Hierarchies of Reward Machines

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Introduction

Humans describe tasks in some language to instruct other humans:

- 'bring coffee to the office, but be careful with the plants!',
- 'make a cake',
- 'patrol locations A, B, C and D in that order',
- •

We want to do the same with Al agents. Example: MineRL BASALT competition.



MakeWaterfall



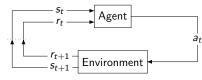
CreateVillageAnimalPen



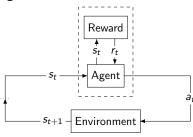
BuildVillageHouse

Introduction

• The interaction hides the reward structure from the agent. . .



 Why not providing these structured task descriptions (e.g., LTL formulas, finite-state machines, grammars) to the agent?



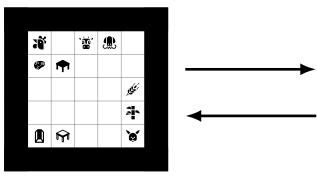
Introduction

- Advantages & drawbacks:
 - + Interpretability.
 - + Enable task decomposition.
 - -/+ Handcrafted but we can learn them!
- Our focus: Express-Exploit-Learn descriptions of tasks that depend on other tasks.

$$\text{'make a cake'} = \begin{cases} \text{'make batter'} = \begin{cases} \text{'collect wheat'}, \\ \text{'collect eggs'}, \\ \text{'mix them'} \end{cases} \\ \text{'make a cake'} = \begin{cases} \text{'make bucket'} = \begin{cases} \text{'collect iron'}, \\ \text{'transform it'} \end{cases} \\ \text{'make sweetened milk'} = \begin{cases} \text{'make milk'} = \begin{cases} \text{'make bucket'} = \begin{cases} \text{'collect iron'}, \\ \text{'transform it'} \end{cases} \\ \text{'make sugar'} = \begin{cases} \text{'collect a sugarcane'}, \\ \text{'transform it'} \end{cases} \end{cases}$$

Motivation

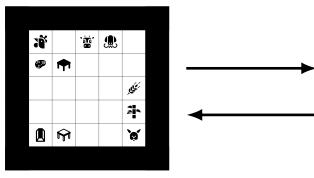
Reward Machines



 $\begin{aligned} & \text{Events} \\ \{ & \P, \P, \#, \#, \#, \\ & \text{\checkmark}, \text{\checkmark}, \#, \text{$\*}, \end{aligned}$

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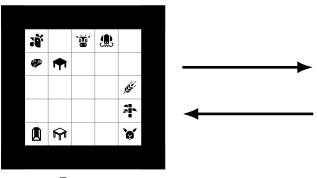
Reward Machines



Events

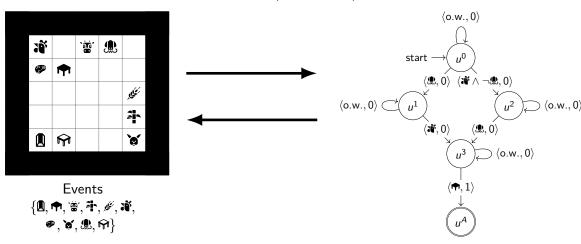
$$\{ \blacksquare, \spadesuit, \ \ \textcircled{a}, \clubsuit, \cancel{\&}, \ \ \textcircled{a}, \\ \ \ \textcircled{\varnothing}, \ \ \textcircled{\&}, \ \ \textcircled{\lozenge} \}$$

Task Collect **இ** and **¾** (in any order), then go to **♠**.

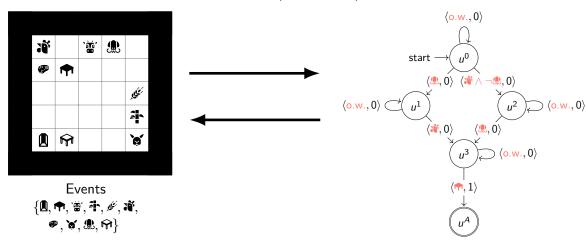


Events {**0**, ♠, ☞, ♣, ⋄, ℩, •, ☞, ℍ, ♠}

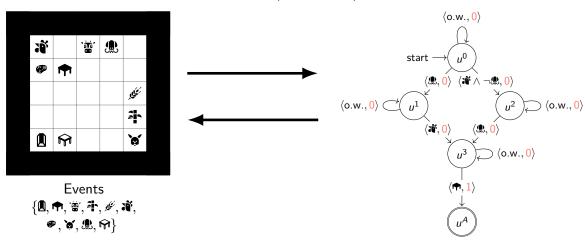
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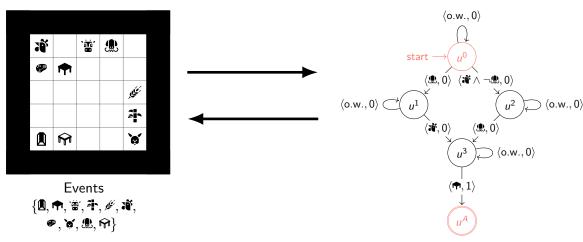
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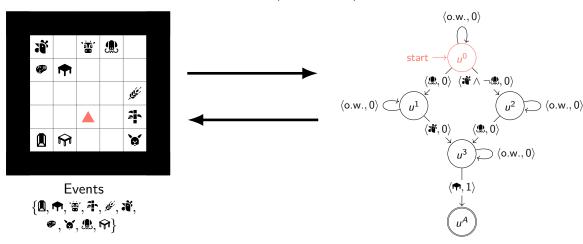
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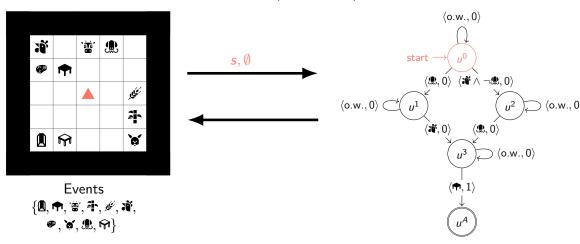
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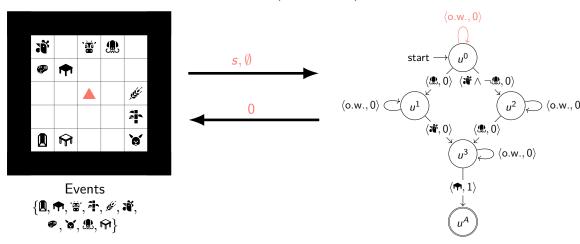
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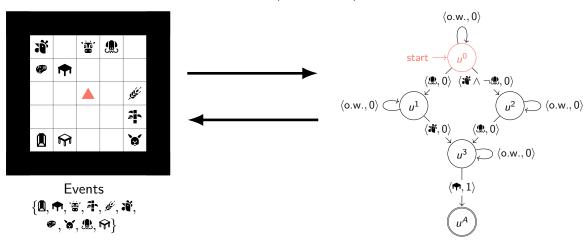
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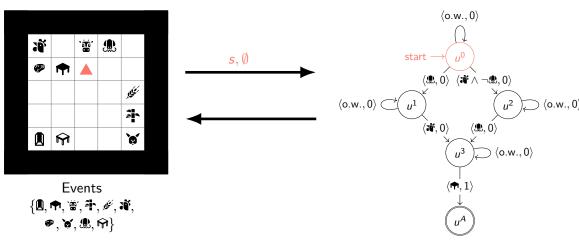
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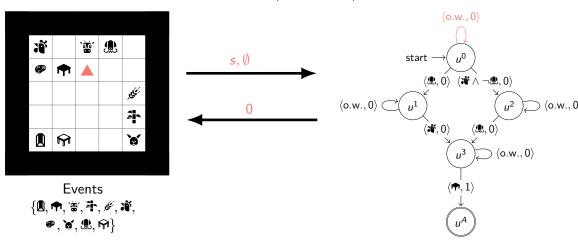
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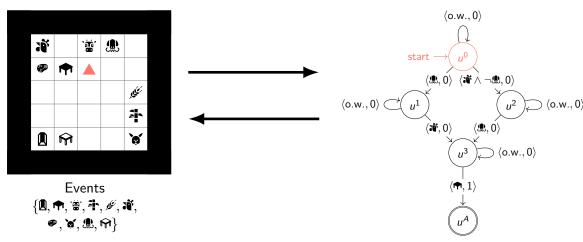
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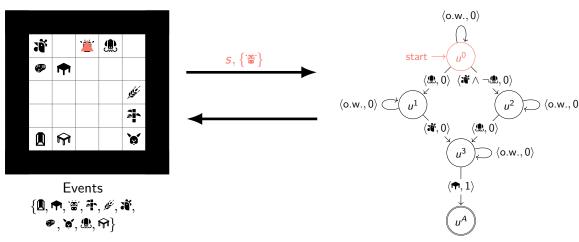
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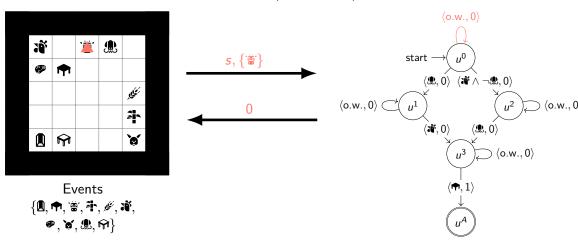
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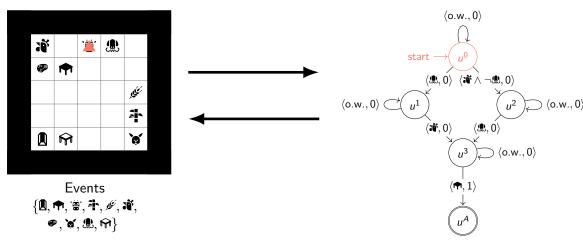
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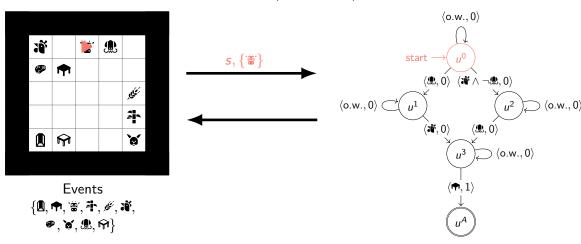
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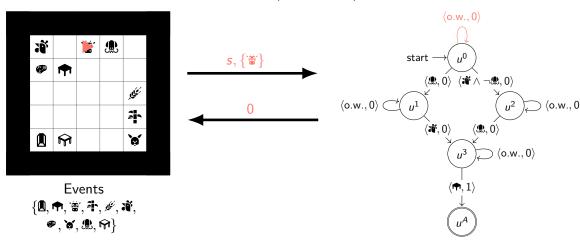
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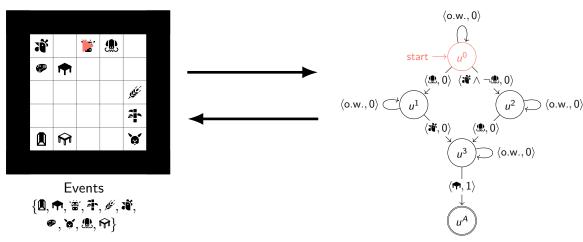
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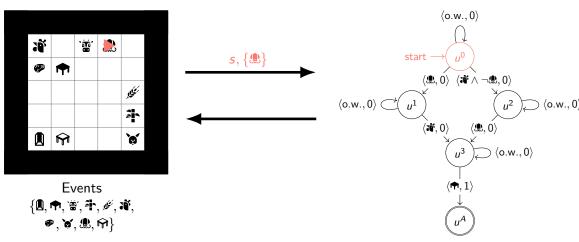
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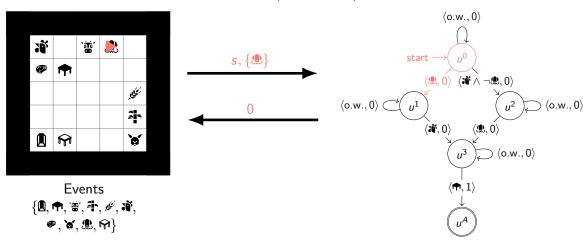
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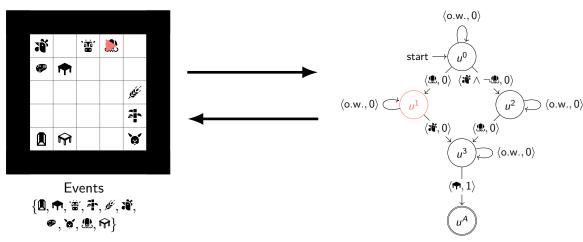
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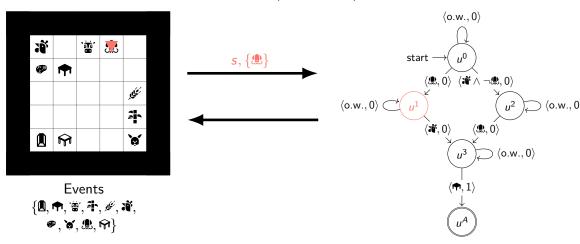
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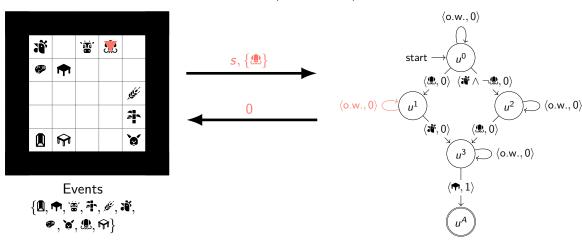
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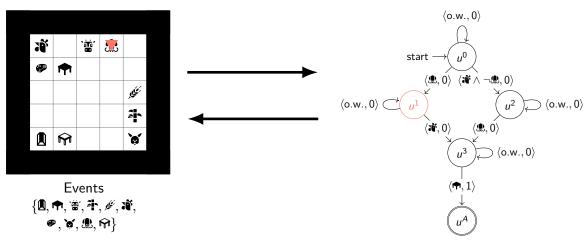
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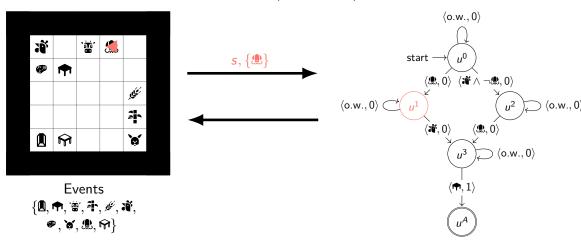
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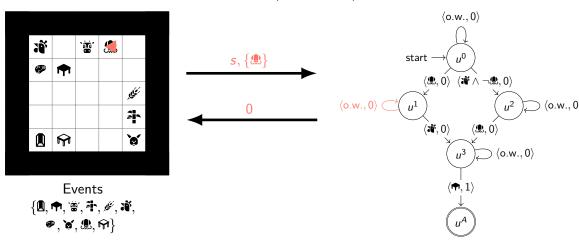
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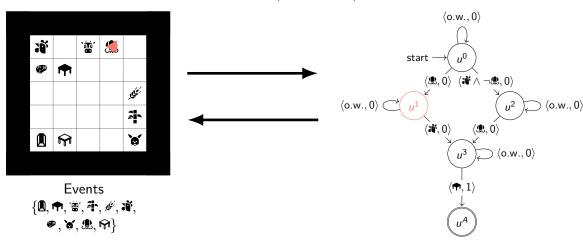
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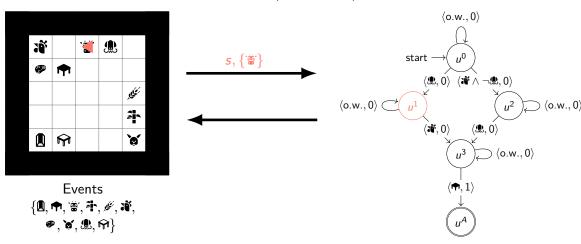
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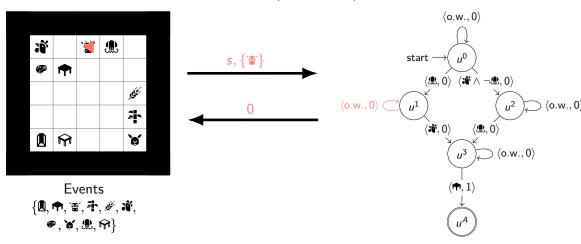
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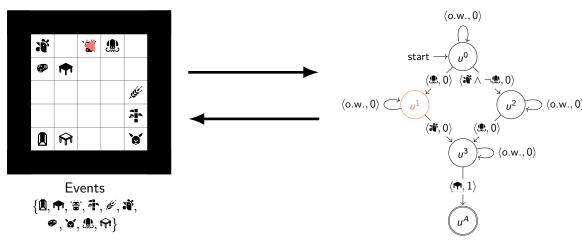
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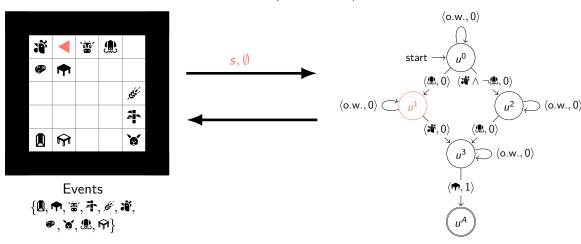
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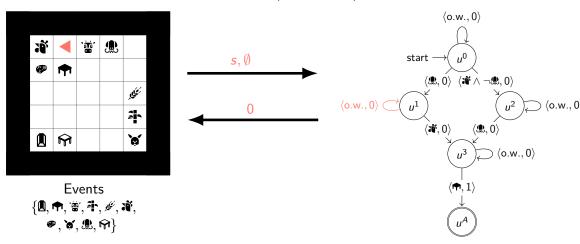
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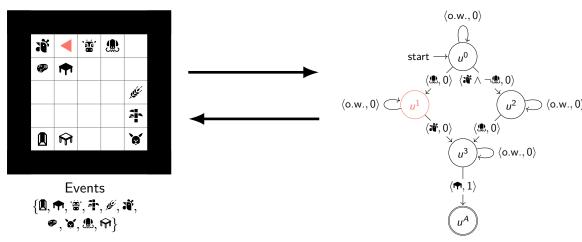
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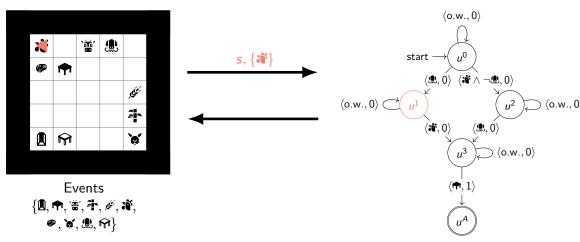
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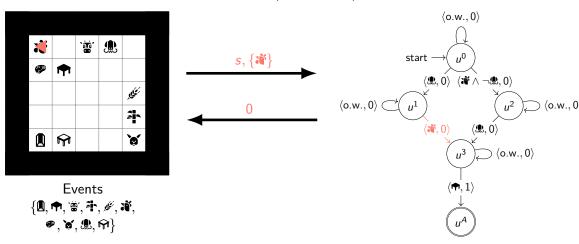
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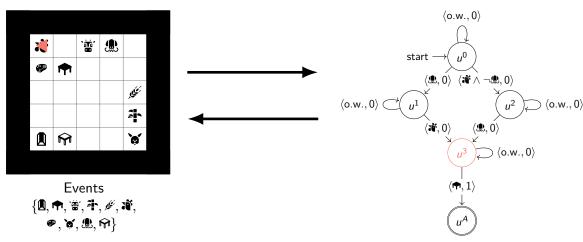
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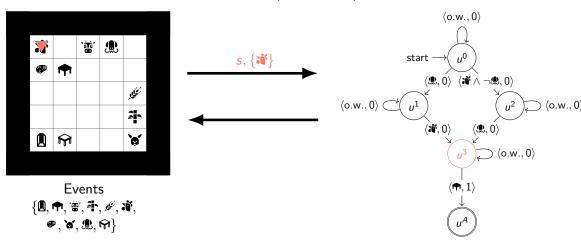
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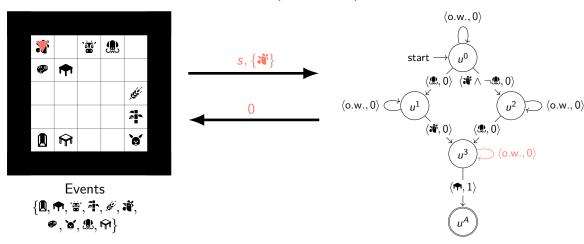
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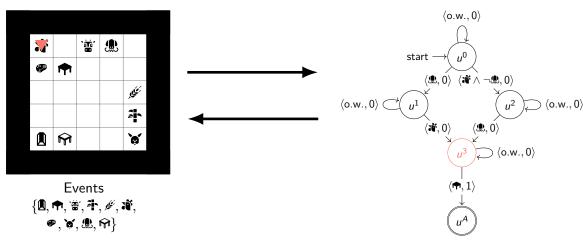
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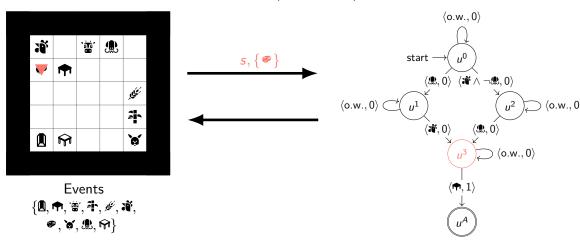
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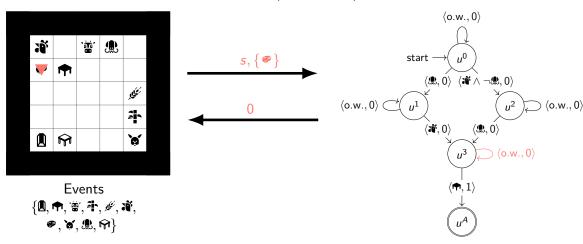
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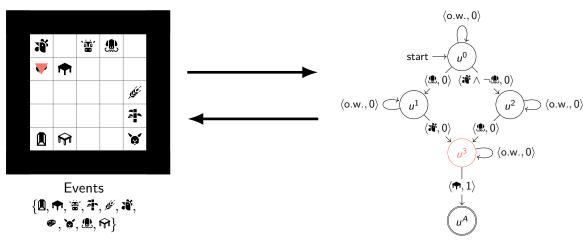
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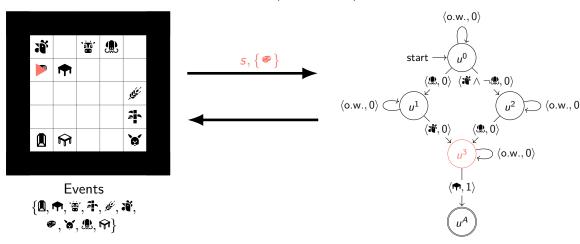
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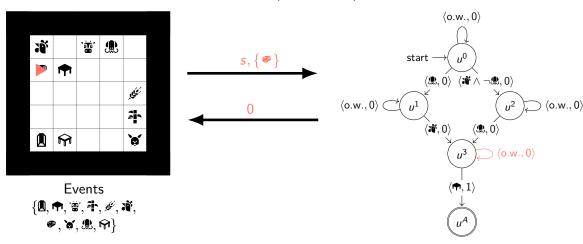
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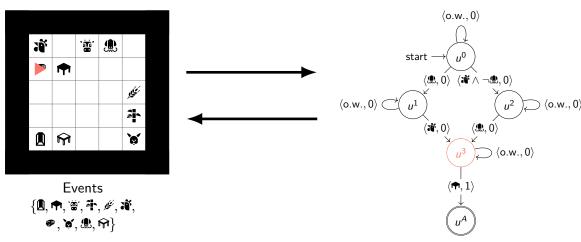
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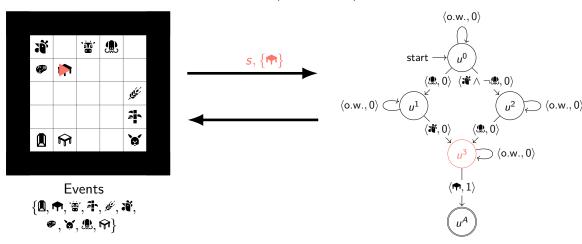
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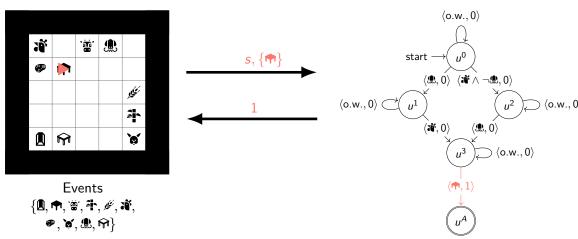
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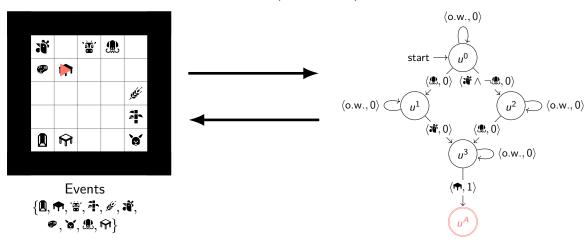
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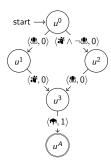


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Reward Machines - Exploitation

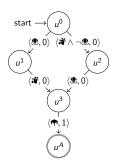
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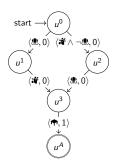
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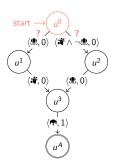
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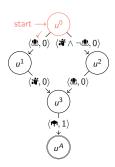
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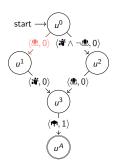
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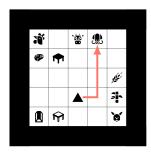




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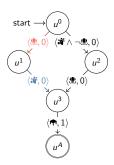
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 - 2 Given a formula, choose an action to (eventually) satisfy it.

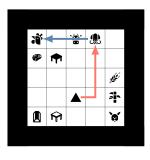




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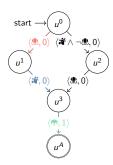
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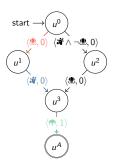
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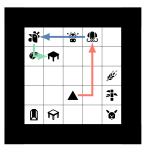




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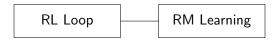
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How can we make RMs **reusable** (i.e., independently solvable subtasks)?

Reward Machines - Learning I



Furelos-Blanco et al. "Induction of Subgoal Automata for Reinforcement Learning". AAAI, 2020.

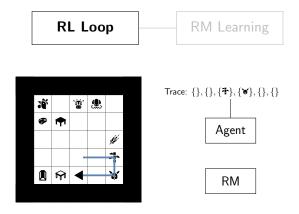
Furelos-Blanco et al. "Induction and Exploitation of Subgoal Automata for Reinforcement Learning". JAIR, 2021.

Toro lcarte et al. "Learning Reward Machines for Partially Observable Reinforcement Learning". NeurIPS, 2019.

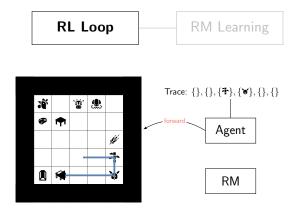
Gaon and Brafman. "Reinforcement Learning with Non-Markovian Rewards". AAAI, 2020.

Xu et al. "Joint Inference of Reward Machines and Policies for Reinforcement Learning". ICAPS, 2020.

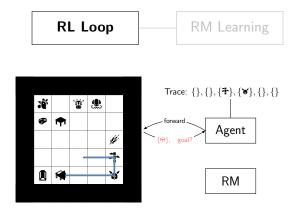
Hasanbeig et al. "DeepSynth: Automata Synthesis for Automatic Task Segmentation in Deep Reinforcement Learning". AAAI, 2021.



- The agent attempts to achieve the task's goal.
- The agent maintains a *trace* of the events observed so far.

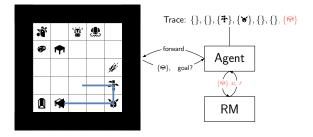


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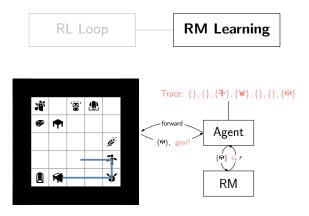
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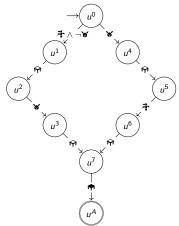
Reward Machines - Learning I



• A *new* RM is learned if the trace is a *counterexample* (e.g., reaches the task's goal but not the accepting state).

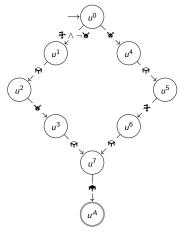
Reward Machines - Learning II

• Learning of *minimal* RMs (i.e., with the fewest possible states) scales poorly with the number of states.



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Can we build large RMs by composing small but easier to learn RMs?

Reward Machines - Research Questions

Question #1

How can we make RMs reusable (i.e., independently solvable subtasks)?

Question #2

Can we build large RMs by composing small but easier to learn RMs?

Motivation

Reward Machines - Research Questions

Question #1

How can we make RMs reusable (i.e., independently solvable subtasks)?

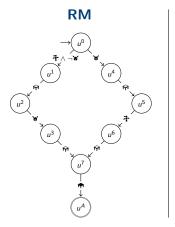
Question #2

Can we build large RMs by composing small but easier to learn RMs?

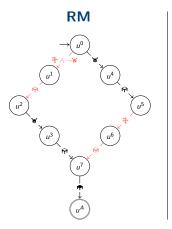
Our Approach

Construct hierarchies of reward machines!

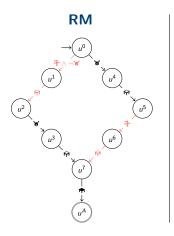
Formalism I

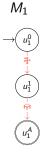


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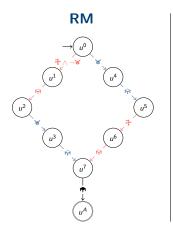


Formalism I



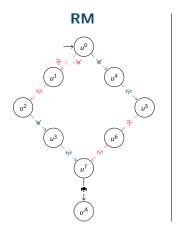


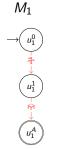
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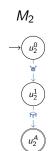


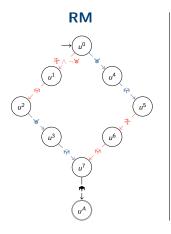


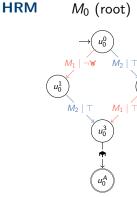
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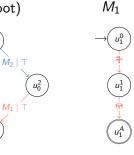


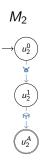




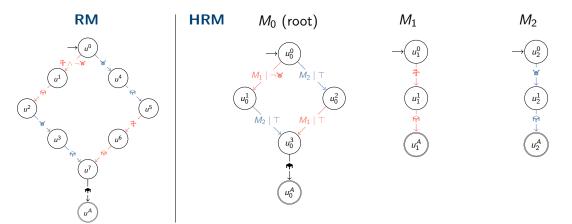






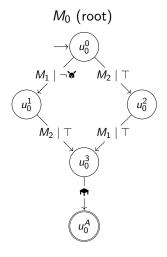


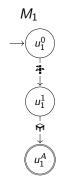
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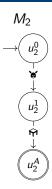


Properties

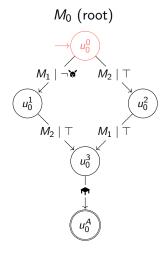
- 1 Given an HRM, there exists an equivalent RM.
- 2 Given an HRM, an equivalent RM may have exponentially more states and edges.

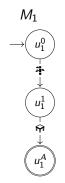


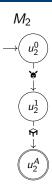




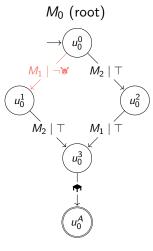
$$\mathsf{Trace} = \langle \\ \mathsf{Stack} = []$$

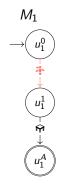


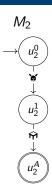


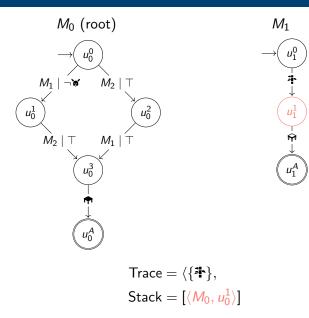


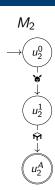
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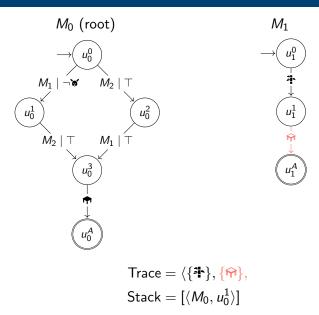


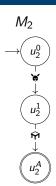


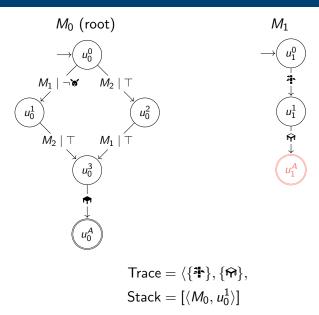


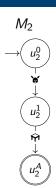


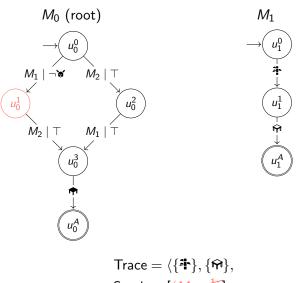


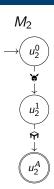






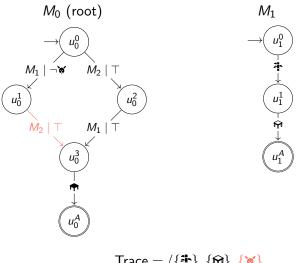


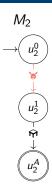




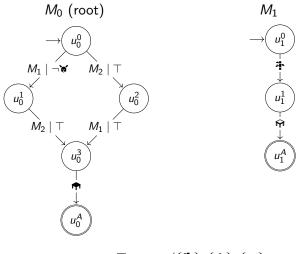
Trace =
$$\langle \{ \stackrel{\bullet}{\bullet} \}, \{ \stackrel{\bullet}{\bullet} \} \rangle$$

Stack = $[\langle M_0, u_0^{\bullet} \rangle]$



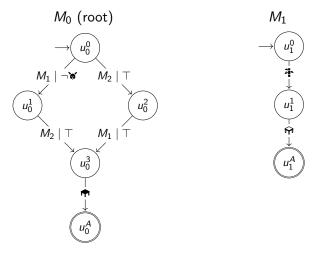


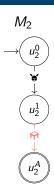
$$\begin{aligned} &\mathsf{Trace} = \langle \{ \clubsuit \}, \{ \image \}, \{ \image \}, \\ &\mathsf{Stack} = [] \end{aligned}$$



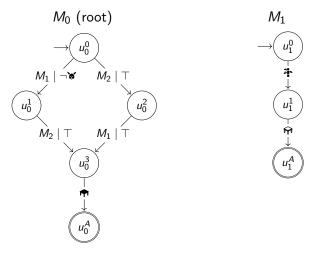


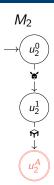
$$\begin{split} &\mathsf{Trace} = \langle \{ \maltese \}, \{ \maltese \}, \{ \maltese \}, \\ &\mathsf{Stack} = [\langle \mathit{M}_0, \mathit{u}_0^3 \rangle] \end{split}$$



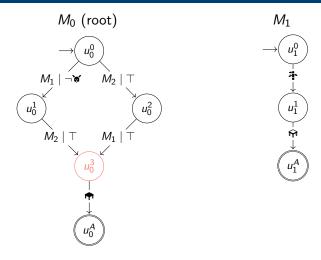


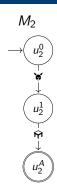
Trace =
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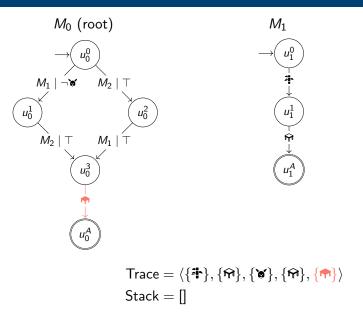


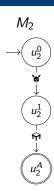
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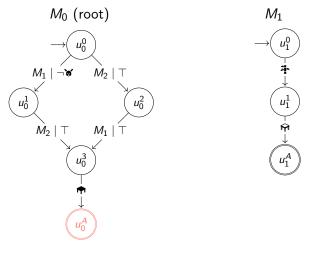


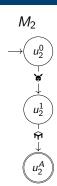


Trace =
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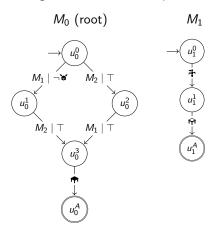


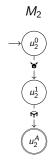






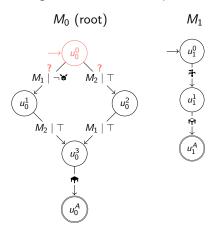
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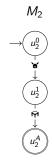






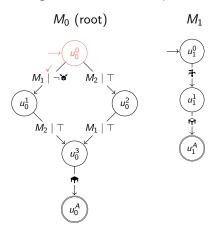
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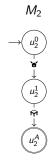






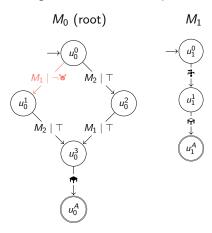
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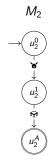






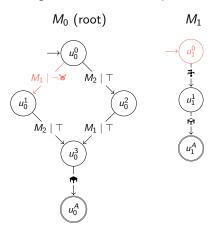
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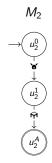






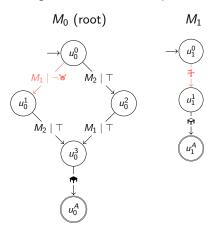
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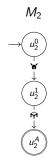






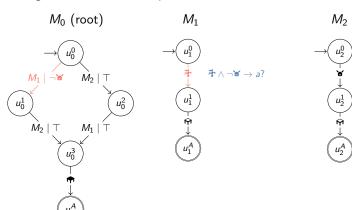
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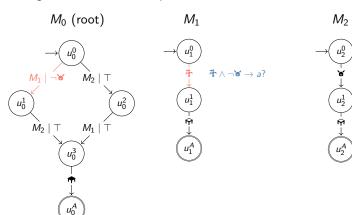


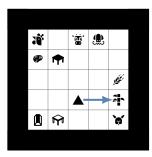
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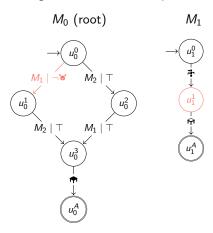


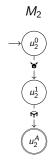
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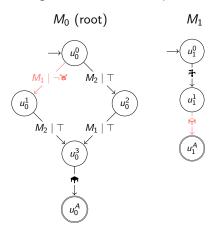
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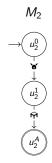






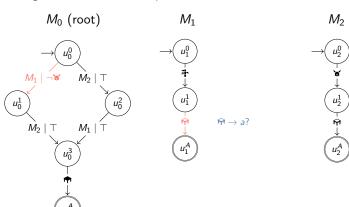
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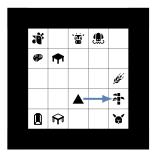




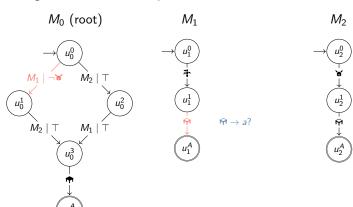


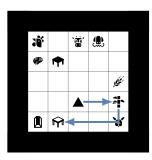
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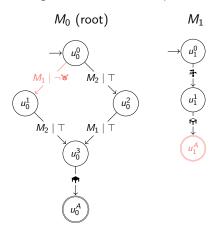


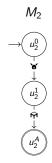
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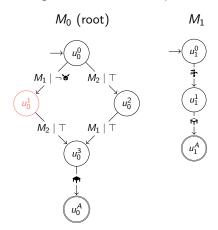
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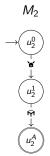


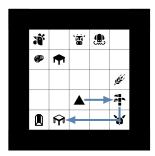




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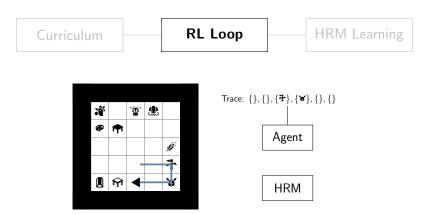
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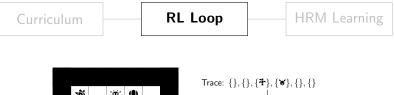


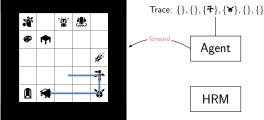
- An HRM is learned for each task.
- Each task has a level h.
- Learning proceeds from lower to higher levels.
- Level is increased when the average performance surpasses a threshold.

| Саке | | | | | | | h = |
|--------|-----------|---------|-----------------|------------|-------|-------|-----|
| | BookQuili | | MilkBucketSugar | | | | h = |
| Воок | | Мар | | MilkBucket | | | h = |
| BATTER | Вискет | Compass | LEATHER | Paper | QUILL | Sugar | h = |



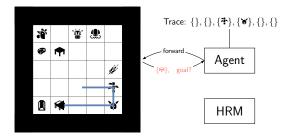
- The agent *selects a task* at the beginning of each episode and attempts to complete it.
- The agent maintains a *trace* of the events observed so far.





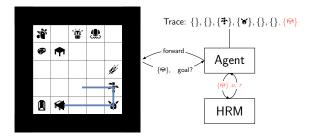
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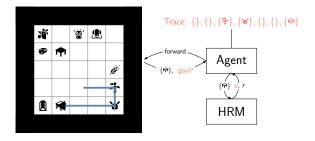
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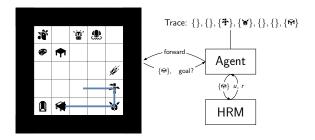
- The agent selects a task at the beginning of each episode and attempts to complete it.
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- A *new* HRM is learned if the trace is a *counterexample* (e.g., reaches the task's goal but not the *root*'s accepting state).
- HRMs are learned using ILASP, an inductive logic programming system.





- HRMs for lower-level tasks may be called.
- Lower-level task policies can be used for exploration: observing goal traces becomes easier!

Learning II





Learning II

Example: Sequence of RMs learned for the task "Collect **1** then go to **1**.".



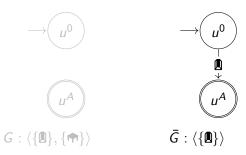


 $G:\langle\{{\bf Q}\},\{{\bf r}\}\rangle$

Learning II

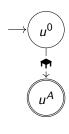


Learning II

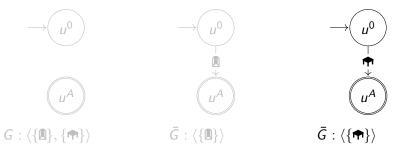


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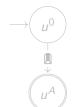
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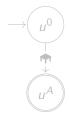




$$G:\langle\{{\bf Q}\},\{{\bf r}\}\rangle$$



$$\bar{G}:\langle\{\mathbf{Q}\}\rangle$$

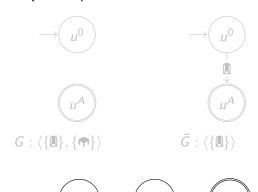


 $\bar{G}:\langle\{
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UNSATISFIABLE, Increment the number of states!

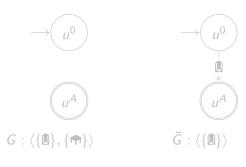
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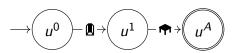
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UNSATISFIABLE, Increment the number of states! **Example:** Sequence of RMs learned for the task "Collect **1** then go to **1**.".







UNSATISFIABLE, Increment the number of states!

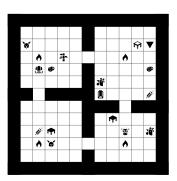
In higher-level tasks, lower-level RMs can be called.

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Environment Based on Minigrid [Chevalier-Boisvert et al., 2023].

Image-like grid observations, discrete actions.

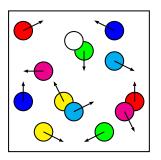
Tasks Visit a sequence of landmark locations.



WATERWORLD [Toro lcarte et al., 2018]

Environment Continuous observations (positions, velocities),

Tasks Observe a sequence of colors.

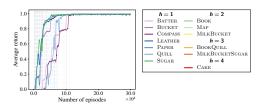


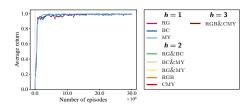
Toro Icarte et al. "Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning". ICML, 2018. Chevalier-Boisvert et al. "Minigrid & Miniworld: Modular & Customizable Reinforcement Learning Environments for Goal-Oriented Tasks". arXiv, 2023.

Learning of HRMs

HRM learning is feasible in two different domains.

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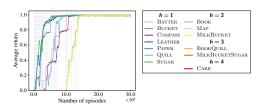


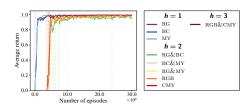


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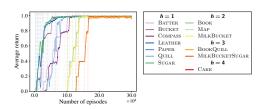


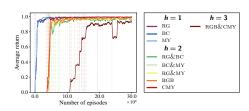


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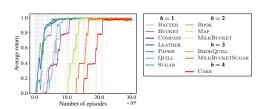


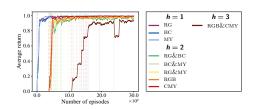


Learning of HRMs

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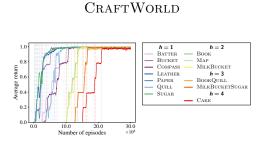




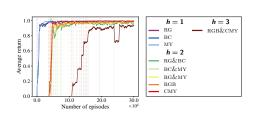


Learning of HRMs

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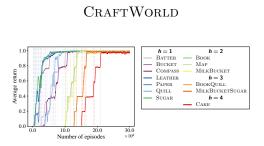
WATERWORLD

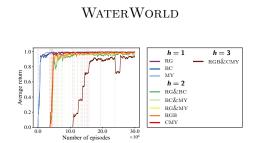


Insights:

Learning of HRMs

HRM learning is feasible in two different domains.



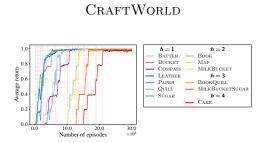


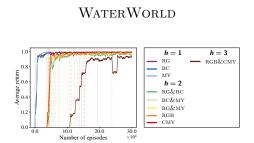
Insights:

1 HRM learning becomes less scalable as the number of tasks and levels grows.

Learning of HRMs

HRM learning is feasible in two different domains.





Insights:

- 1 HRM learning becomes less scalable as the number of tasks and levels grows.
- 2 Exploration with low-level policies enables observing goal trace examples faster.

HRM Learning vs RM Learning

RM Learning Baselines:

- Minimal RMs: Ours (but learning a flat HRM) and JIRP [Xu et al., 2020].
- RMs that predict the next event accurately: DeepSynth [Hasanbeig et al., 2021] and LRM [Toro Icarte et al., 2019].

Observations:

- Minimal RM learning methods poorly scale as the number of states increases.
- 2 DeepSynth and LRM tend to overfit to the observed traces.
- 3 DeepSynth, JIRP and LRM need exponentially more edges in WATERWORLD since they do not use formulas.

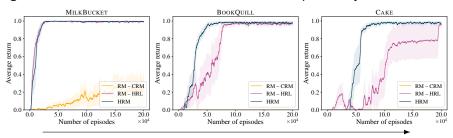
Policy Learning

Baselines:

- Hierarchical method on an RM (i.e., flat HRM).
- CRM [Toro Icarte et al., 2022] Learns a global policy over an RM (i.e., not hierarchical).

Observations:

- Hierarchical policy learning can be faster in HRMs than in RMs.
- Convergence is faster w.r.t. CRM, which does not independently solve the subtasks.



Task Complexity

Future Work

Remove Handcrafted Event Set

- The agent learns its own mapping from observations to propositional events.
- Need for supporting noisy events (i.e., the mapping might make mistakes).
- Loss of interpretability.

Remove Known Task Set

- The agent makes its own set of tasks over the event set.
- Autocurricula: start from simpler tasks and build upon them to perform high-level behaviors.

Continual Learning

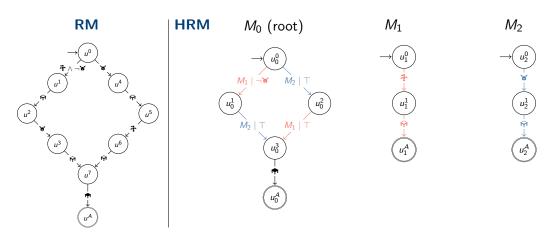
• Build RM learning methods that adapt to changing environments or agent capabilities (e.g., traces that achieved the goal but later do not).

Key Insights

- Reveal the task structure to the agent.
- Learn reusable policies and task structures.
- Learning the structures alleviates human intervention, but does not remove it.

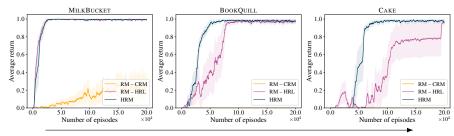
Conclusions

1 HRMs, a formalism for hierarchically composing RMs.



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- 1 HRMs, a formalism for hierarchically composing RMs.
- 2 A method that *exploits* the structure of an HRM.

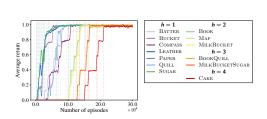


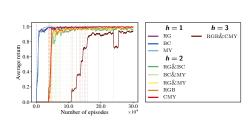
Task Complexity

Conclusions

- 1 HRMs, a formalism for hierarchically composing RMs.
- 2 A method that exploits the structure of an HRM.
- 3 A method for *learning a collection of HRMs* from traces.

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Questions?