s):
    if m == 0 and s.at("A"):
        m = 1
    if m == 1 and s.at("B"):
        m = 2
    if m == 2 and s.at("C"):
        m = 3
    if m == 3 and s.at("D"):
        m = 0
    return 1
return 0
```

Task: Patrol A, B, C, and D.

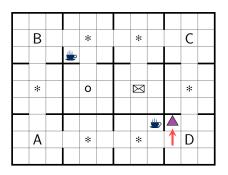
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    if m == 1 and s.at("B"):
        Reward Function
        m = 3
    if m == 3 and s.at("B"):
        m = 0
        return 1
    return 0
```

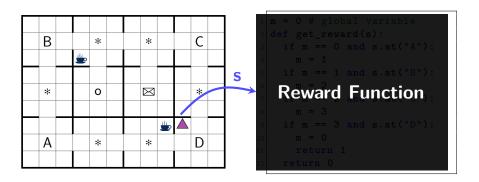
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- The reward function is then often treated as a black box.

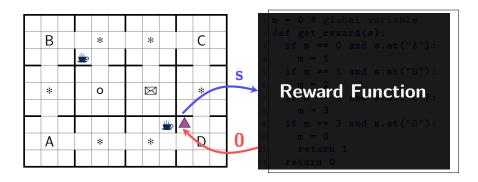


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We previously introduced reward machines in an ICML paper.<sup>1</sup>

Suppose we have a vocabulary  $\ensuremath{\mathcal{P}}$  to label environment states, e.g.,

$$\mathcal{P} = \{ \clubsuit, \bowtie, o, *, A, B, C, D \}.$$

- A finite set of states, with an initial state  $u_0$
- A set of transitions labelled by:
  - a logical condition (using the vocabulary) and
  - a reward (or more generally a reward function).

 $<sup>\</sup>langle \neg A, 0 \rangle$   $\langle D, 1 \rangle$   $\langle D, 0 \rangle$   $\langle C, 0 \rangle$   $\langle C, 0 \rangle$   $\langle B, 0 \rangle$   $\langle C, 0 \rangle$   $\langle C, 0 \rangle$   $\langle C, 0 \rangle$   $\langle C, 0 \rangle$ 

<sup>&</sup>lt;sup>1</sup>Rodrigo Toro Icarte et al. "Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning". In: *ICML*. 2018, pp. 2112–2121.

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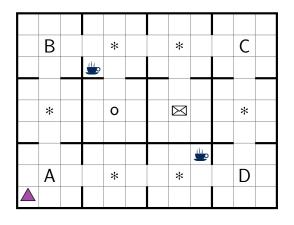
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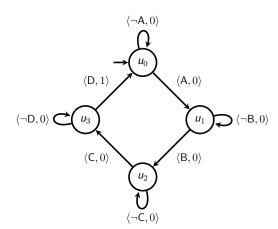
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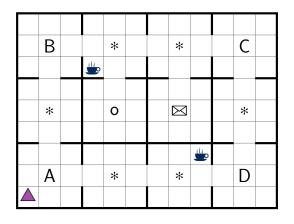
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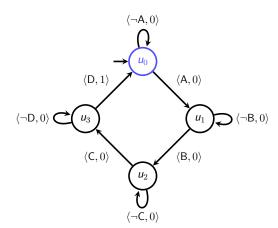
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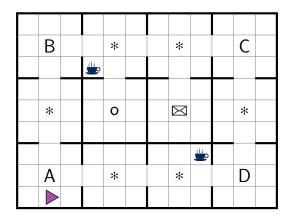
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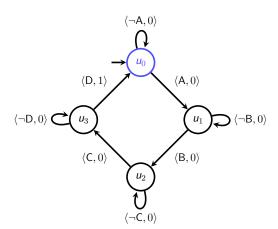


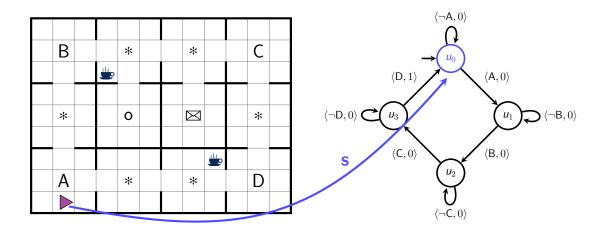


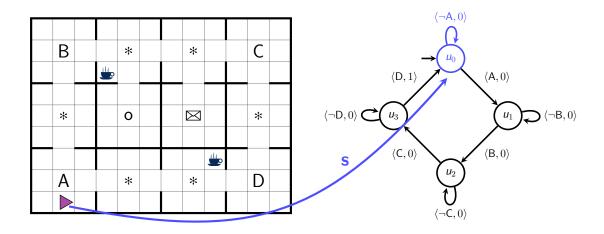


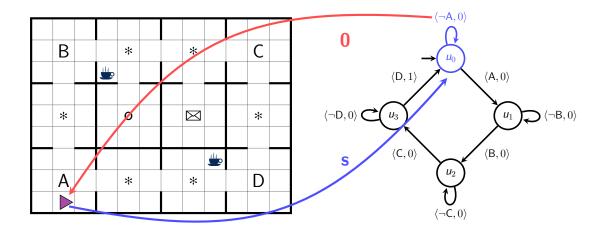


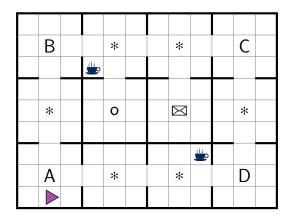


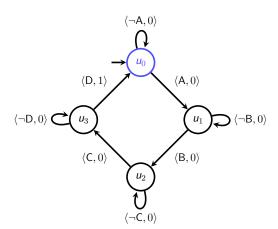


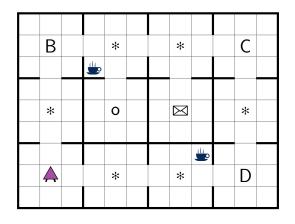


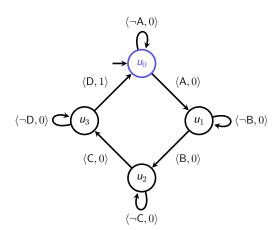


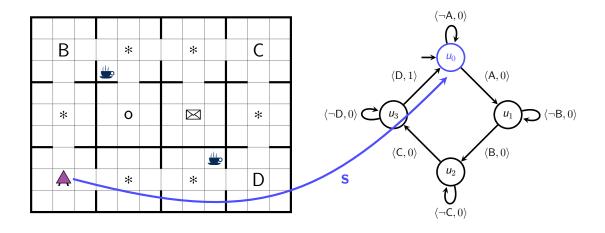


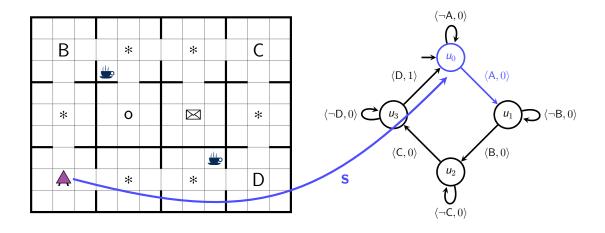


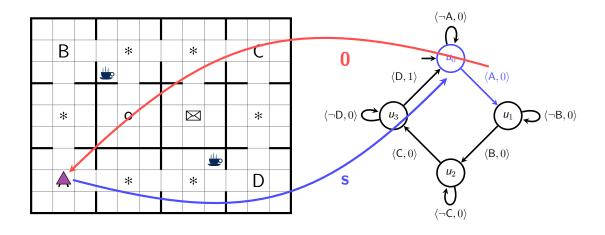


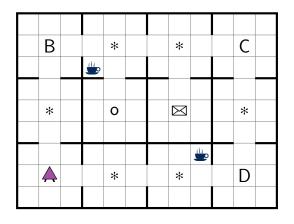


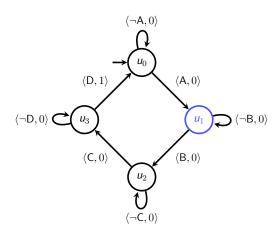


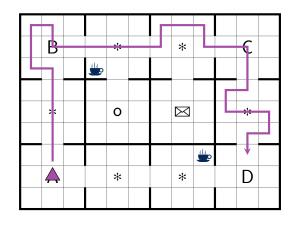


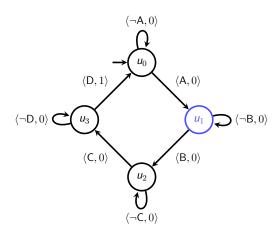


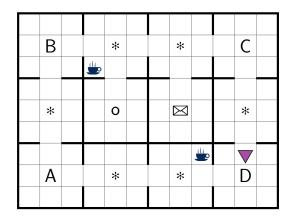


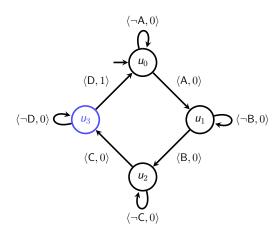


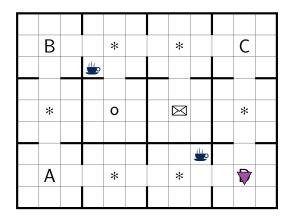


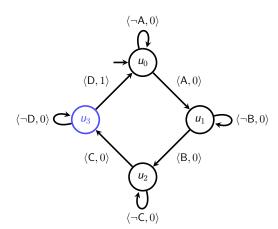


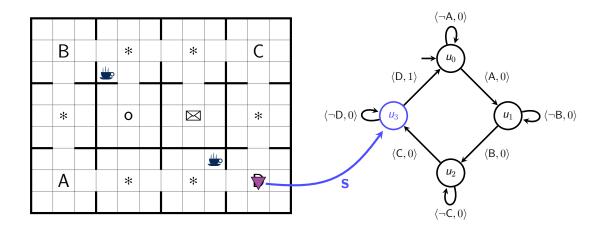


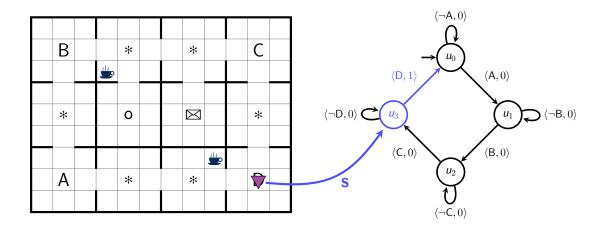


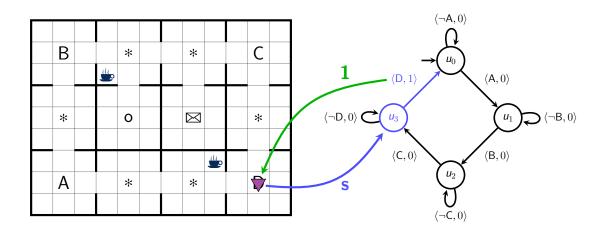


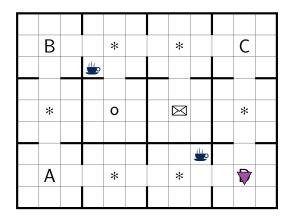


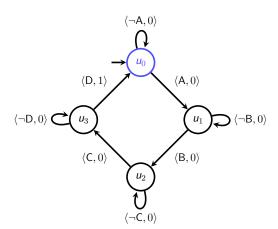




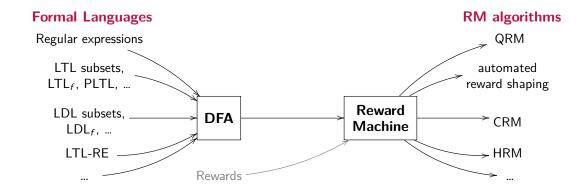






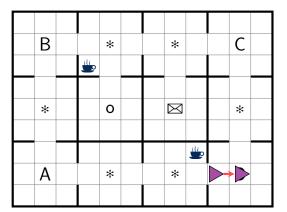


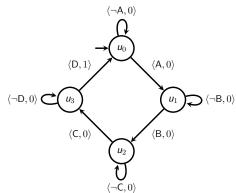
### Transforming formal language specifications into reward machines



## The QRM algorithm<sup>2</sup>

When the agent acts while in RM state  $u_i$ , we can compute what reward would have been received if had acted in any other RM state  $u_j$ .



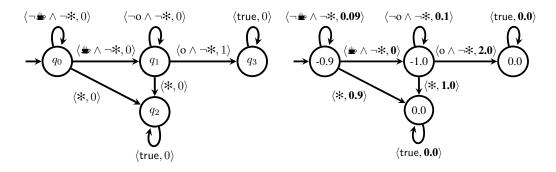


QRM generates such synthetic, **counterfactual** experiences for use in training.

<sup>&</sup>lt;sup>2</sup>Rodrigo Toro Icarte et al. "Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning". In: *ICML*. 2018, pp. 2112–2121.

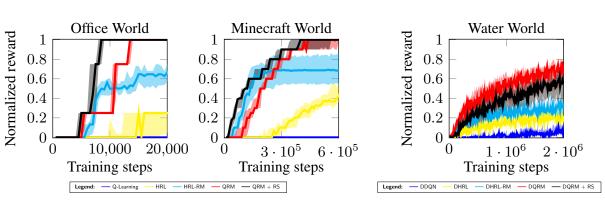
### **Automated reward shaping**

- Treat the RM itself as a (deterministic) MDP, and use **value iteration** to determine the value of each state.
- Then, use these values to define potentials for potential-based<sup>3</sup> reward shaping.



<sup>&</sup>lt;sup>3</sup>Andrew Y. Ng et al. "Policy invariance under reward transformations: Theory and application to reward shaping". In: *ICML*. 1999, pp. 278–287.

## **Experimental results**



By exploiting reward machine structure, our algorithms outperform the baselines.

#### Conclusion

- Reward machines (RMs) are a form of automaton that are a way of representing (temporally extended) reward functions.
- Formulas in many temporal languages (e.g.,  $LTL_f$ ) can be **translated** into RMs.
- Once a reward function is represented as an RM, its structure can be exploited by various RM-specific **algorithms** for more efficient reinforcement learning.

#### Code:

- Reward machine algorithms: https://bitbucket.org/RToroIcarte/qrm
- Translating formal languages into reward machines: http://fl-at.jaimemiddleton.cl/4

<sup>&</sup>lt;sup>4</sup> Jaime Middleton et al. *FL-AT: A Formal Language–Automaton Transmogrifier*. System demonstration at ICAPS 2020. 2020.