Learning Reward Machines for Partially Observable Reinforcement Learning

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AAAI SSS-23

What is a

Reward Machine (RM)?

*Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning by Toro Icarte et al. (ICML, 2018)

Reward Machines (RMs)

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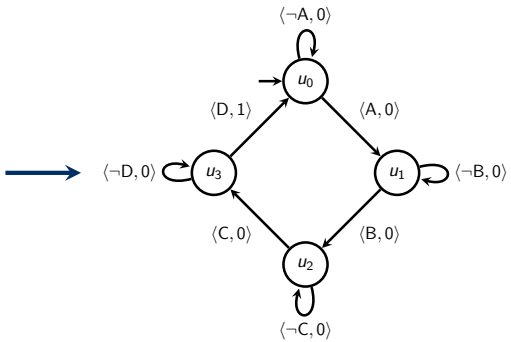
m = 0 # global variable
def get_reward(s):
  if m == 0 and s.at("A"):
    m = 1
  if m == 1 and s.at("B"):
    m = 2
  if m == 2 and s.at("C"):
    m = 3
  if m == 3 and s.at("D"):
    m = 0
    return 1
  return 0
```



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6      m = 2
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8      m = 3
9    if m == 3 and s.at("D"):
10     m = 0
11     return 1
12   return 0
```
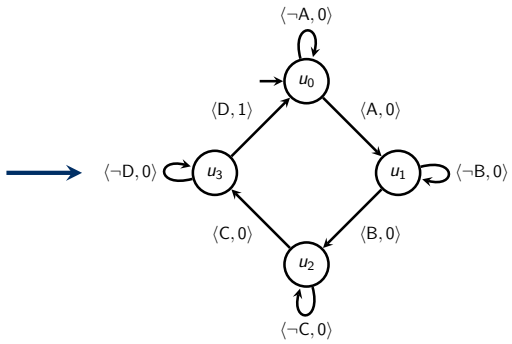
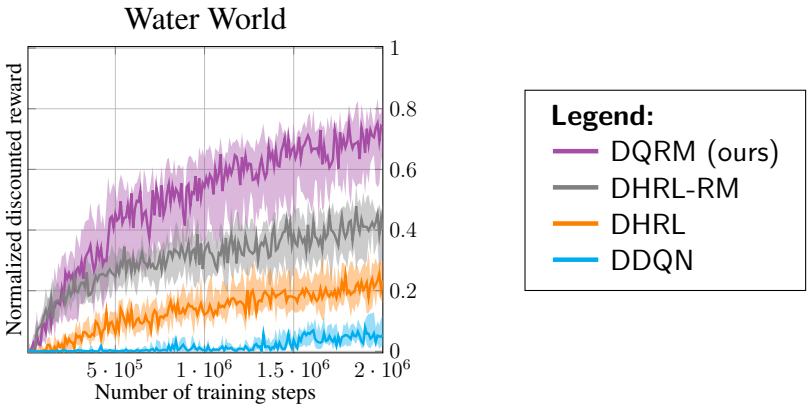
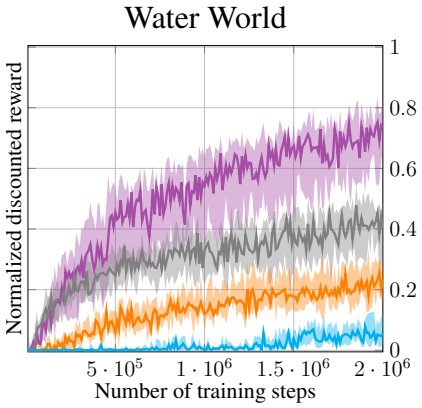



... that allow for **learning policies faster**.

Reward Machines (RMs)



Reward Machines (RMs)



Legend:
- DQRM (ours)
- DHRL-RM
- DHRL
- DDQN

... but the RMs were **handcrafted**.

Learning Reward Machines for Partially Observable RL

This work:

1. Shows how to learn RMs from experiences (LRM).

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Learning Reward Machines for Partially Observable RL

This work:

1. Shows how to learn RMs from experiences (LRM).
2. Uses RMs as memory for partially observable RL.
3. Extends QRM to work under partial observability.
4. Provides a theoretical and empirical analysis of LRM.

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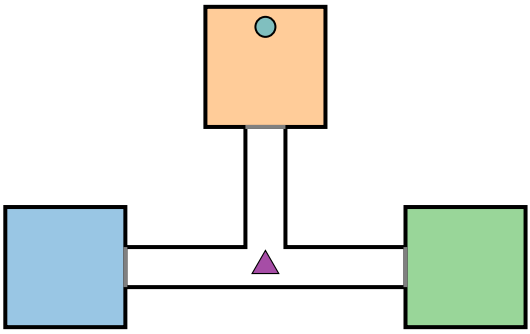

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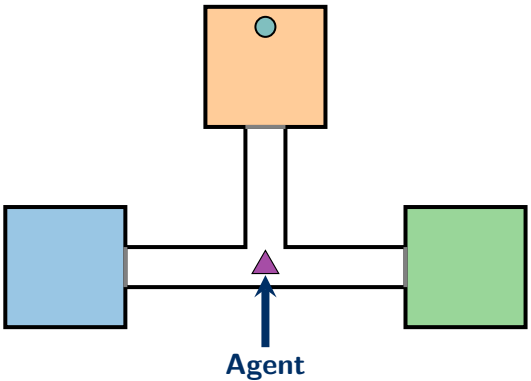

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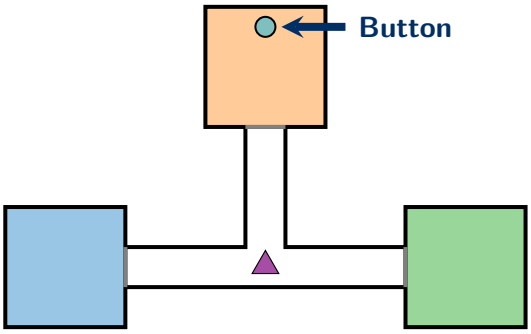

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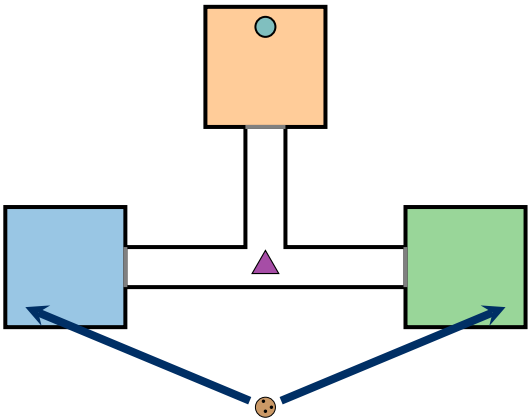

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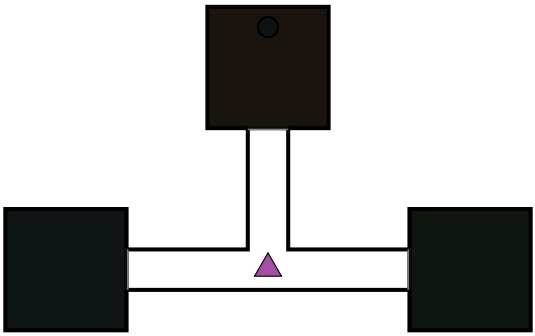

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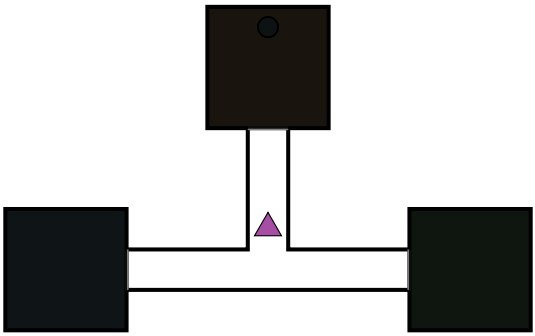

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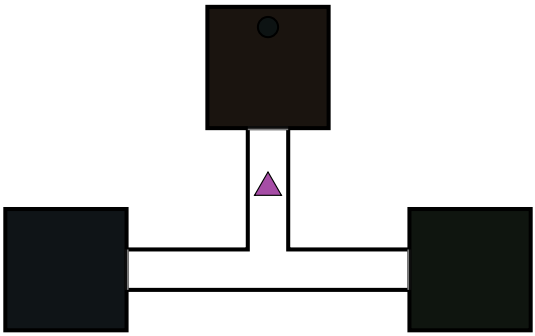

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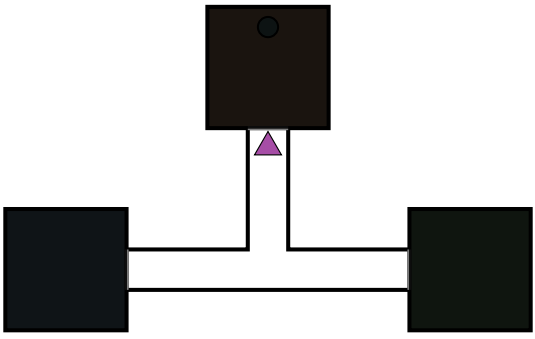

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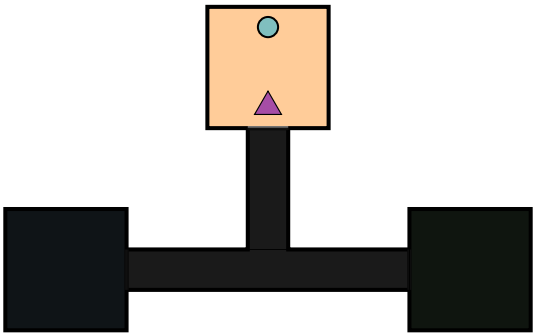

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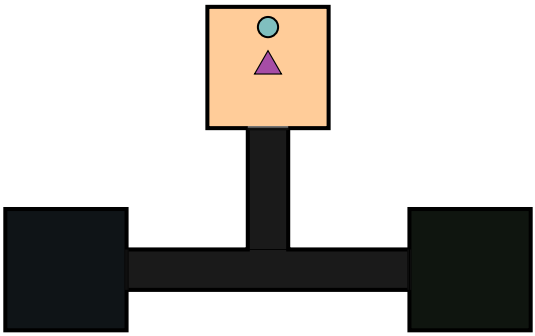

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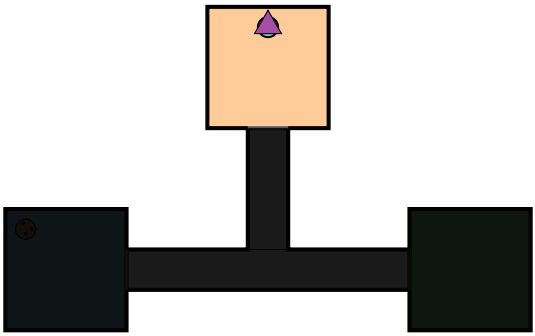

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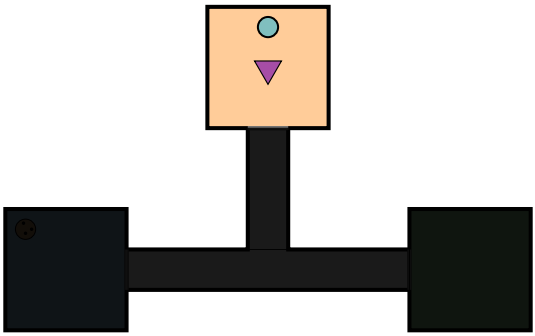

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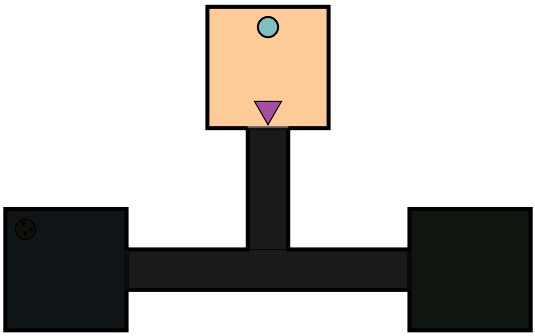

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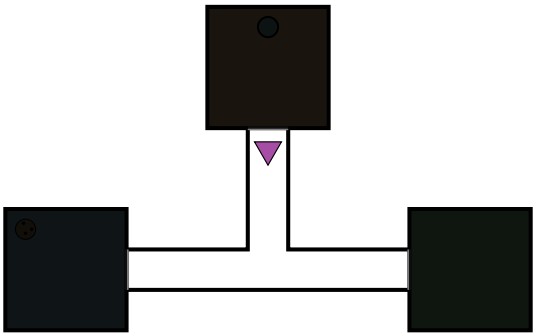

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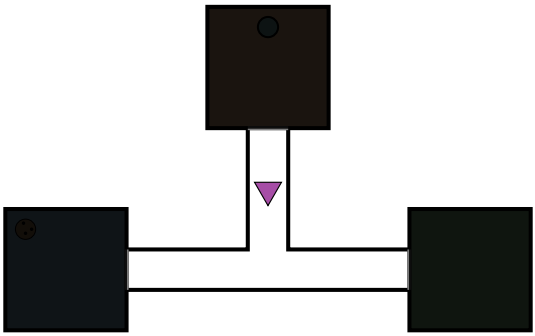

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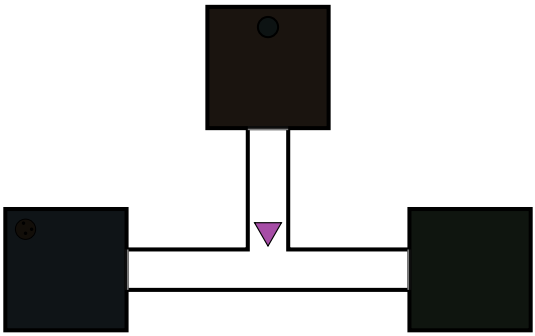

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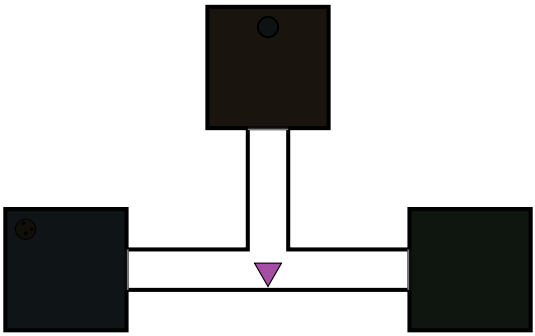

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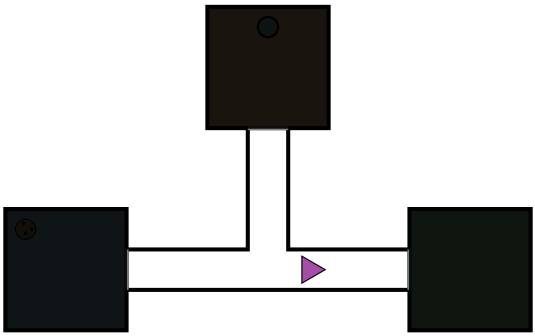

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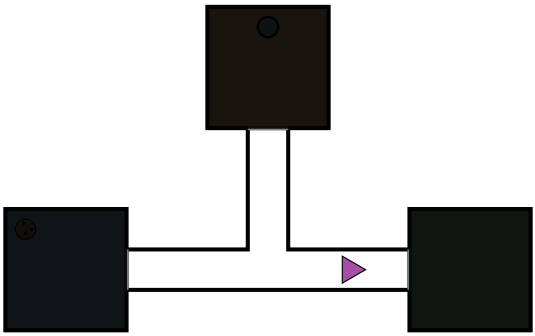

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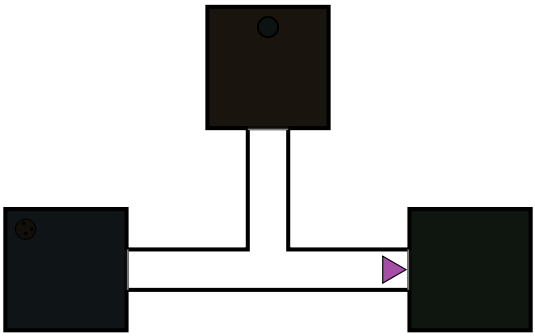

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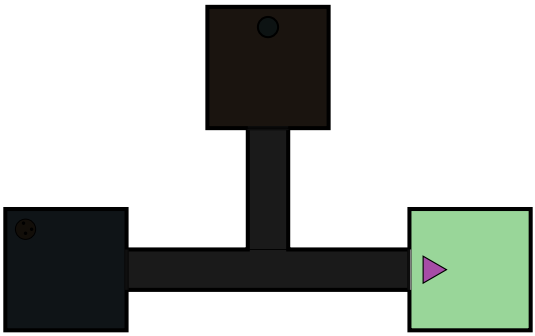

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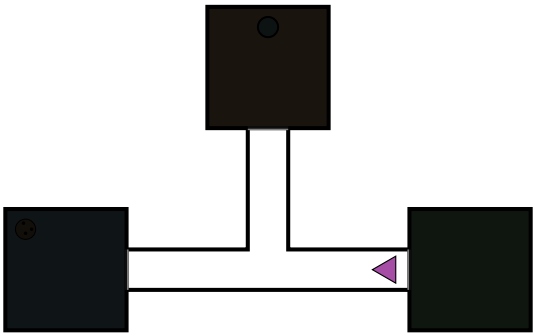

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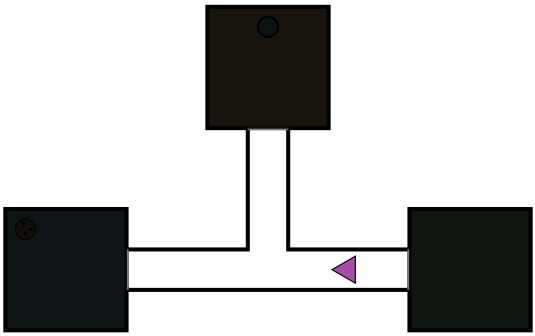

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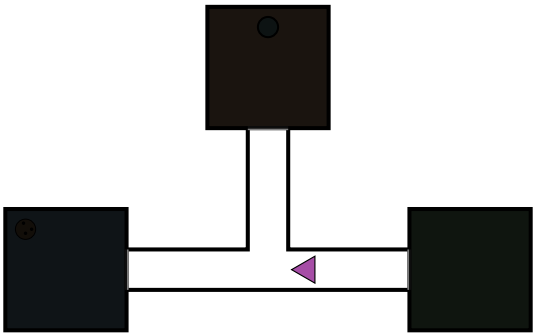

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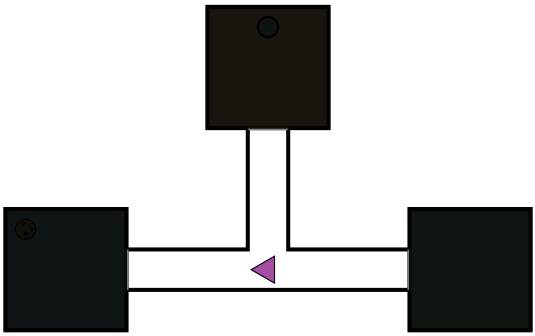

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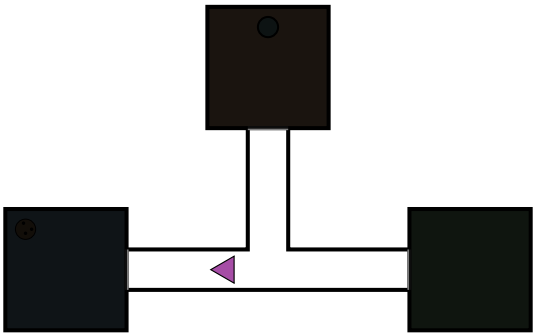

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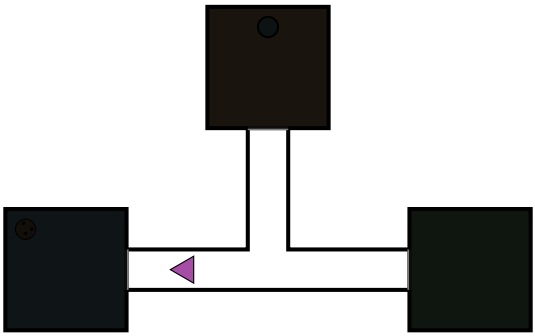

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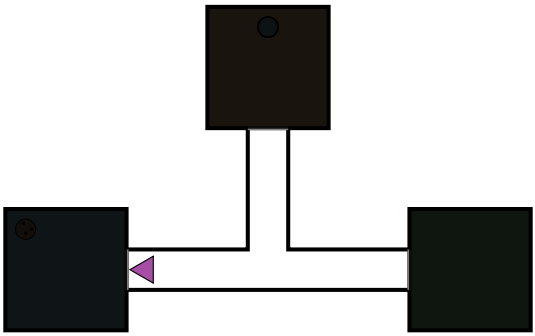

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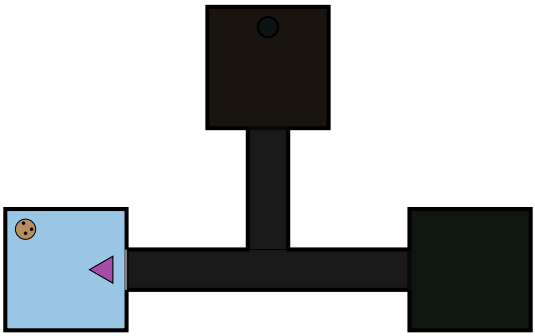

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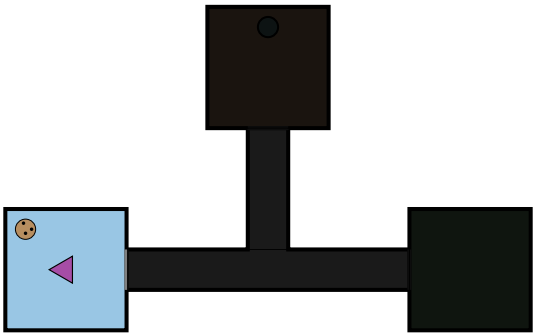

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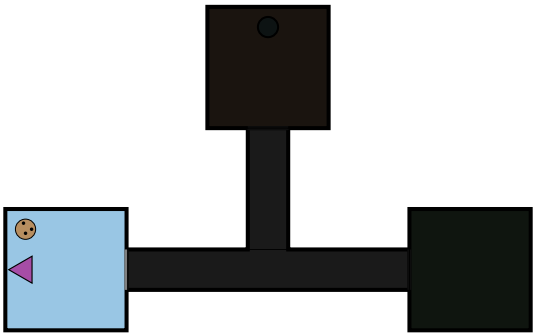

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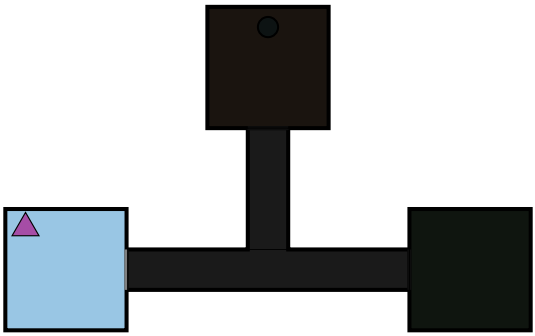

(+1 Reward)

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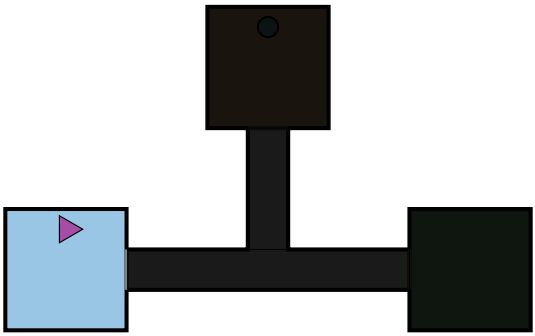

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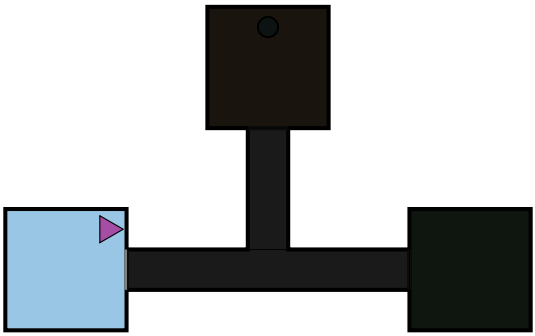

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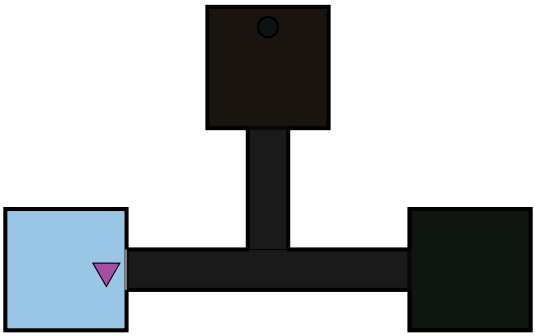

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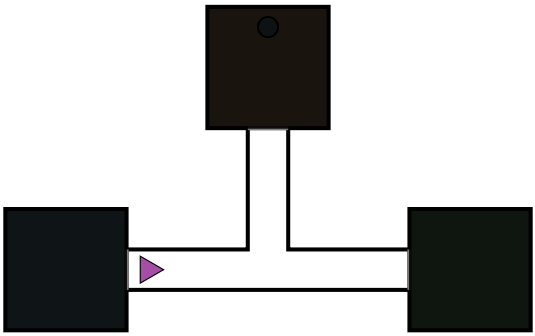

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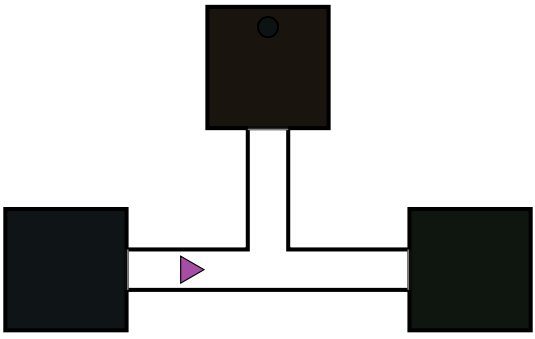

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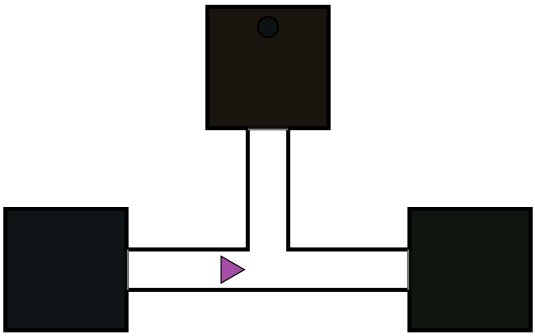

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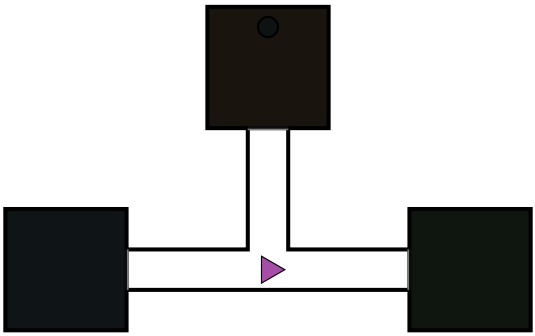

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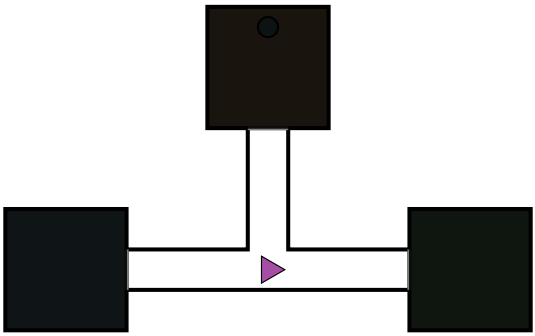

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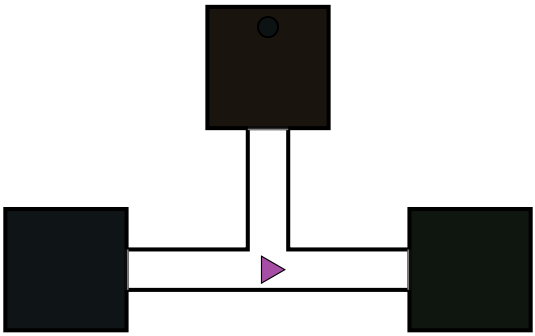

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$$\pi^*(a|o_t) \ll \pi^*(a|o_0, \cdots, o_t)$$

Partially Observable RL

The most popular approach:

Training LSTMs policies using a policy gradient method.

Partially Observable RL

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Training LSTMs policies using a policy gradient method.

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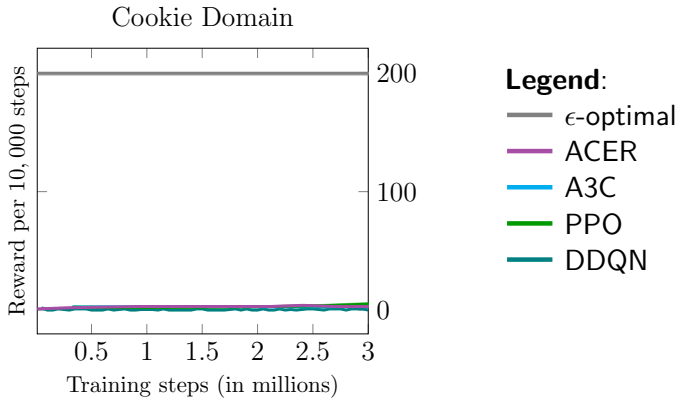


RMs as memory

Reward Machines as memory

If the agent can detect the color of the rooms (🟩, ⬜, 🟦, 🟧),

Reward Machines as memory

If the agent can detect the color of the rooms (■, □, ■, ■), and when it presses the button (●),

Reward Machines as memory

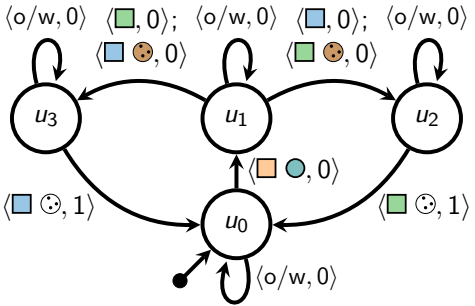
If the agent can detect the color of the rooms (🟩, ⬜, 🟦, 🟧), and when it presses the button (🔵), eats a cookie (🍪),

Reward Machines as memory

If the agent can detect the color of the rooms (🟩, ⬜, 🟦, 🟧), and when it presses the button (🔵), eats a cookie (🍪), and sees a cookie (🍪),

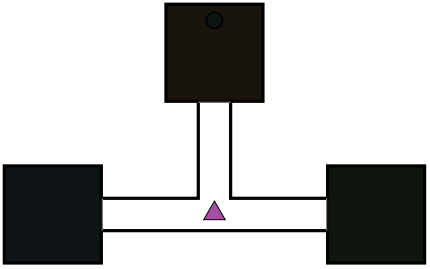
Reward Machines as memory

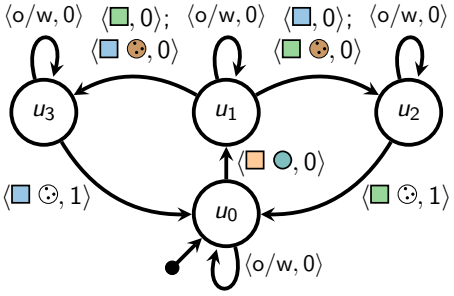
If the agent can detect the color of the rooms (■, □, ■, ■), and when it presses the button (●), eats a cookie (🍪), and sees a cookie (🍪), then:



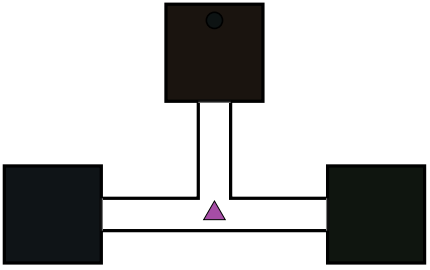
... becomes a **"perfect" memory** for the cookie domain.

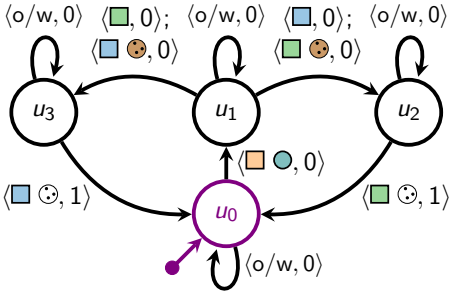
Reward Machines as memory



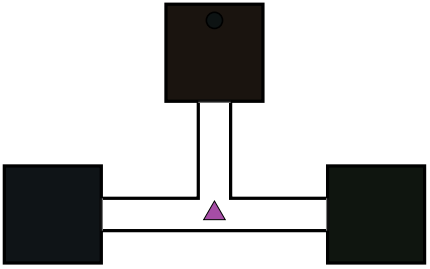


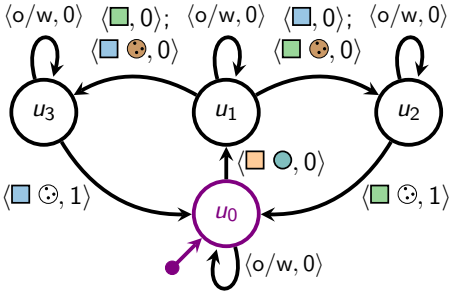
Reward Machines as memory





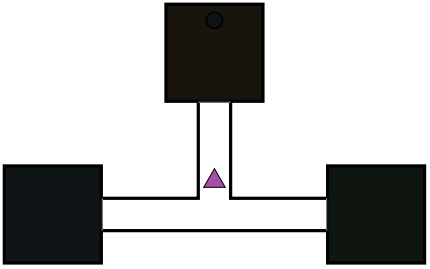
Reward Machines as memory

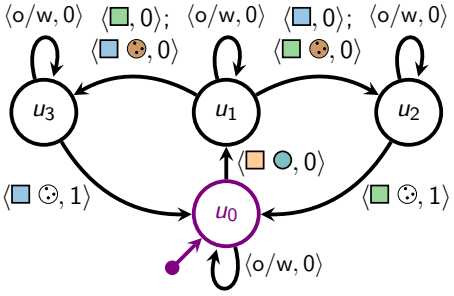




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

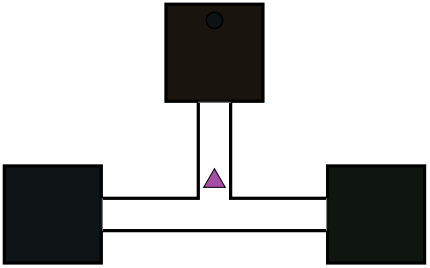
Reward Machines as memory

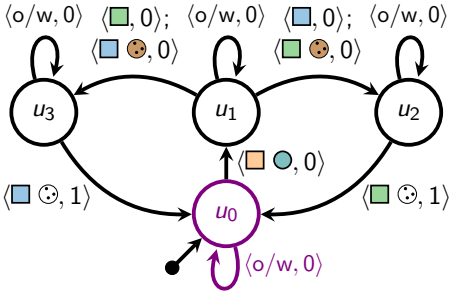




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

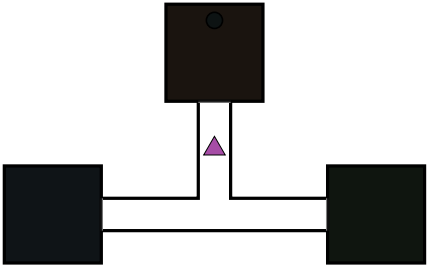
Reward Machines as memory

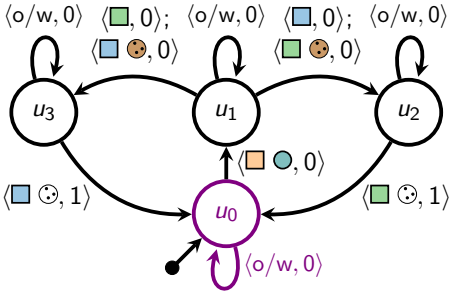




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

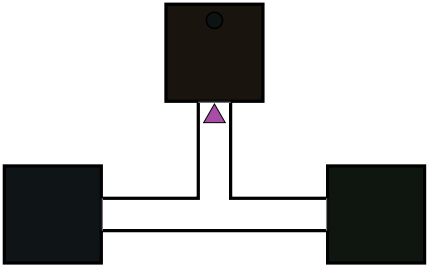
Reward Machines as memory

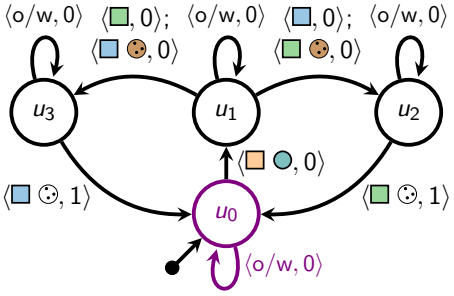




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

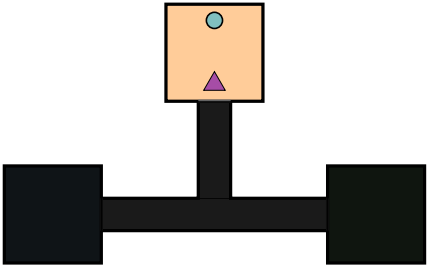
Reward Machines as memory

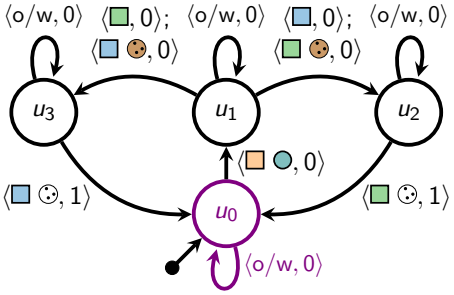




conditions at state u_0		
if ( )	$\rightarrow$	**goto** u_1
else	$\rightarrow$	**goto** u_0

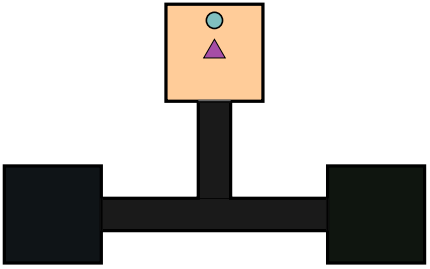
Reward Machines as memory

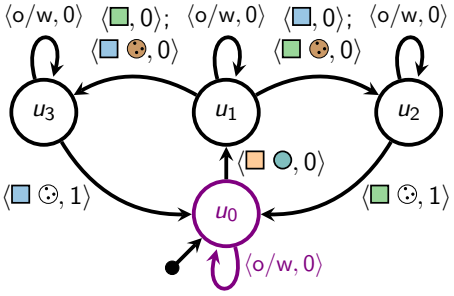




conditions at state u_0		
if ( )	$\rightarrow$	**goto** u_1
else	$\rightarrow$	**goto** u_0

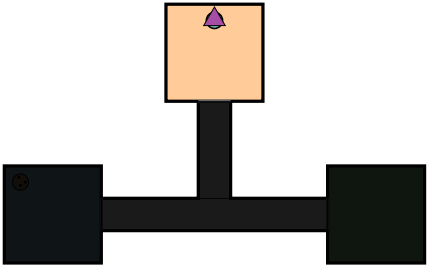
Reward Machines as memory

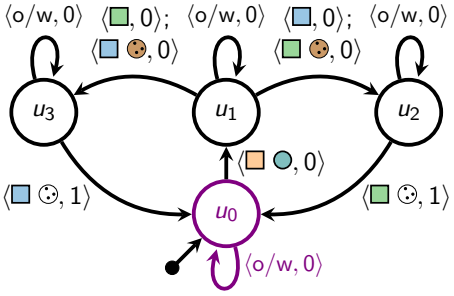




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

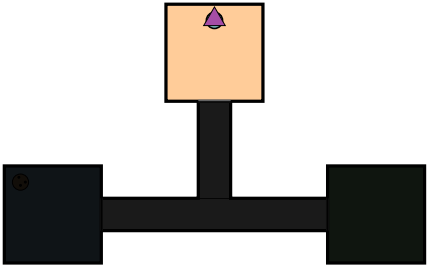
Reward Machines as memory

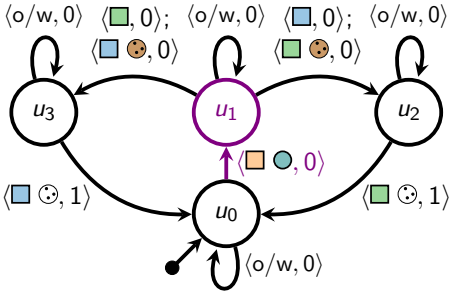




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

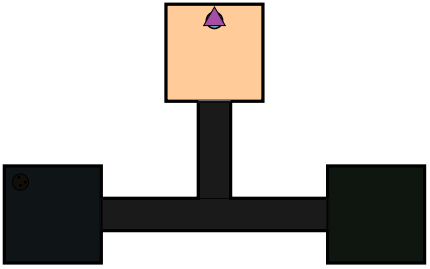
Reward Machines as memory

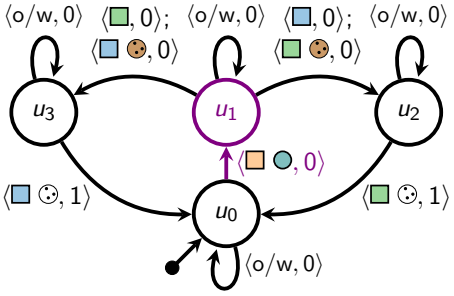




conditions at state u_0		
if (□ ○)	→	**goto** u_1
else	→	**goto** u_0

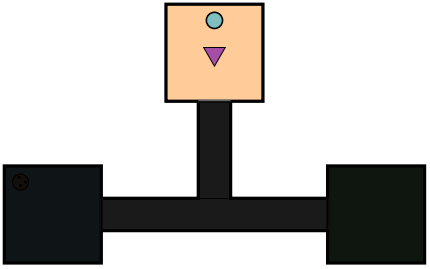
Reward Machines as memory

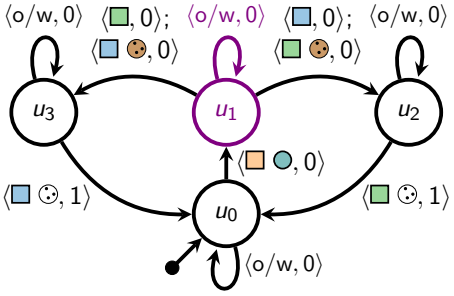




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

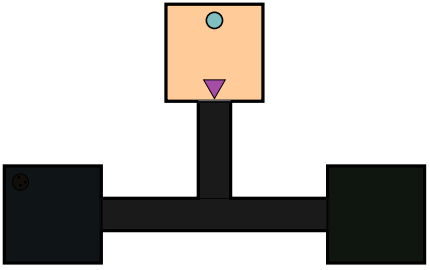
Reward Machines as memory

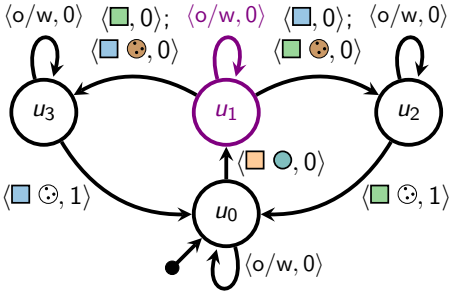




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

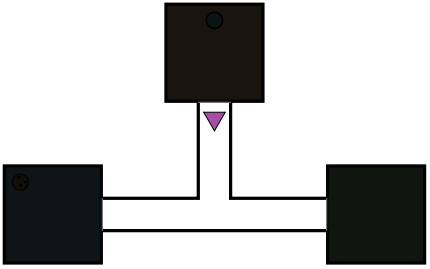
Reward Machines as memory

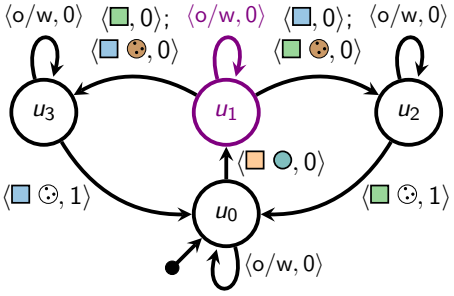




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

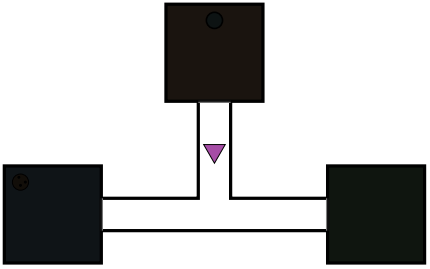
Reward Machines as memory

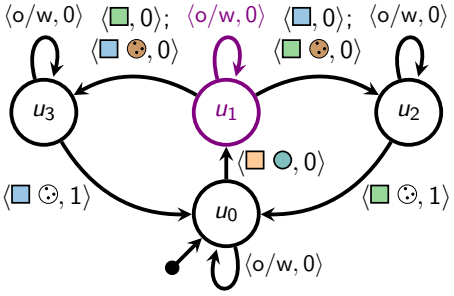




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

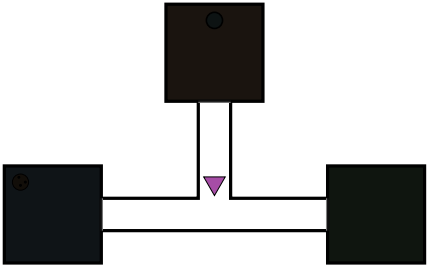
Reward Machines as memory

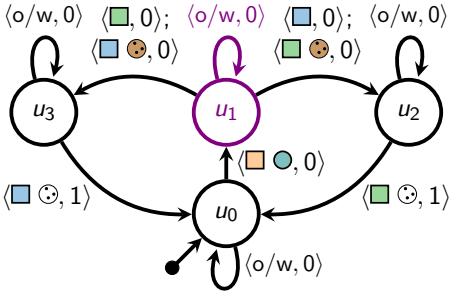




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

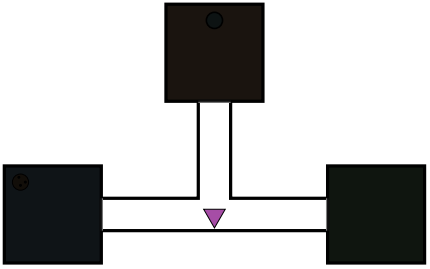
Reward Machines as memory

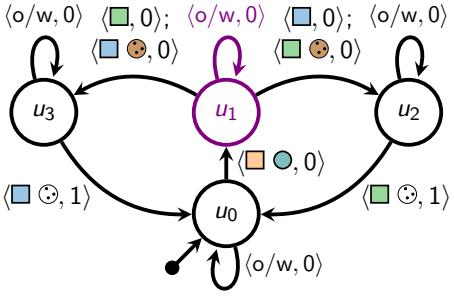




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

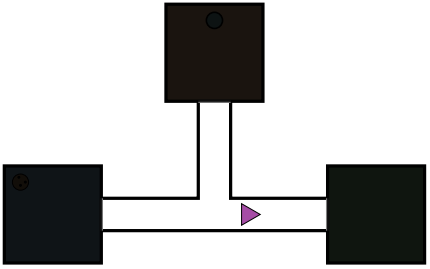
Reward Machines as memory

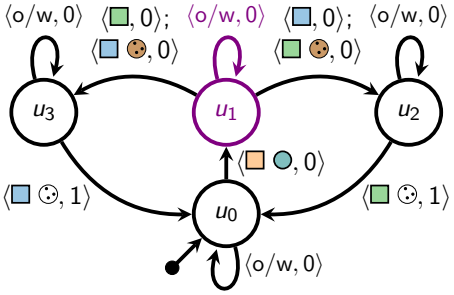




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

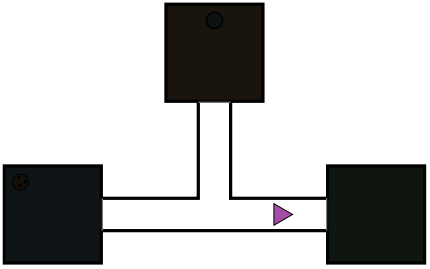
Reward Machines as memory

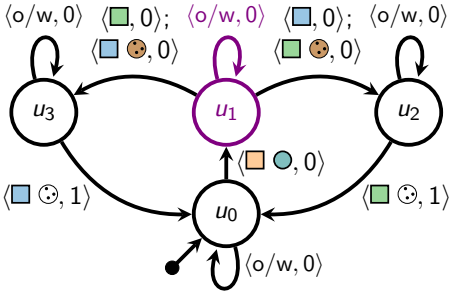




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

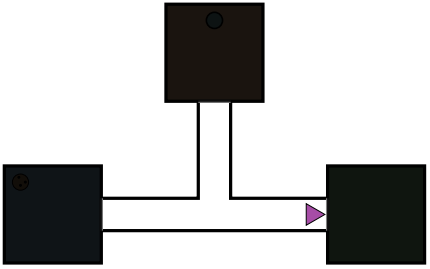
Reward Machines as memory

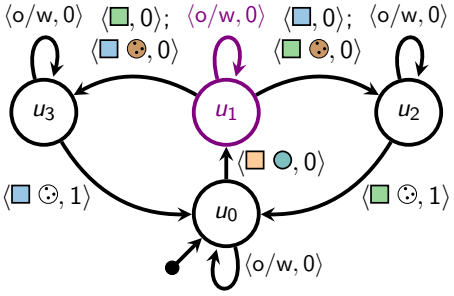




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

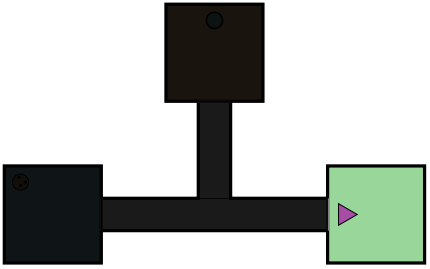
Reward Machines as memory

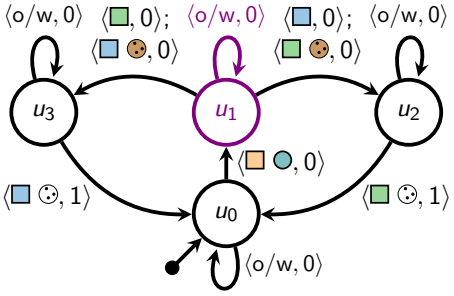




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

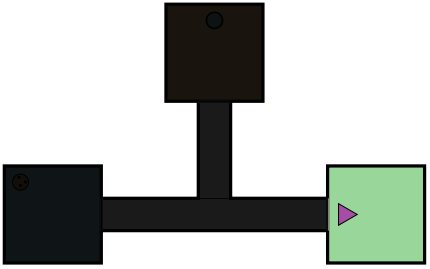
Reward Machines as memory

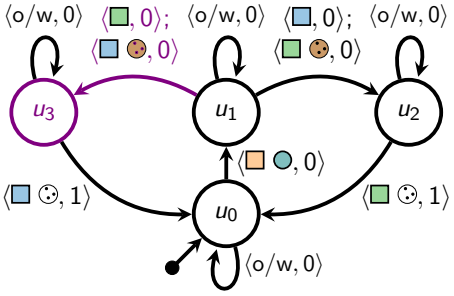




conditions at state u_1		
if (□ **or** □ ●)	→	**goto** u_2
if (□ **or** □ ●)	→	**goto** u_3
else	→	**goto** u_1

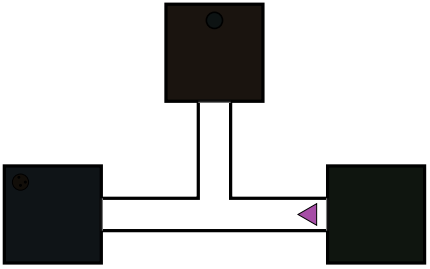
Reward Machines as memory

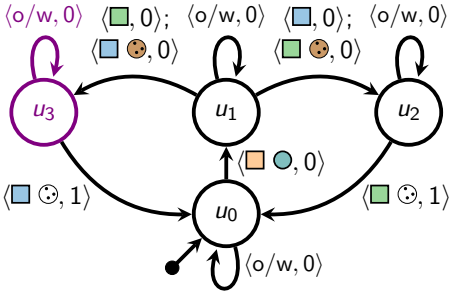




conditions at state u_3		
if (□ ☺)	→	**goto** u_0
else	→	**goto** u_3

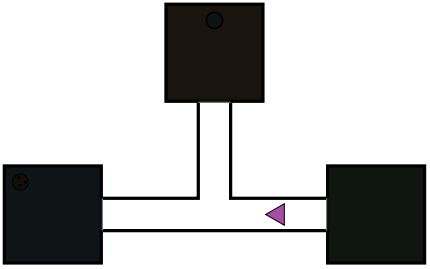
Reward Machines as memory

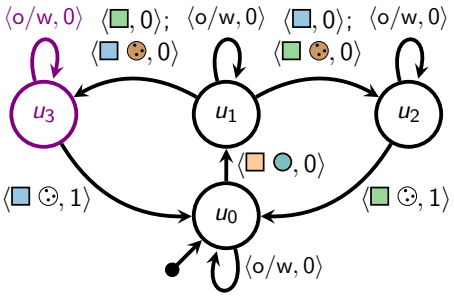




conditions at state u_3		
if (□ ⚉)	→	**goto** u_0
else	→	**goto** u_3

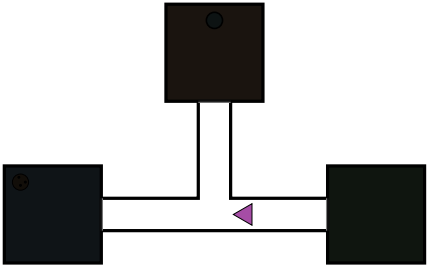
Reward Machines as memory

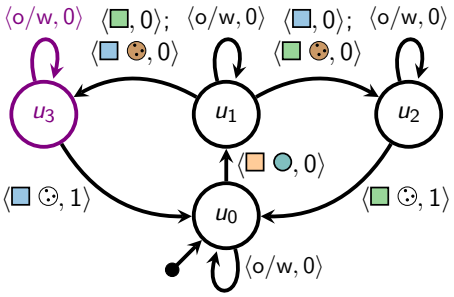




conditions at state u_3		
if (□ ⚽)	→	**goto** u_0
else	→	**goto** u_3

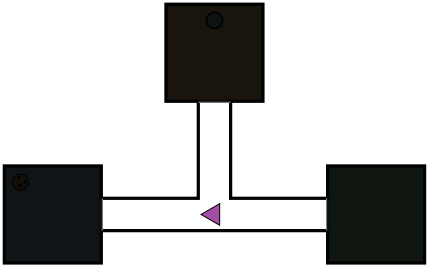
Reward Machines as memory

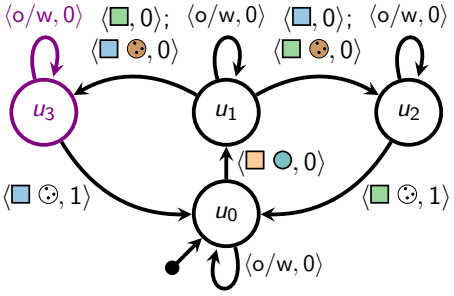




conditions at state u_3		
if (□ ⚇)	→	**goto** u_0
else	→	**goto** u_3

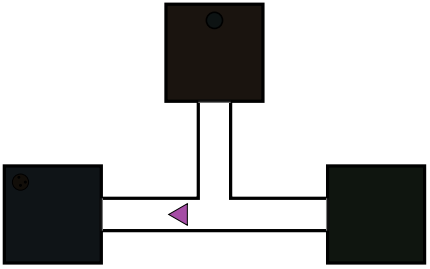
Reward Machines as memory

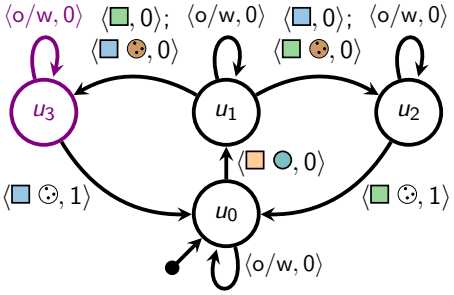




conditions at state u_3		
if (□ ⚽)	→	**goto** u_0
else	→	**goto** u_3

Reward Machines as memory





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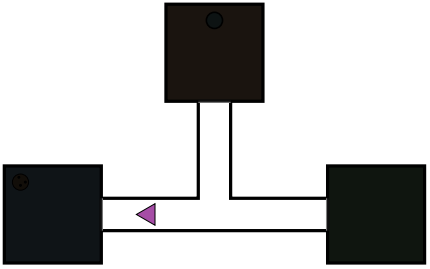

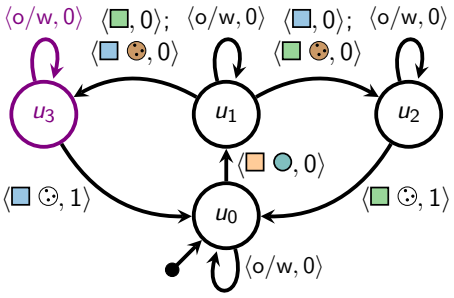

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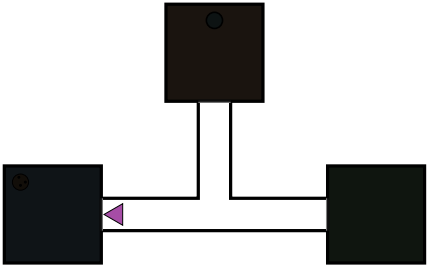

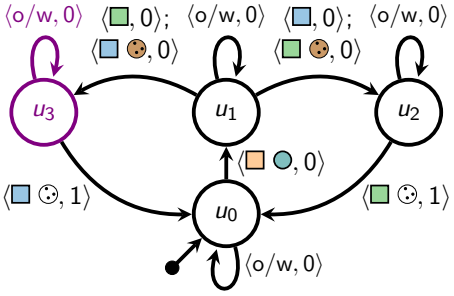

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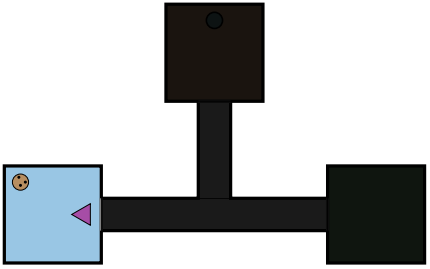

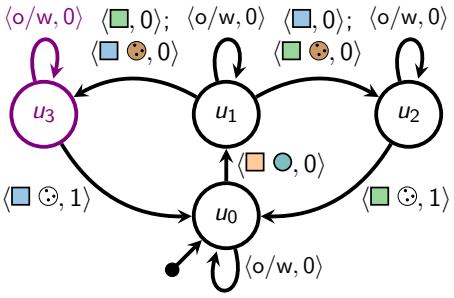

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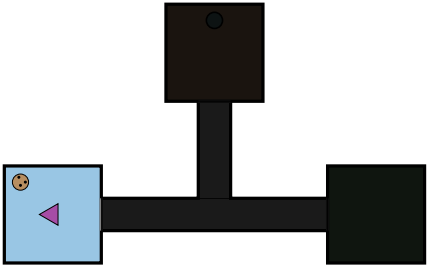

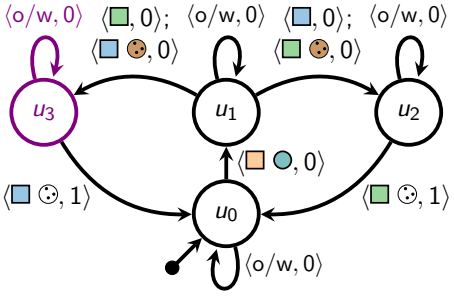

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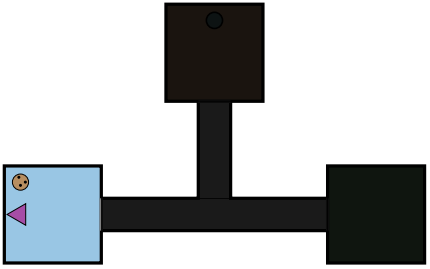

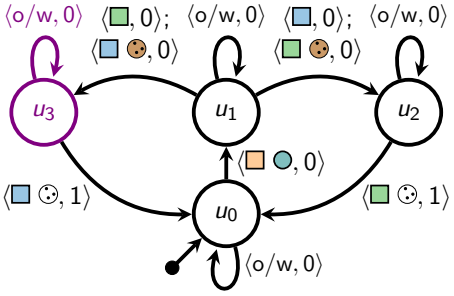

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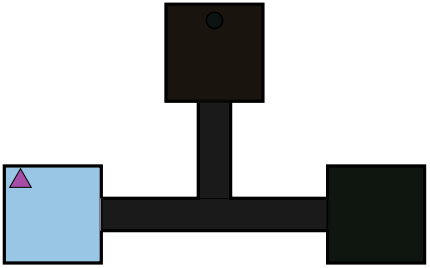

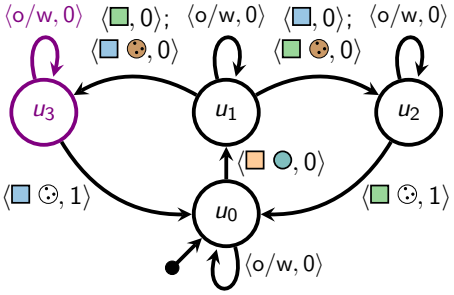

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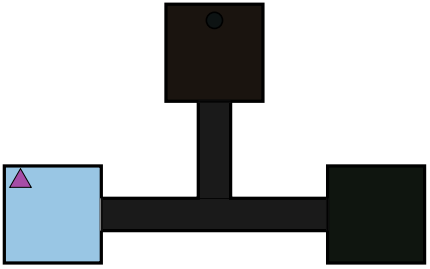

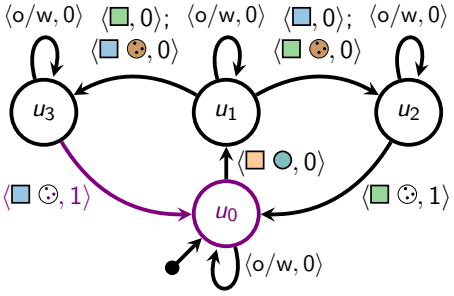

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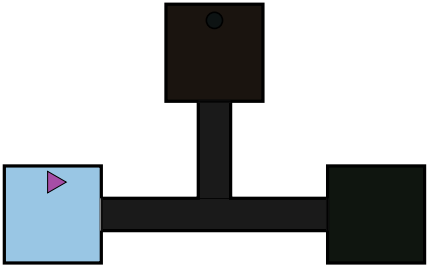

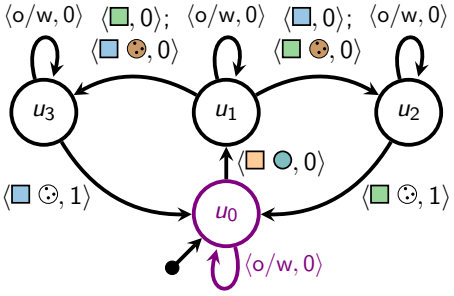

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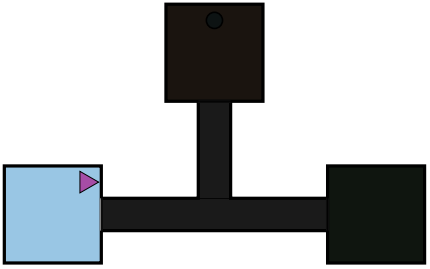

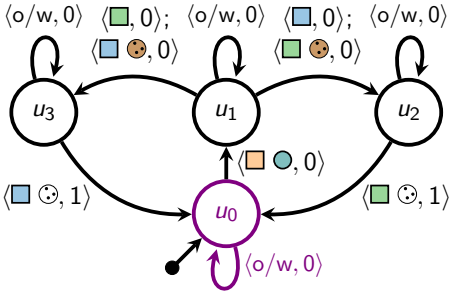

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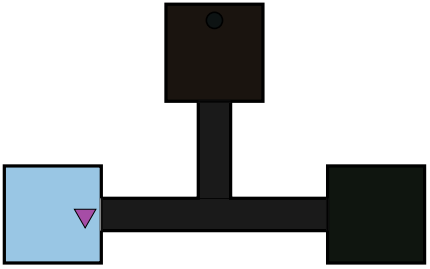

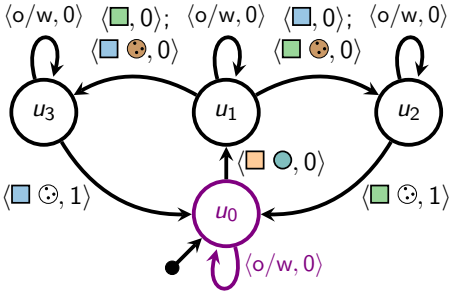

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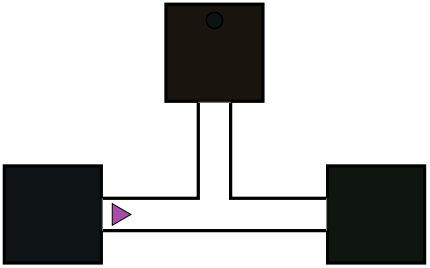

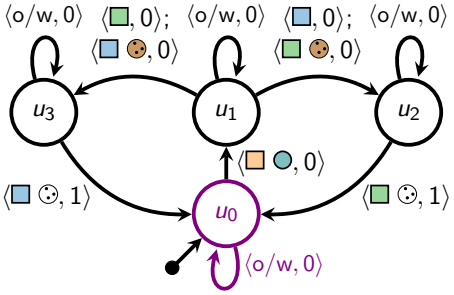

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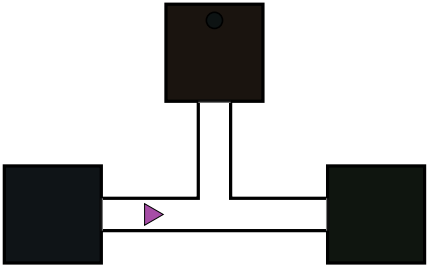

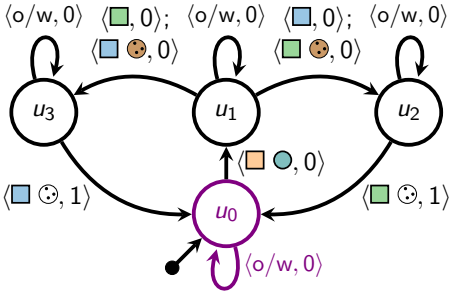

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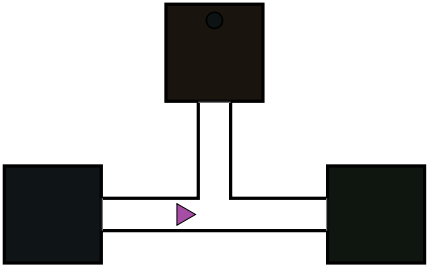

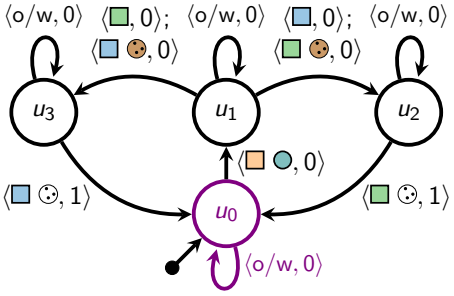

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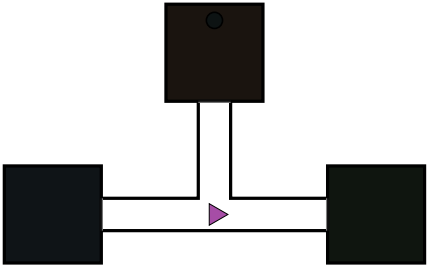

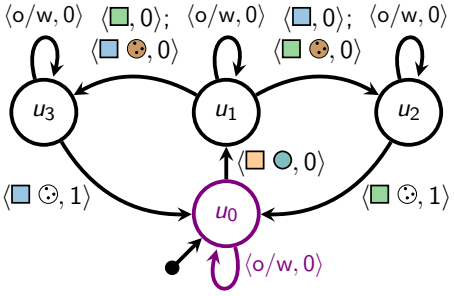

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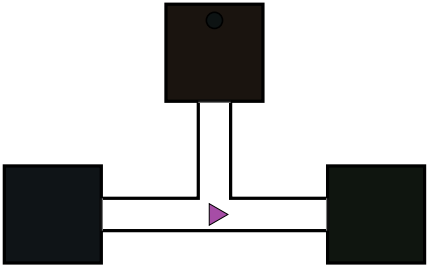
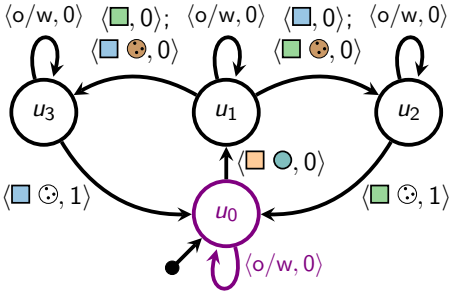
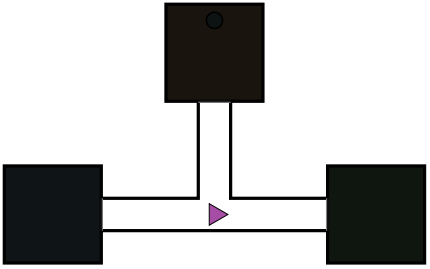
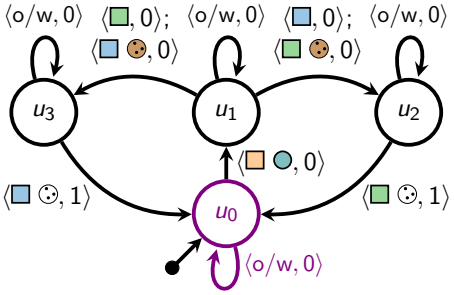




Why is this a perfect memory?

Reward Machines as memory





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$$\pi^*(a|o_0, \cdots, o_t) = \pi^*(a|o_t, u_t)$$

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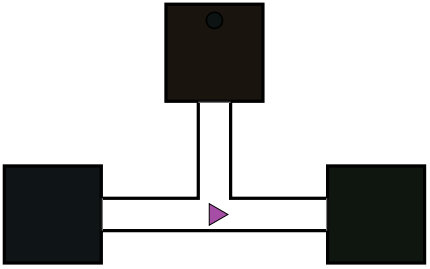

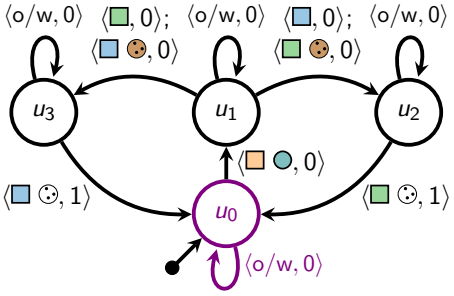

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Hard problem $\xrightarrow{\text{RM}}$ Easy problem

How to learn such RMs?

Learning Reward Machines

Given a set of detectors (e.g., $\{$  ,  ,  ,  ,  ,  ,  $\}$) and traces $\mathcal{T}$,

Learning Reward Machines

Given a set of detectors (e.g., $\{$  $\}$) and traces $\mathcal{T}$, learning RMs is a **discrete optimization** problem:

$$\underset{\langle U, u_0, \delta_u, \delta_r \rangle}{\text{minimize}} \sum_{i \in I} \sum_{t \in T_i} \log(|N_{x_{i,t}, L(e_{i,t})}|) \tag{LRM}$$

$$s.t.\ \langle U, u_0, \delta_u, \delta_r \rangle \in \mathcal{R}_{\mathcal{P}} \tag{1}$$

$$|U| \leq u_{\max} \tag{2}$$

$$x_{i,t} \in U \qquad \forall i \in I, t \in T_i \cup \{t_i\} \tag{3}$$

$$x_{i,0} = u_0 \qquad \forall i \in I \tag{4}$$

$$x_{i,t+1} = \delta_u(x_{i,t}, L(e_{i,t+1})) \qquad \forall i \in I, t \in T_i \tag{5}$$

$$N_{u,l} \subseteq 2^{2^{\mathcal{P}}} \qquad \forall u \in U, l \in 2^{\mathcal{P}} \tag{6}$$

$$L(e_{i,t+1}) \in N_{x_{i,t}, L(e_{i,t})} \qquad \forall i \in I, t \in T_i \tag{7}$$

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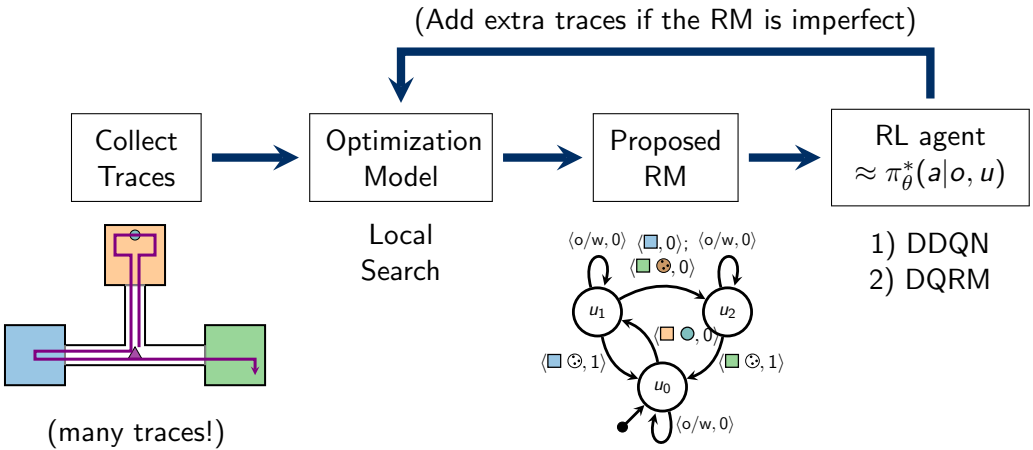
... that we solved using **local search**.

Overall approach



Results

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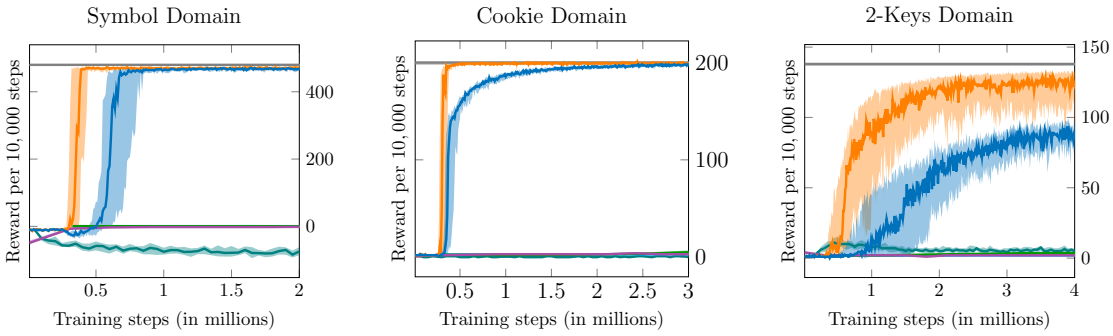

*__Note__: The detectors were also given to the baselines.

Discussion

Frequently asked questions

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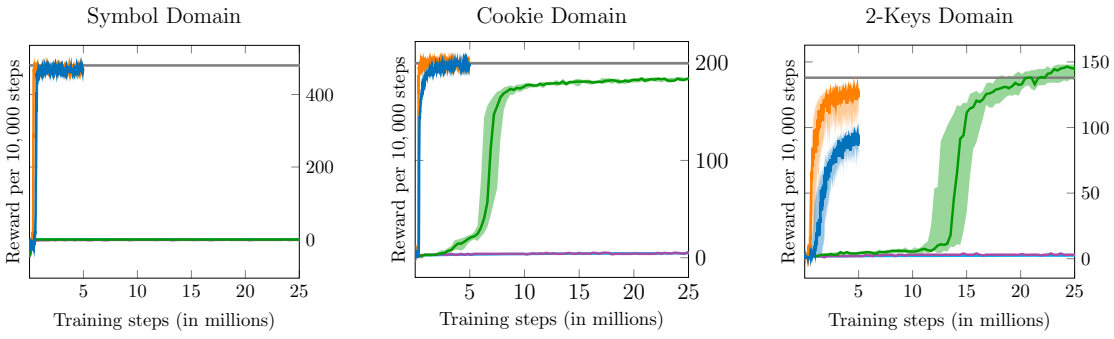

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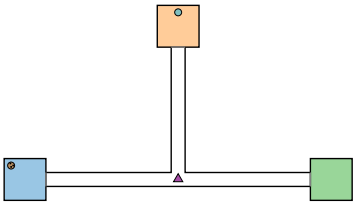

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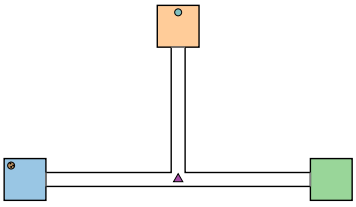

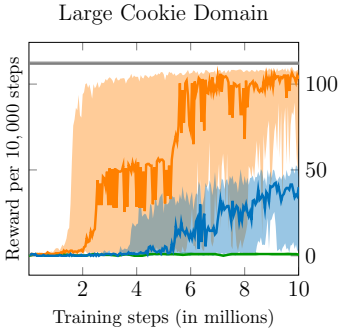

Legend: ϵ-optimal, A3C, ACER, PPO, DDQN, LRM+DDQN, LRM+DQRM

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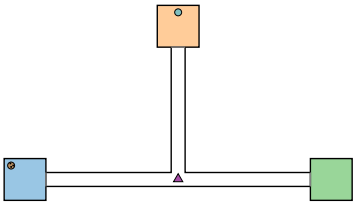

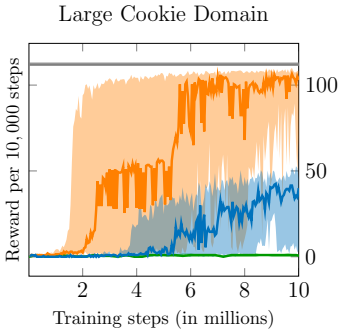

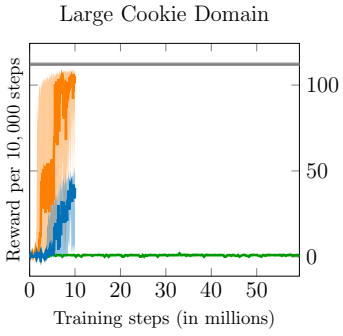

Legend:
ϵ-optimal
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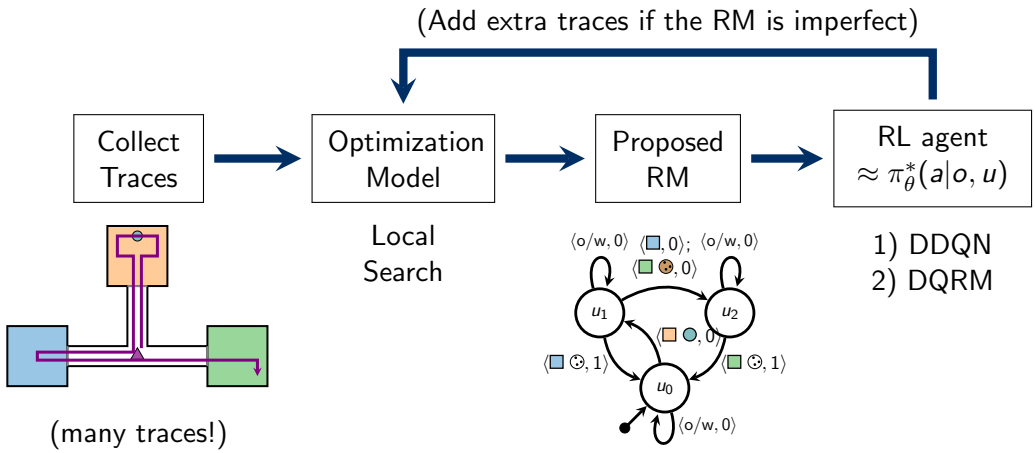

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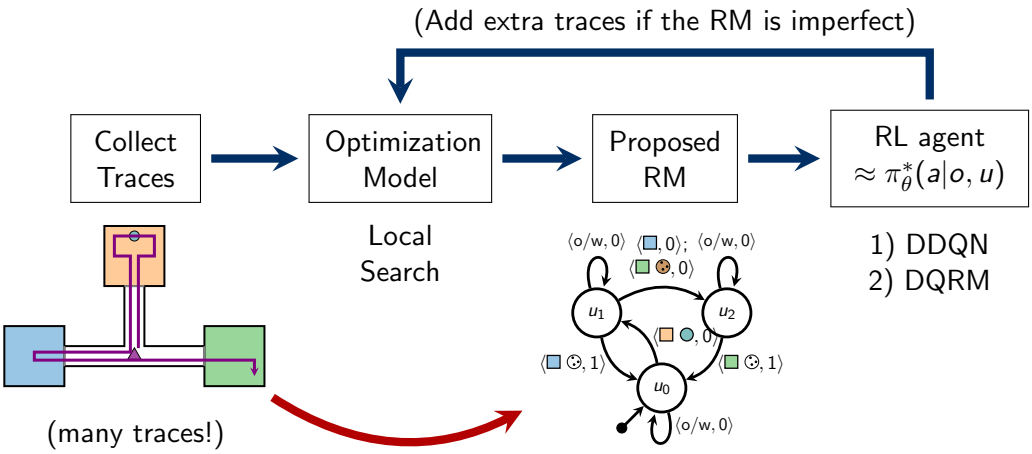

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A. LRM tries to solve POMDPs

Frequently asked questions

2) How does LRM relate to other methods that learn automata to aid RL agents?

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POMDPs are hard because:

- $P(o_{t+1}|o_0, \cdots, o_t, a_t) \neq P(o_{t+1}|o_t, a_t)$
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Result: $\pi^*(a_t|o_t, u_t)$ optimally solves the POMDP.

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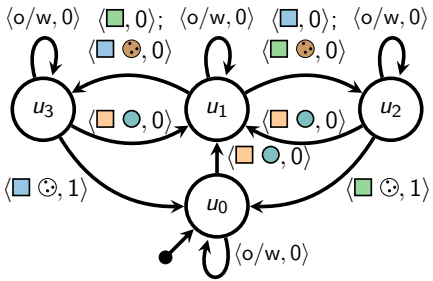

In the cookie domain, LRM learns this RM because it holds that

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Result: $\pi^*(a_t|o_t, u_t)$ optimally solves the NMRDP.

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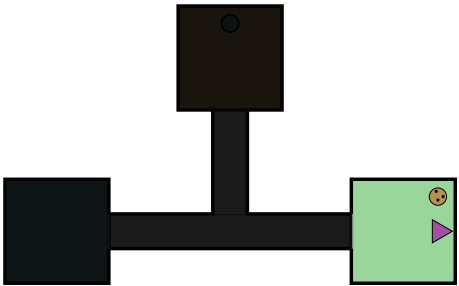

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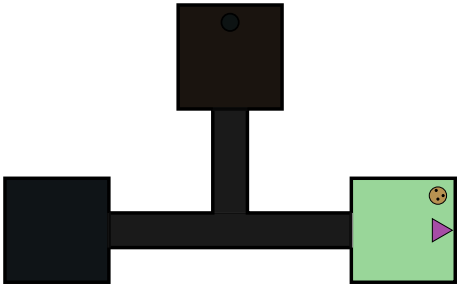

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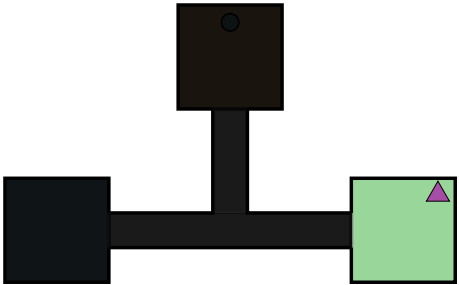

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Thus, their learning objective is to find the smallest machine such that:

- It accepts traces that **can** be generated by interacting with the environment.
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Result: They learn a high-level model that is then used to encourage exploration.

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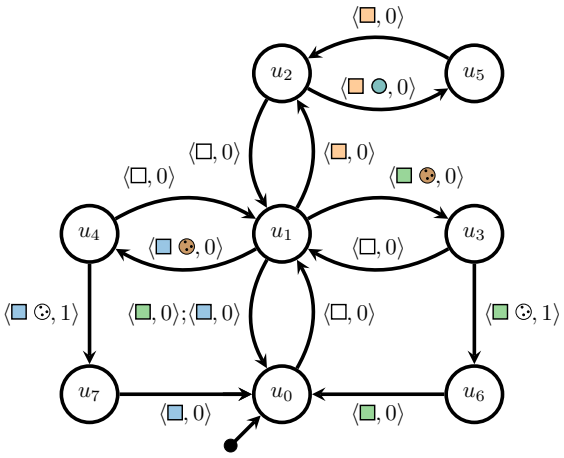

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Summary

There are three learning objectives for combining automata learning with RL:

A. [LRM] Learn an RM that makes the whole problem Markovian.
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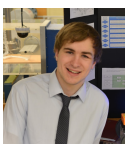
Method	Cookie	Symbol	2-Keys
JIRP	0.6 ± 0.8	-31.1 ± 13.5	2.0 ± 1.4
DeepSynth	0.4 ± 0.6	-30.4 ± 14.0	2.4 ± 1.5
LRM (ours)	**197.2 ± 2.1**	**460.4 ± 15.7**	**86.6 ± 9.4**

Concluding Remarks

https://bitbucket.org/RToroIcarte/lrm

Thanks! :)


Rodrigo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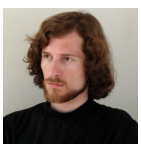
Toryn


Rick


Margarita


Sheila