Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning

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Outline

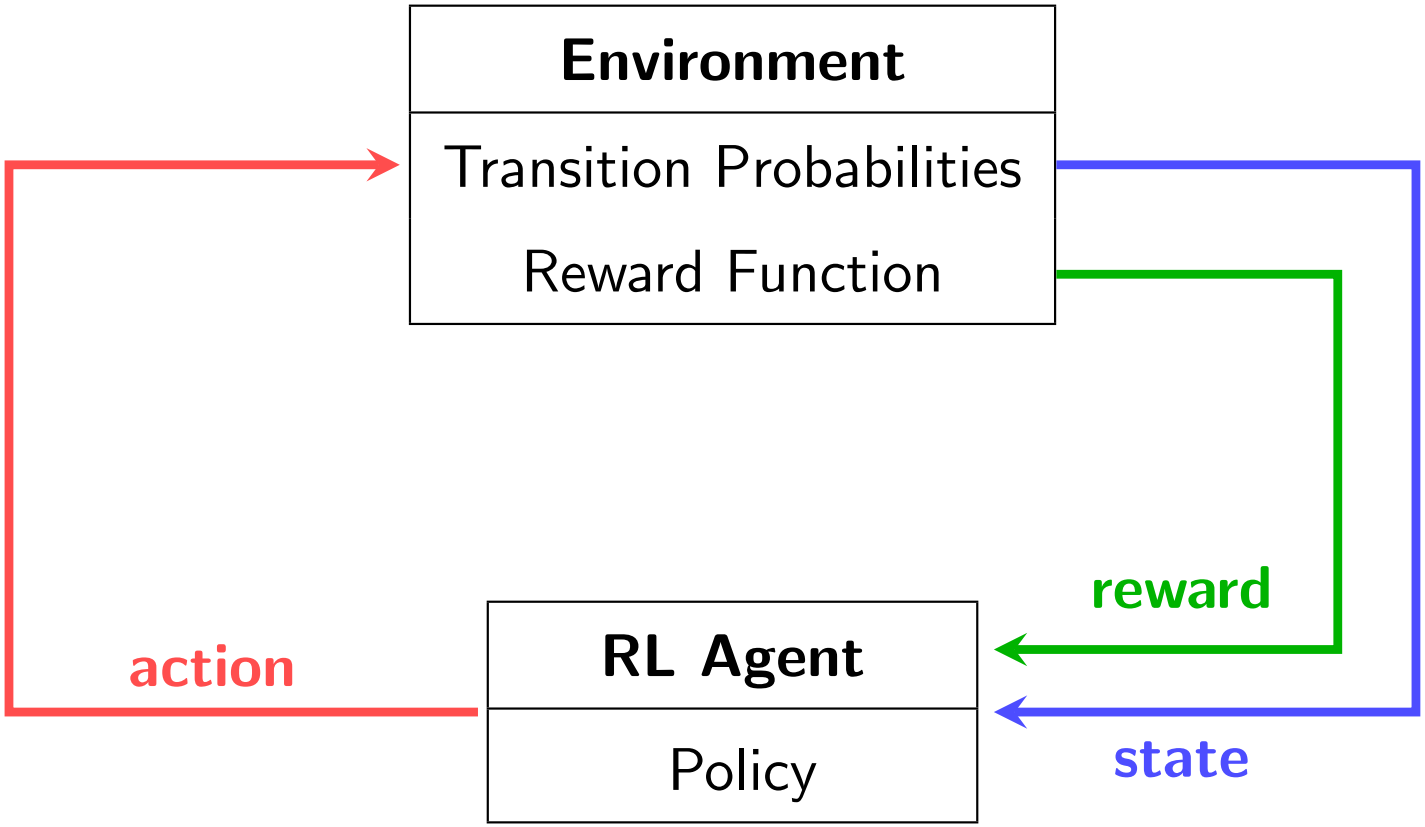
Outline

About this work

\To summarize, a nice simple idea exposing more of the structure of an RL problem and the bene ts thereof."

— Third reviewer

Reinforcement learning



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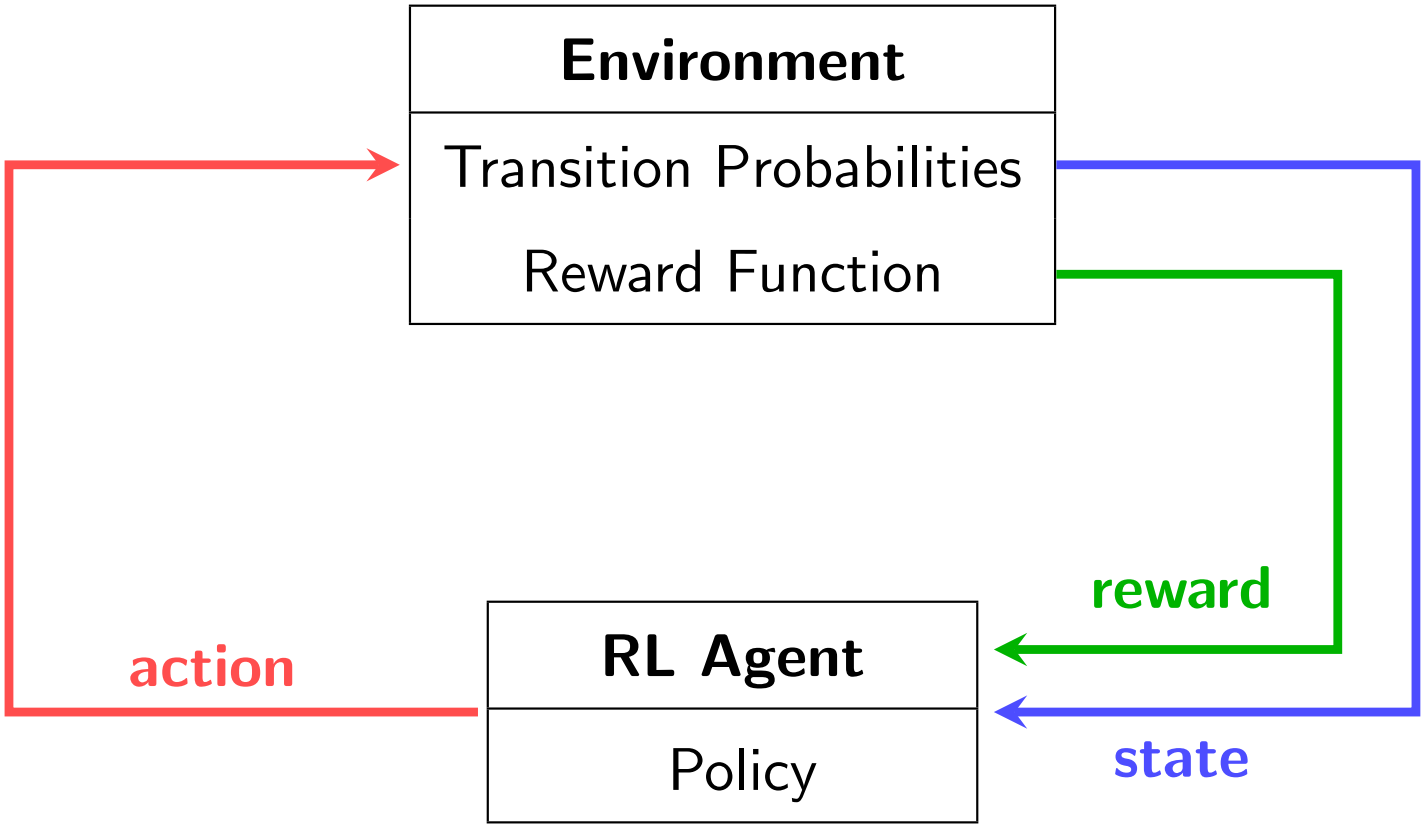
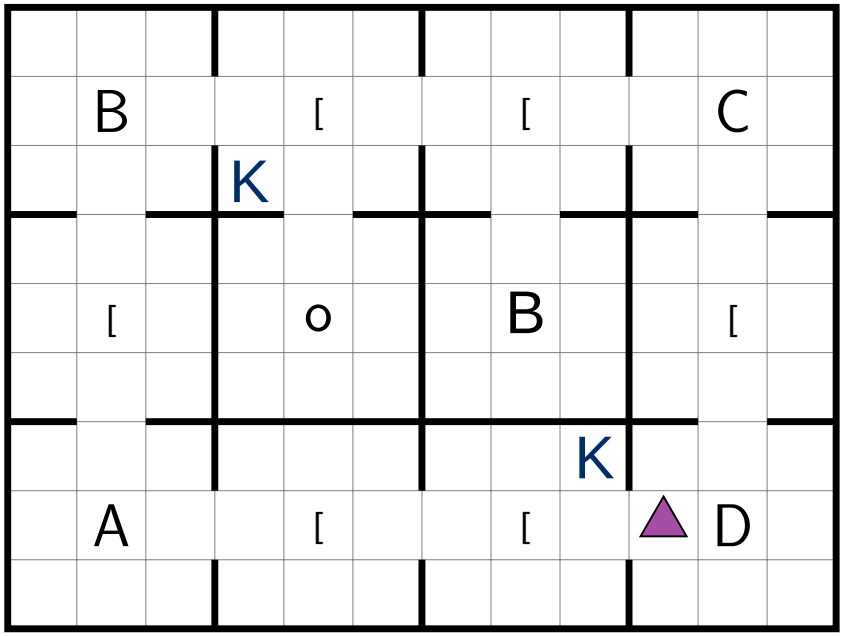


The environment might be the real world.

Running example



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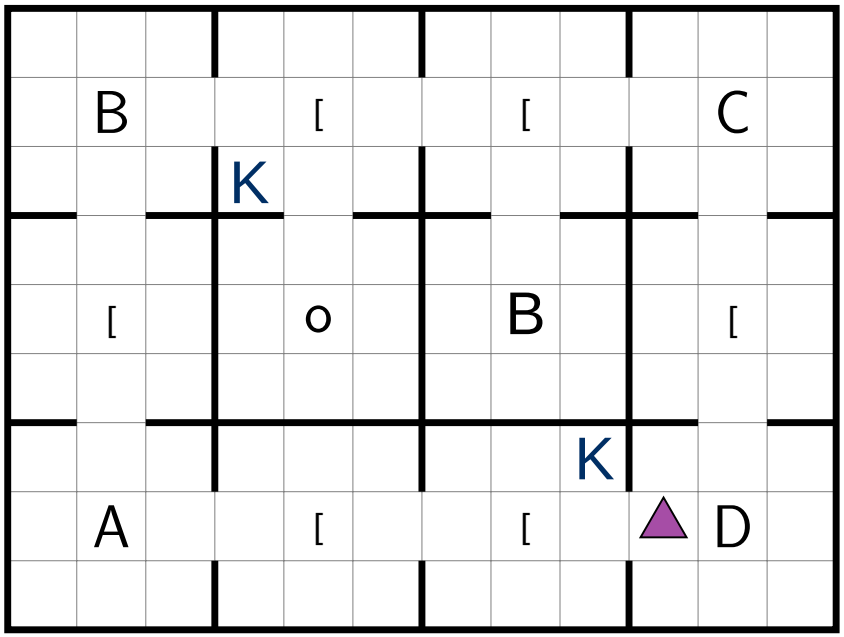

Symbol	Meaning
▲	Agent
[	Furniture
K	Coffee machine
B	Mail room
o	Office
A,B,C,D	Marked locations

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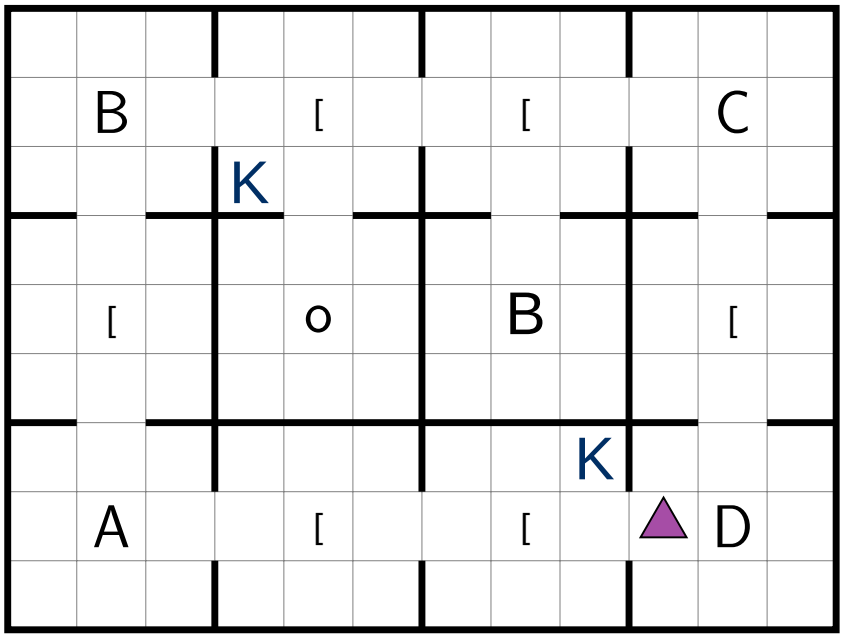

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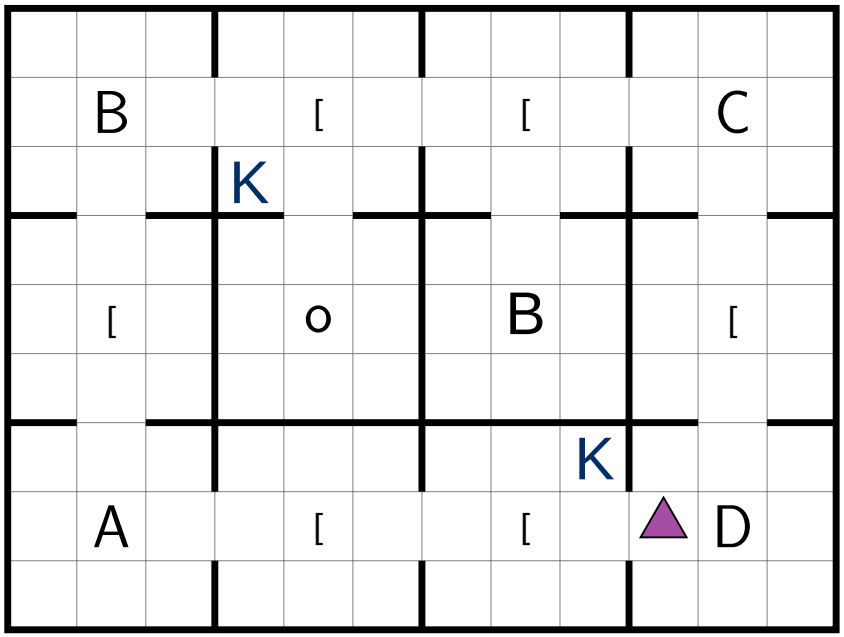

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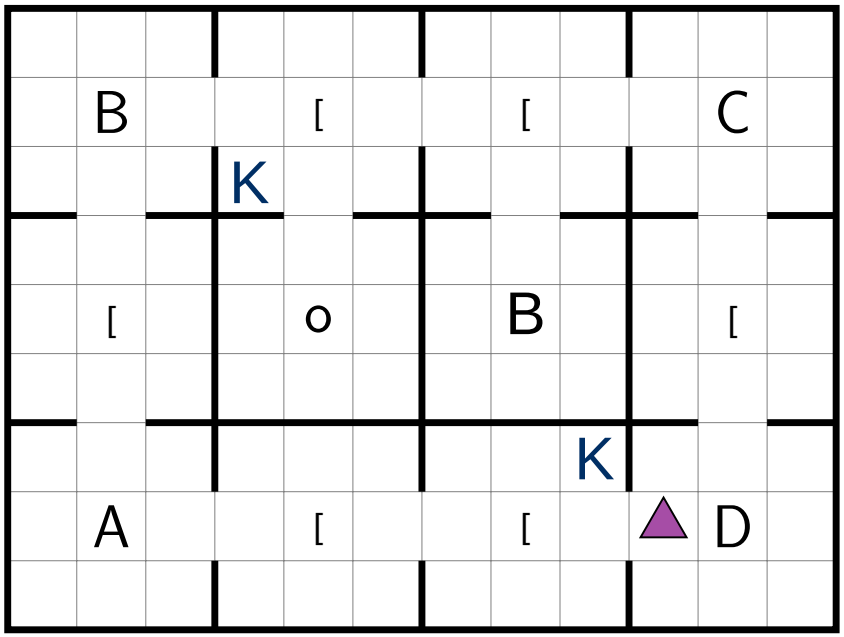

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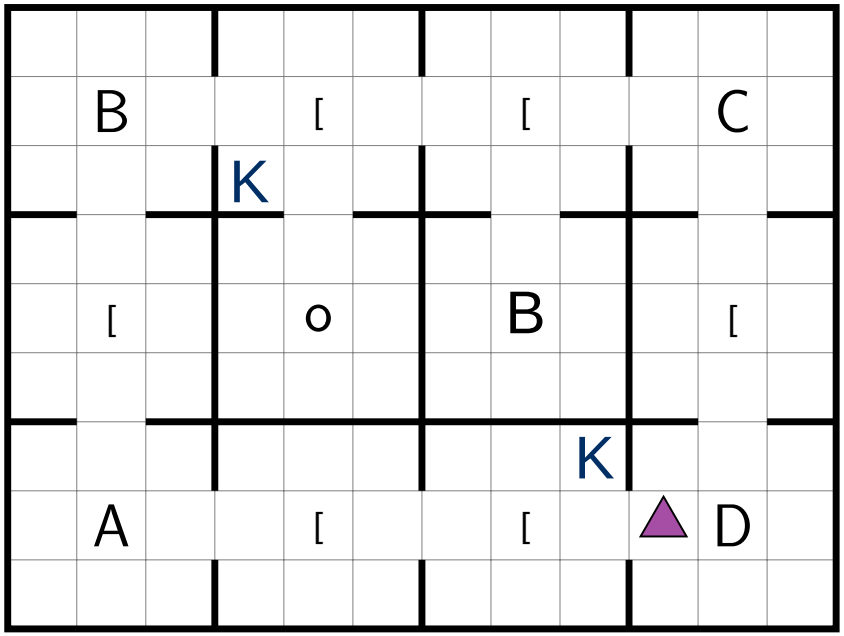


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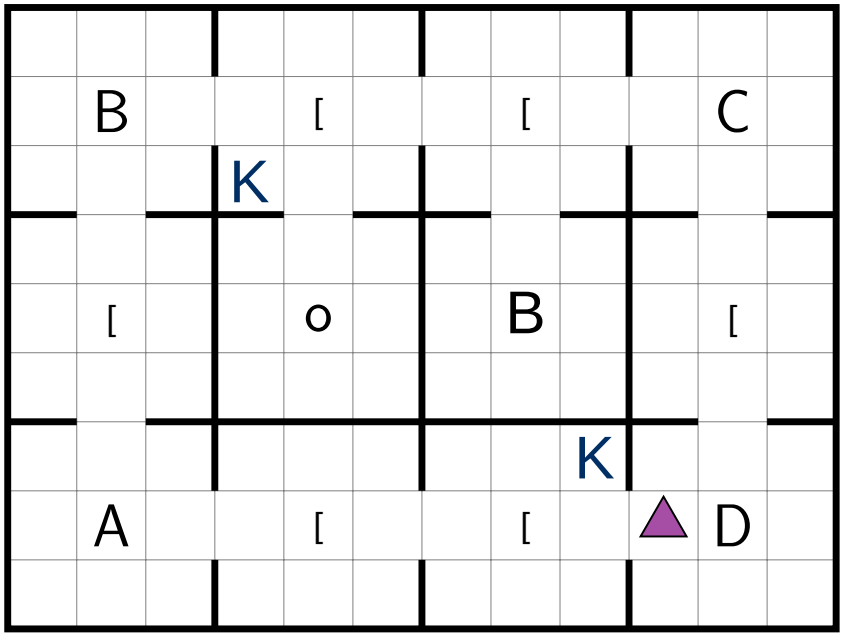


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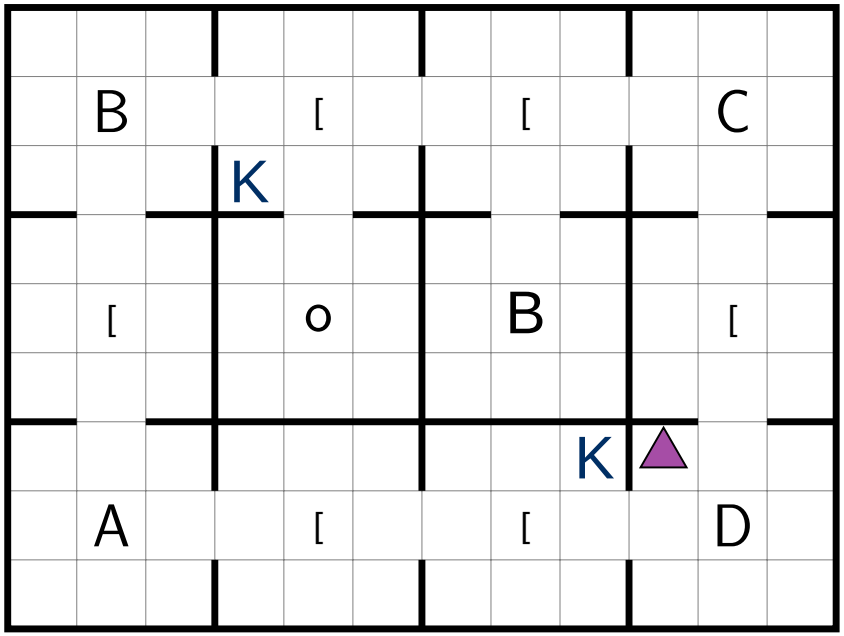


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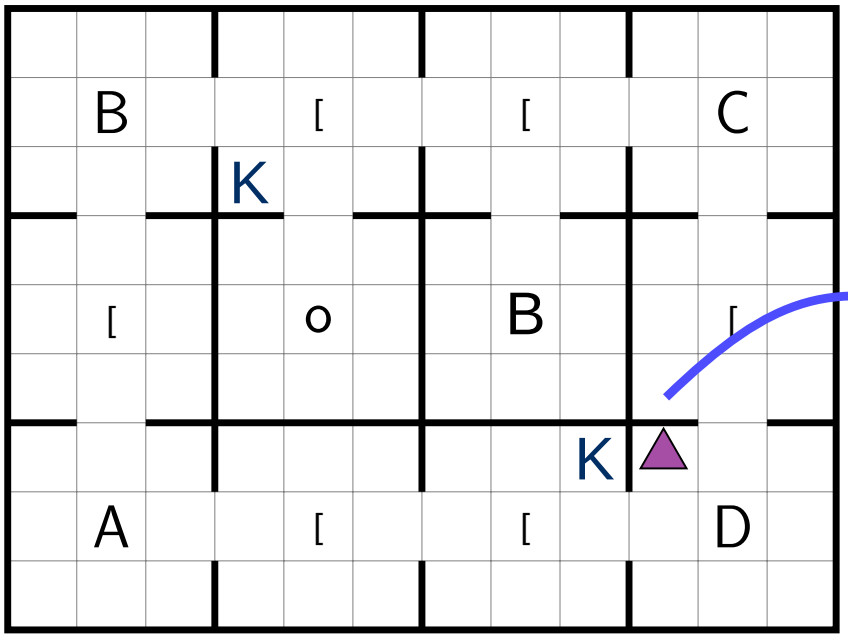

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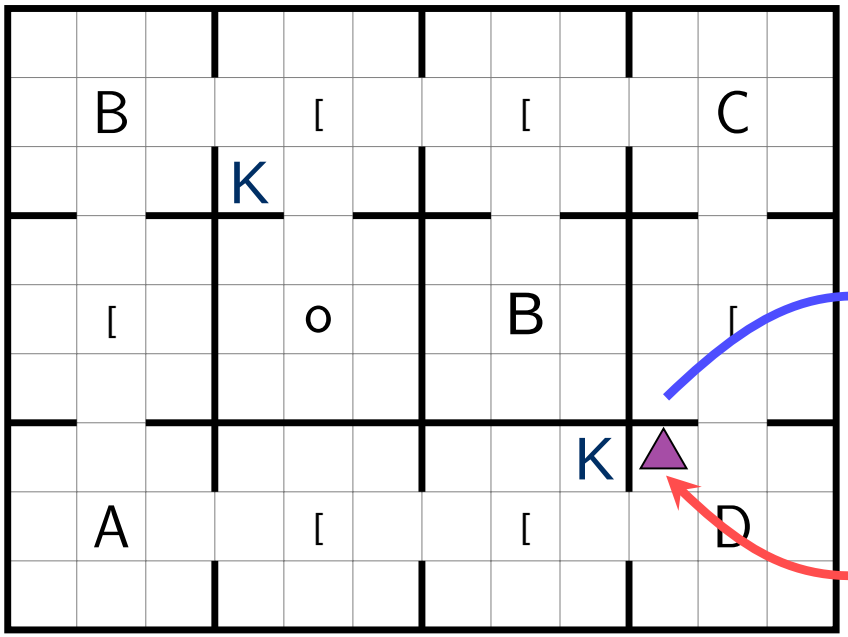

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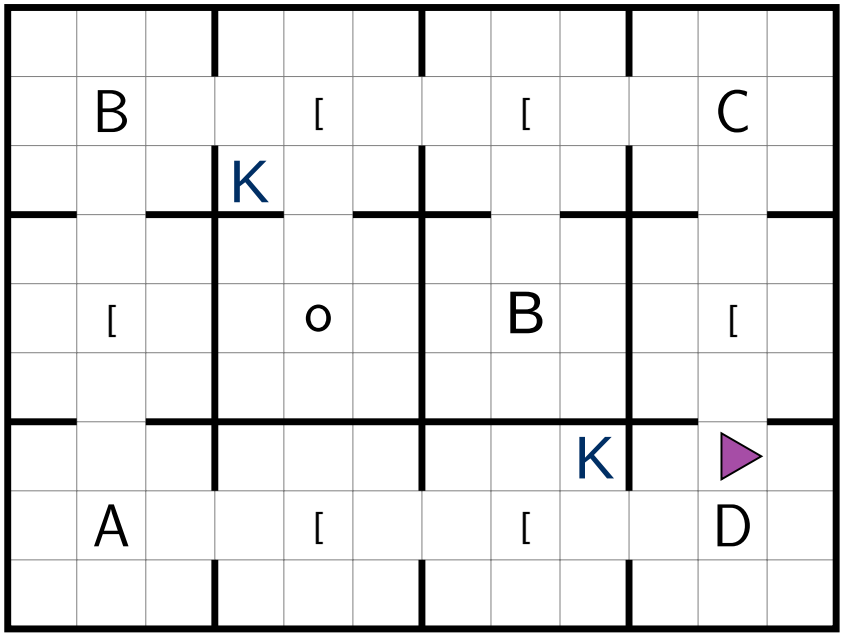


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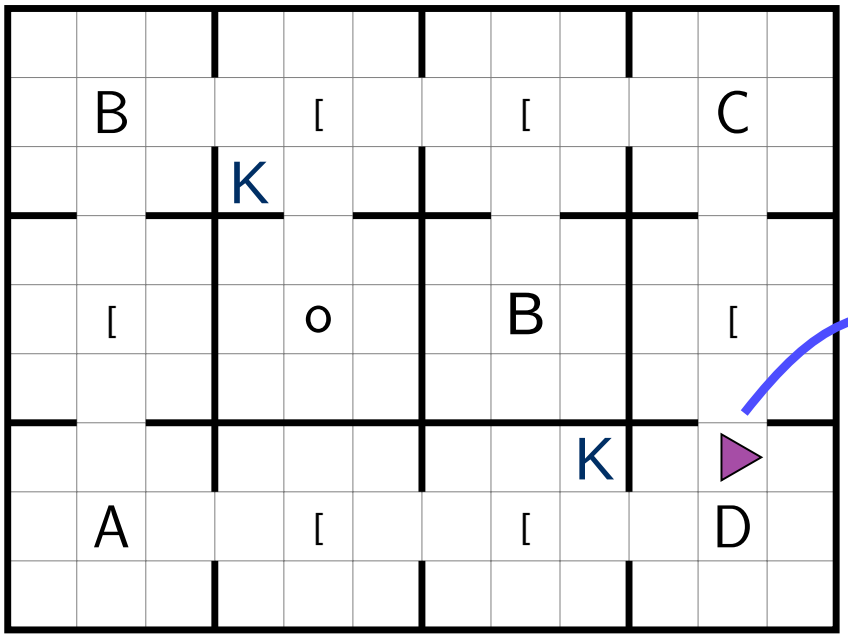

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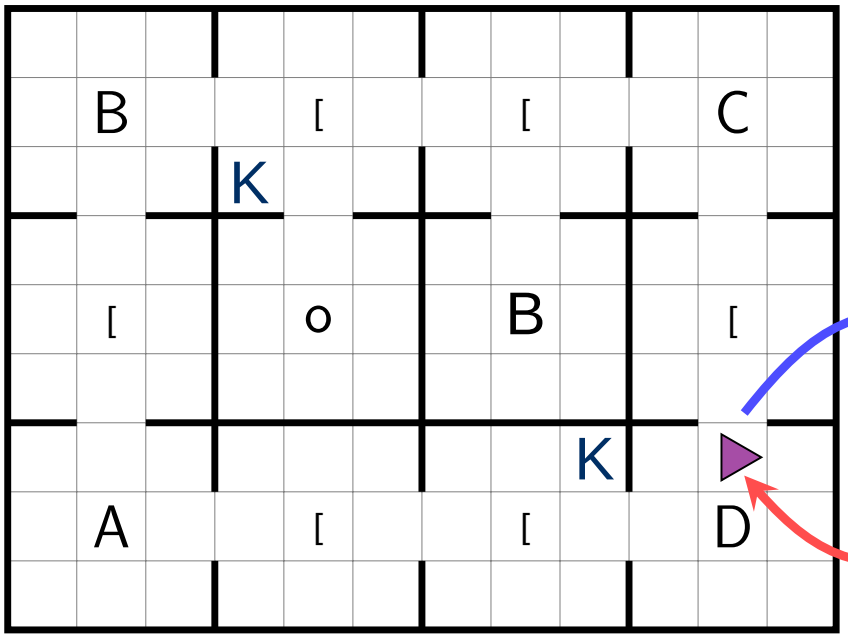

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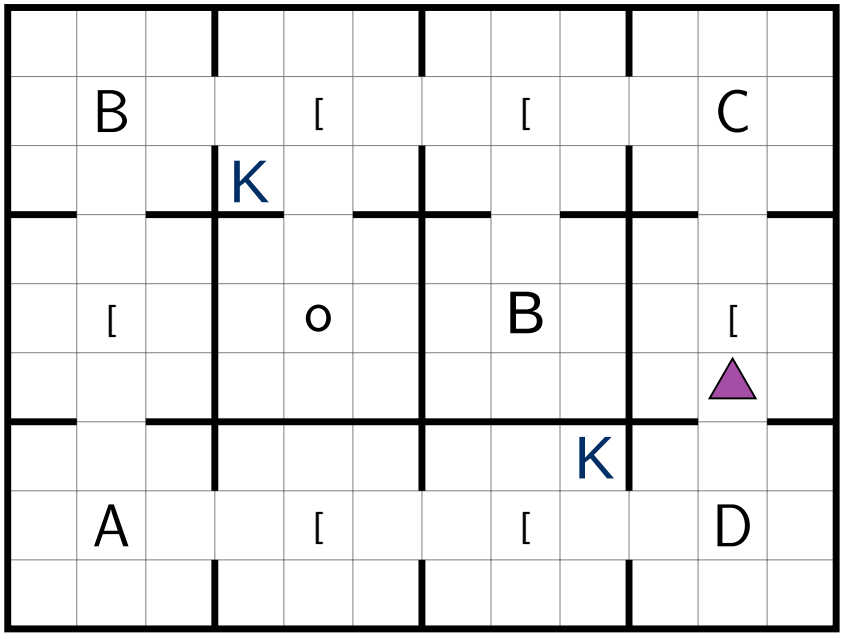


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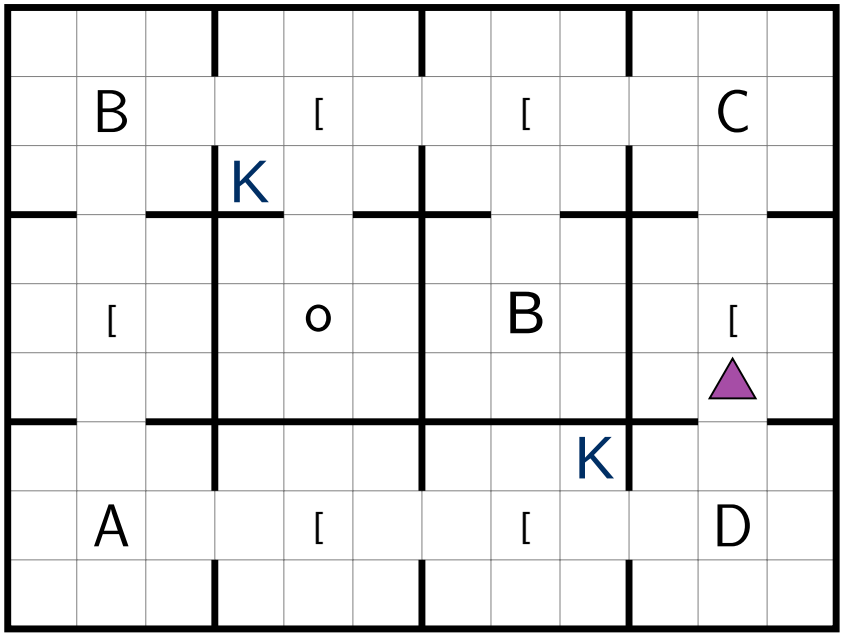


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Reward Function

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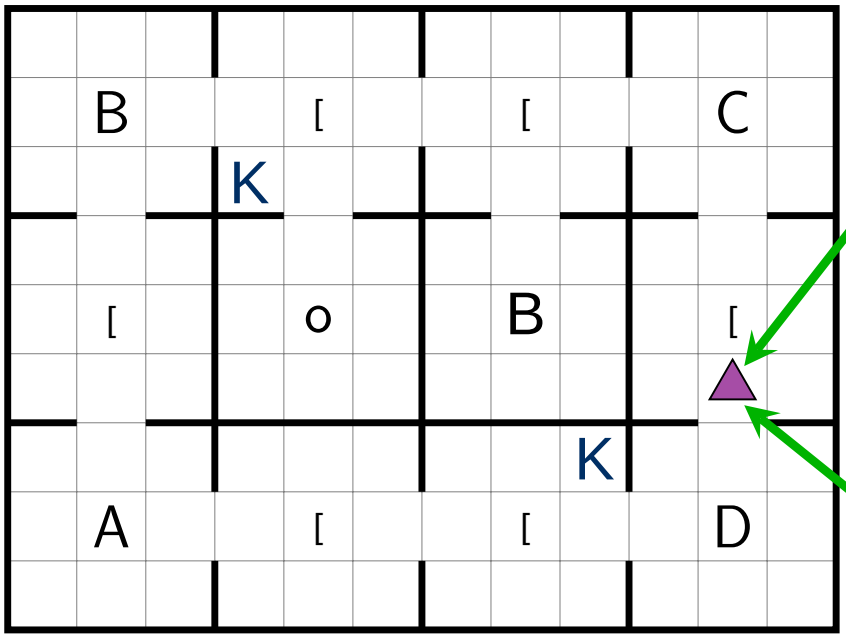


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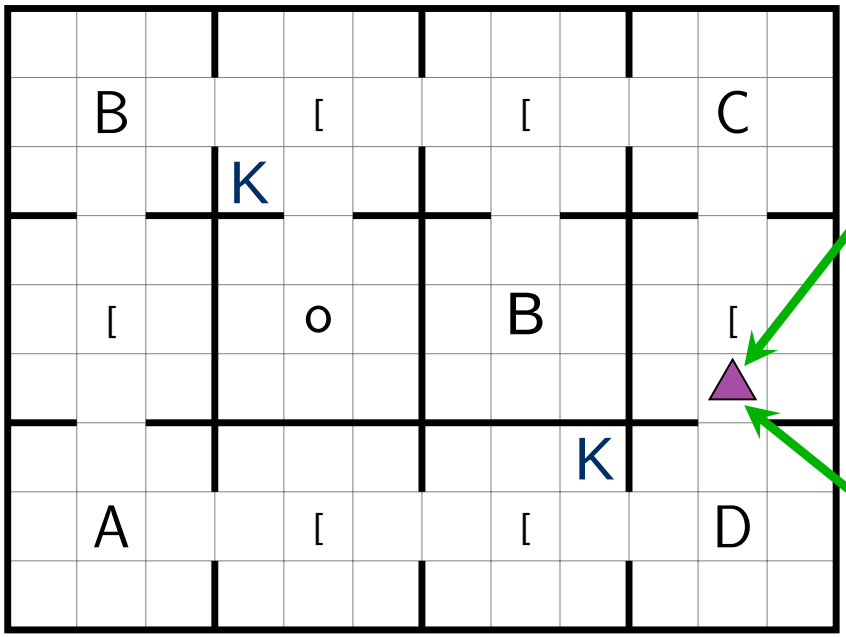


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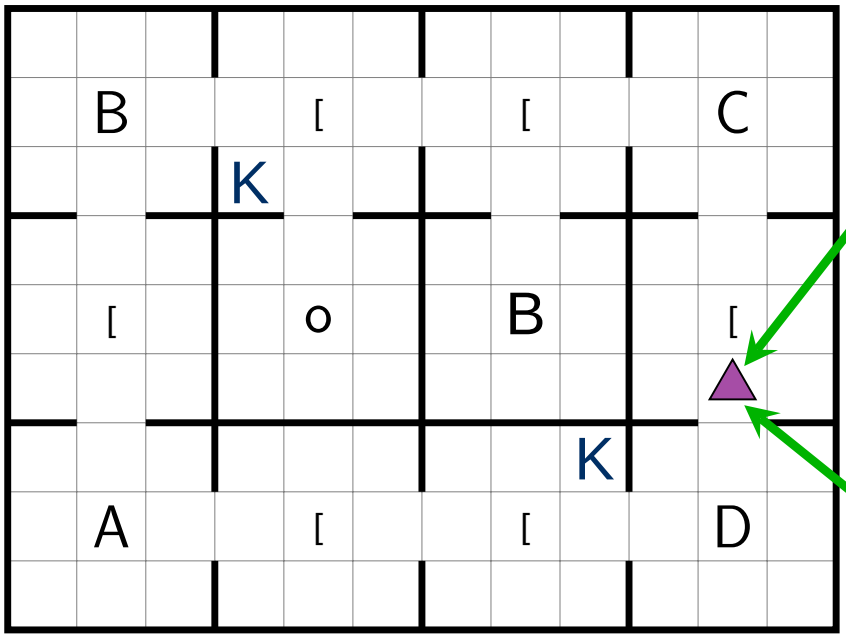


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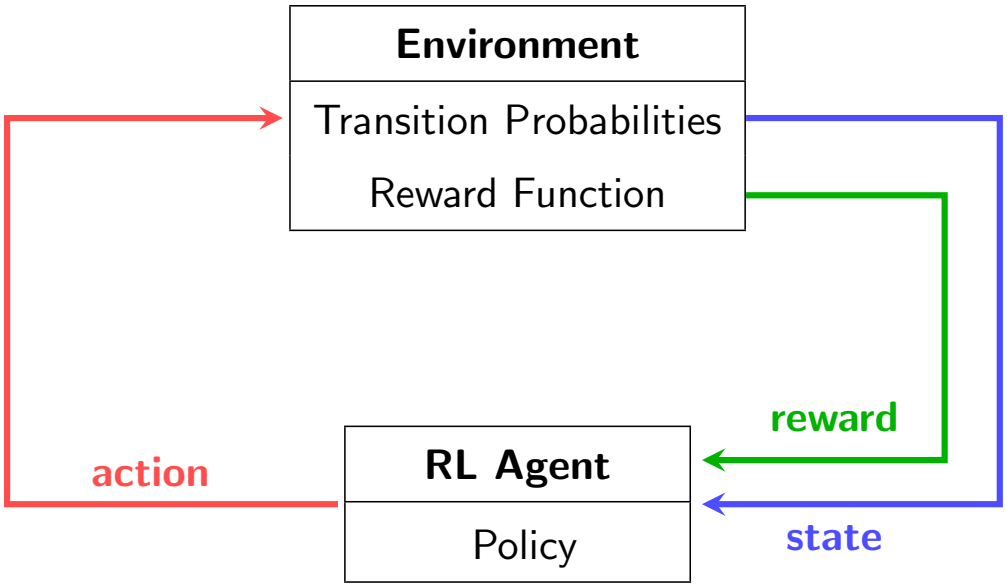
What if we give the agent access to the reward function?

Is there any advantage of doing do?
The agent can exploit the reward structure!

The simple idea



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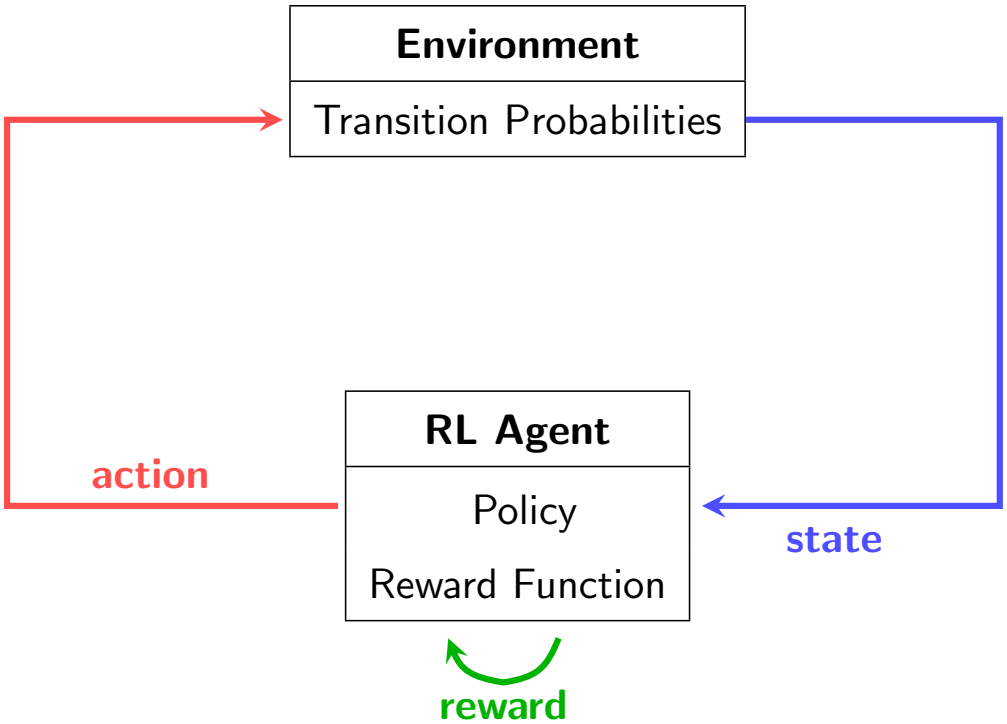

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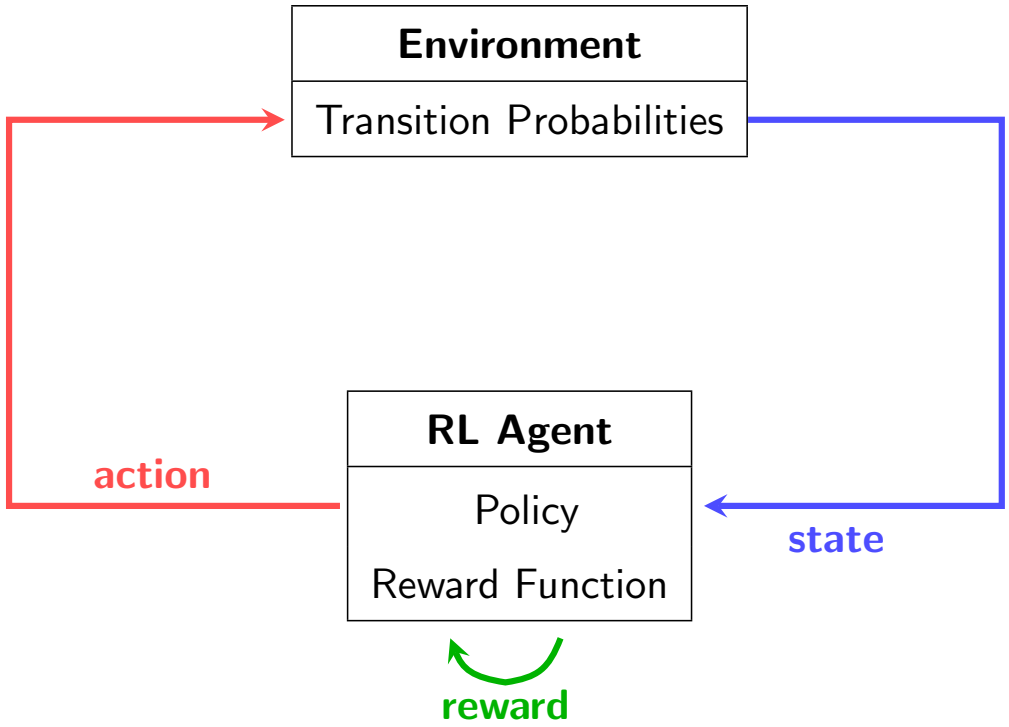
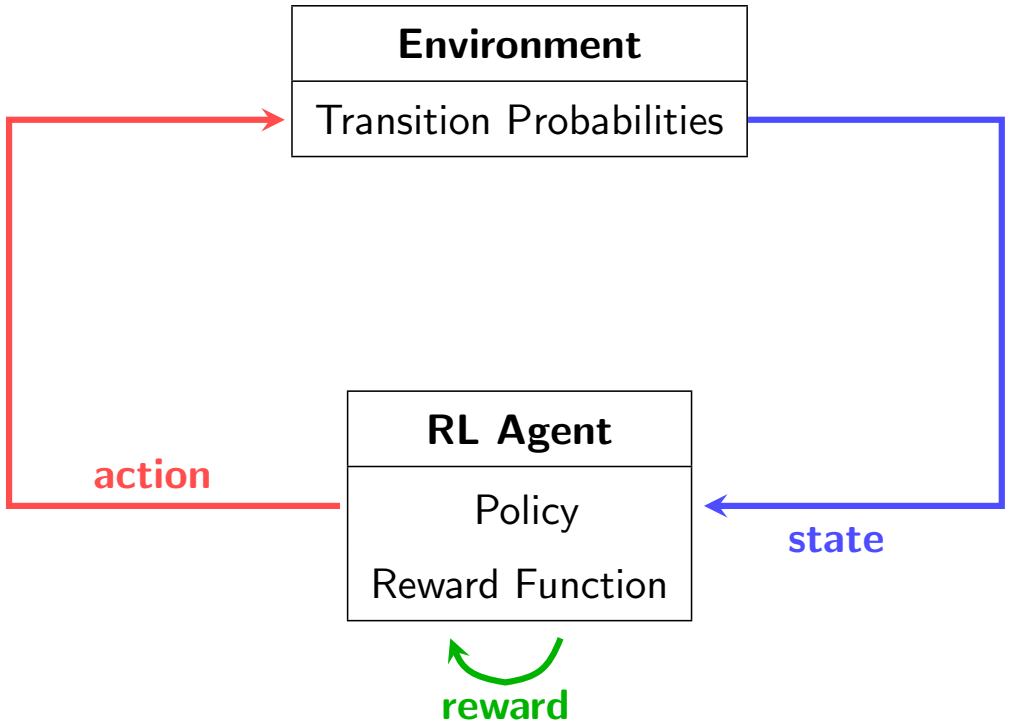


How to exploit the reward function definition

The simple idea



How to exploit the reward function definition

1. **RMs**: A novel language to define reward functions.
2. **QRM**: An RL algorithm that exploits RM's structure.

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We encode reward functions using a finite state machine.

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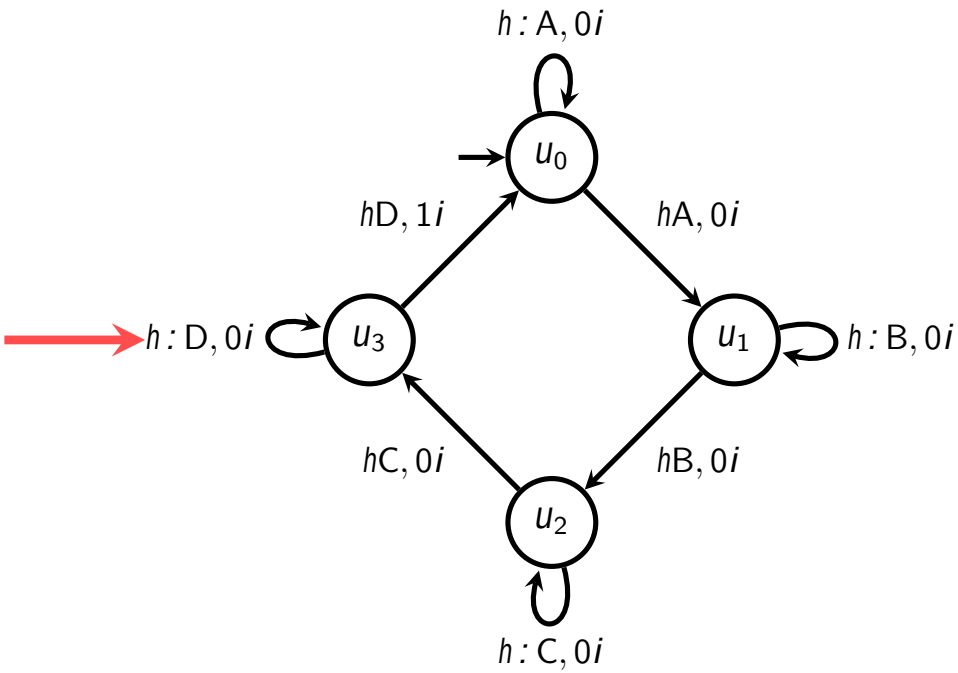
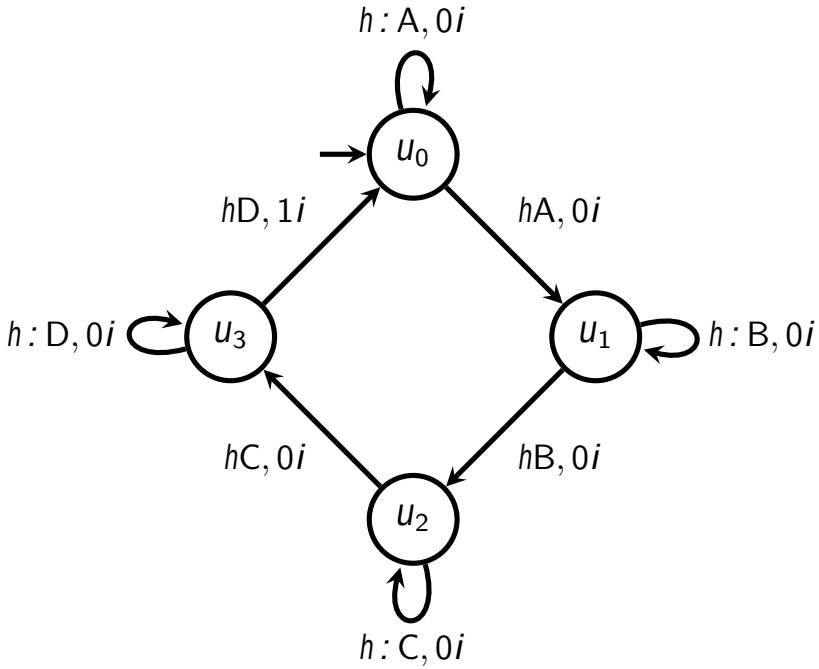


Reward machines

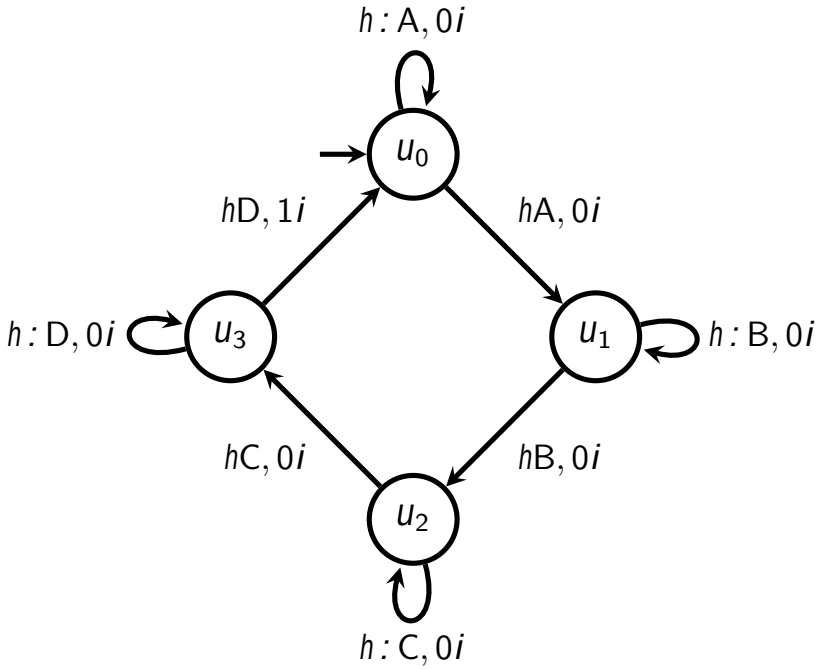
A reward machine



Reward machines

A reward machine

A finite set of states U



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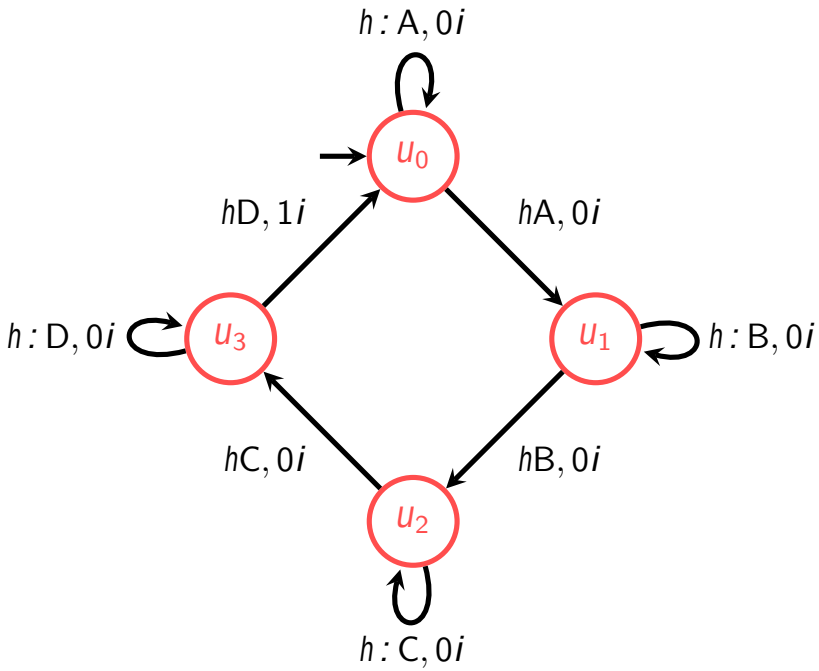

Reward machines

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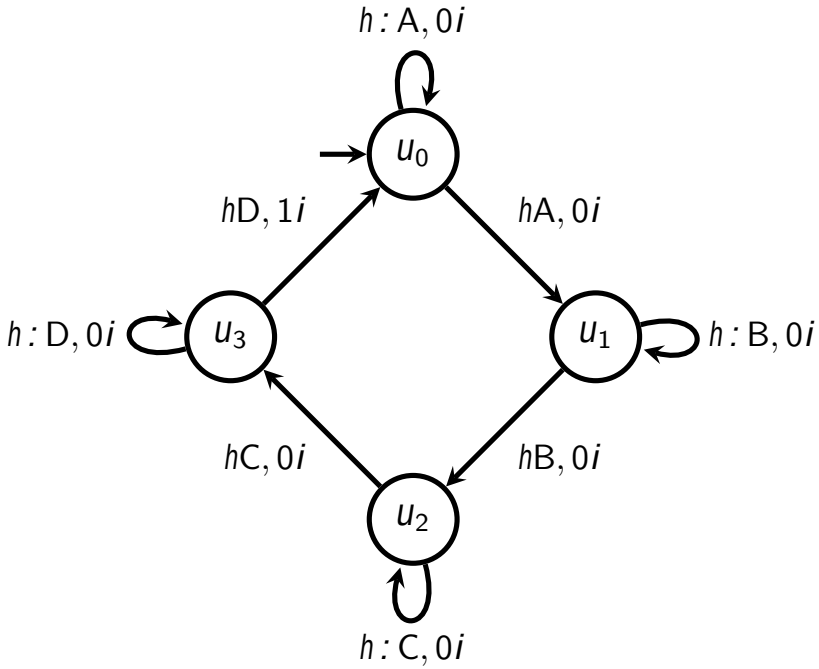
An initial state u_0 *2* U



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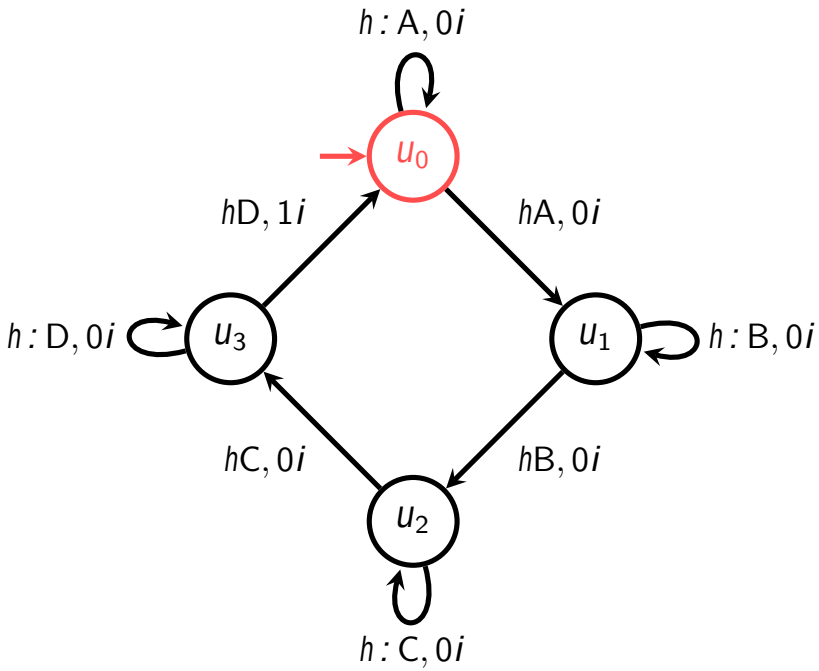

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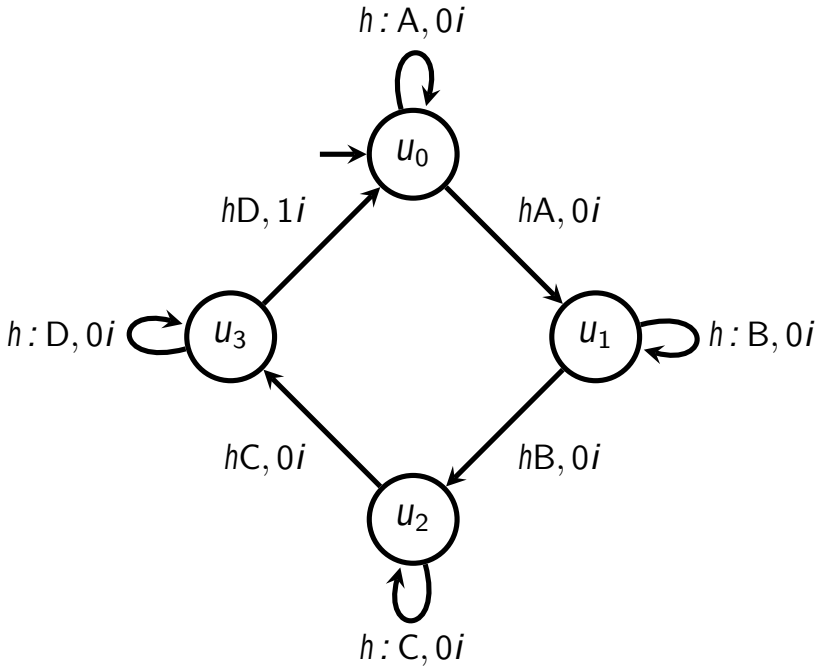

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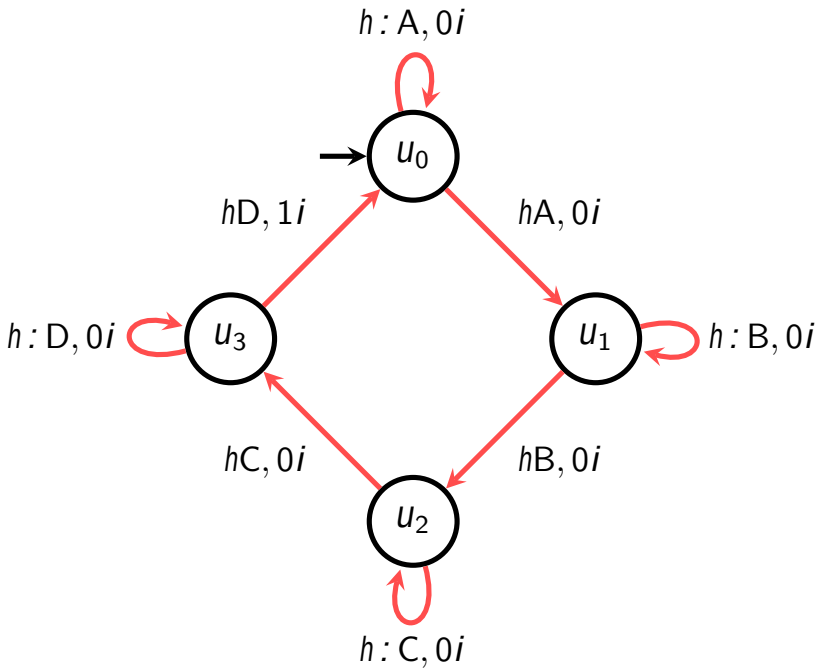

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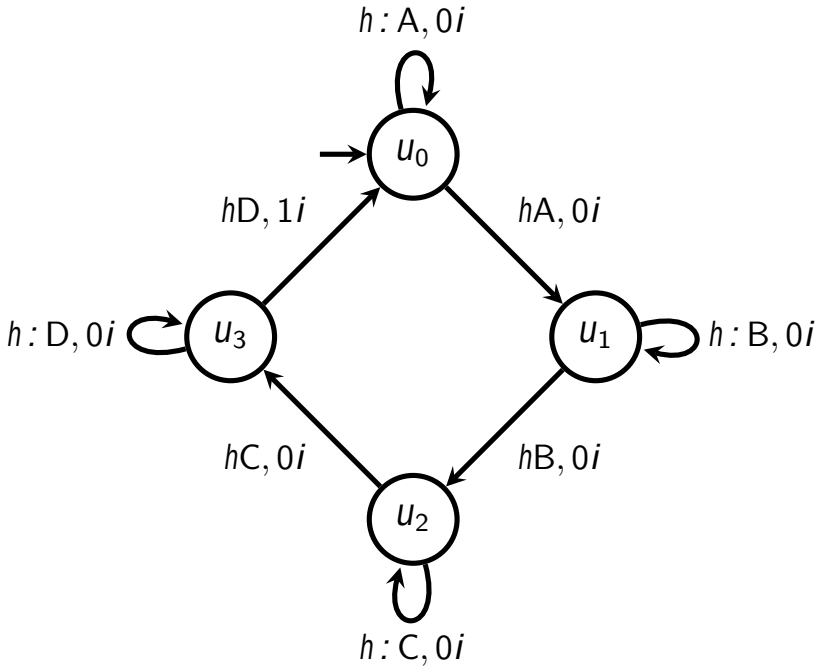

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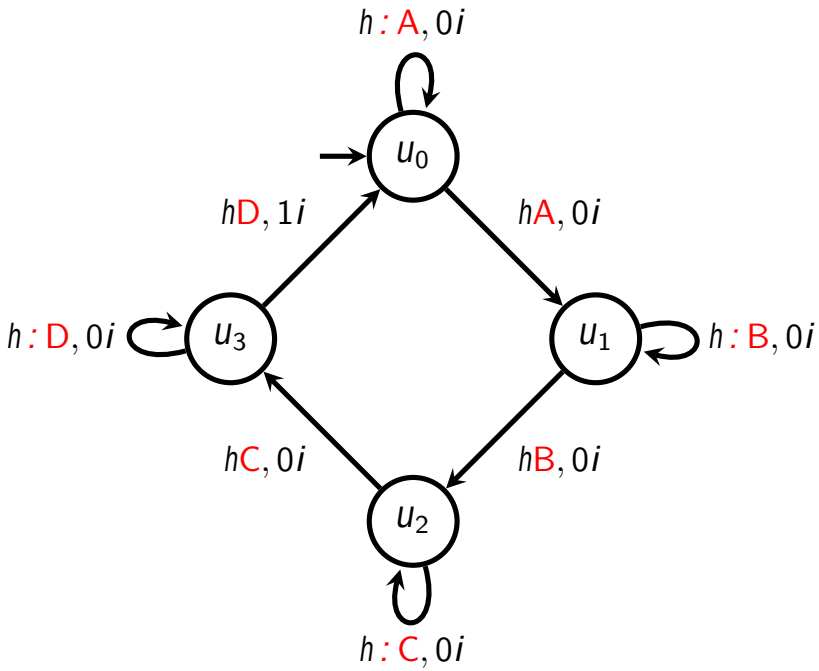

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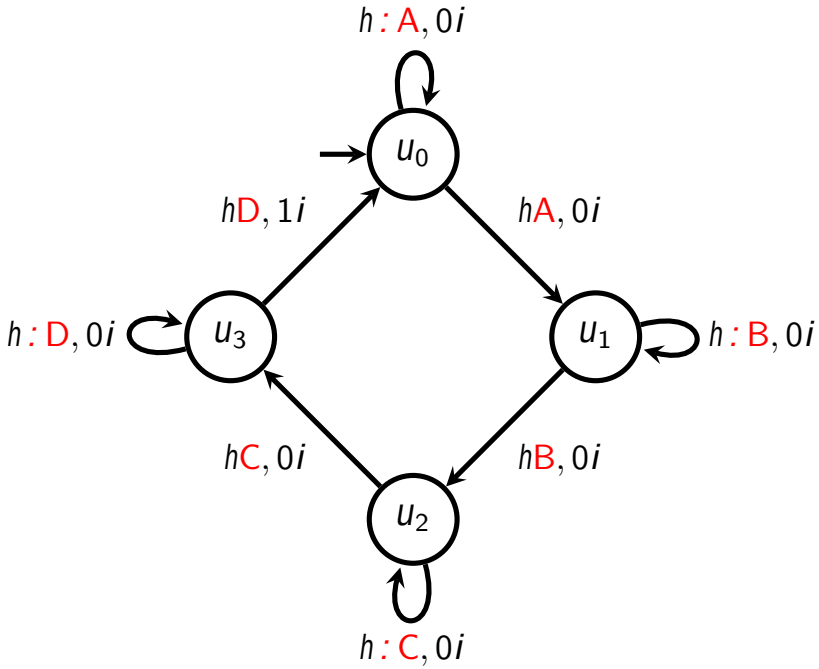

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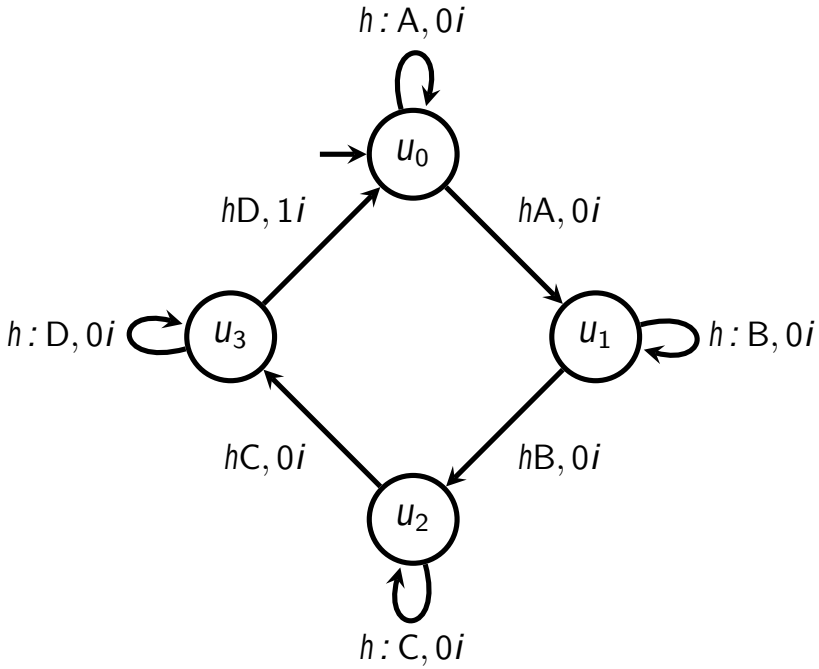

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Reward machines

A **simple** reward machine

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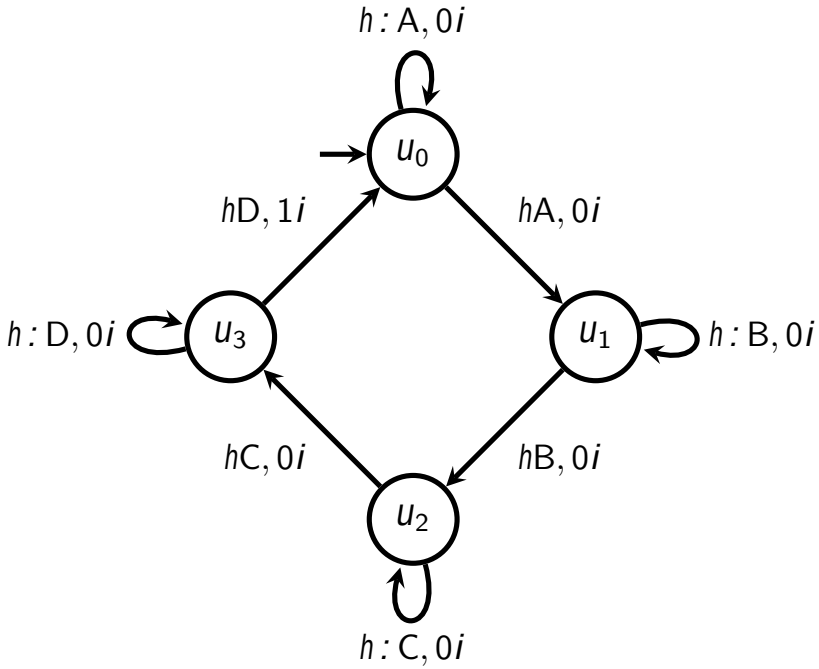

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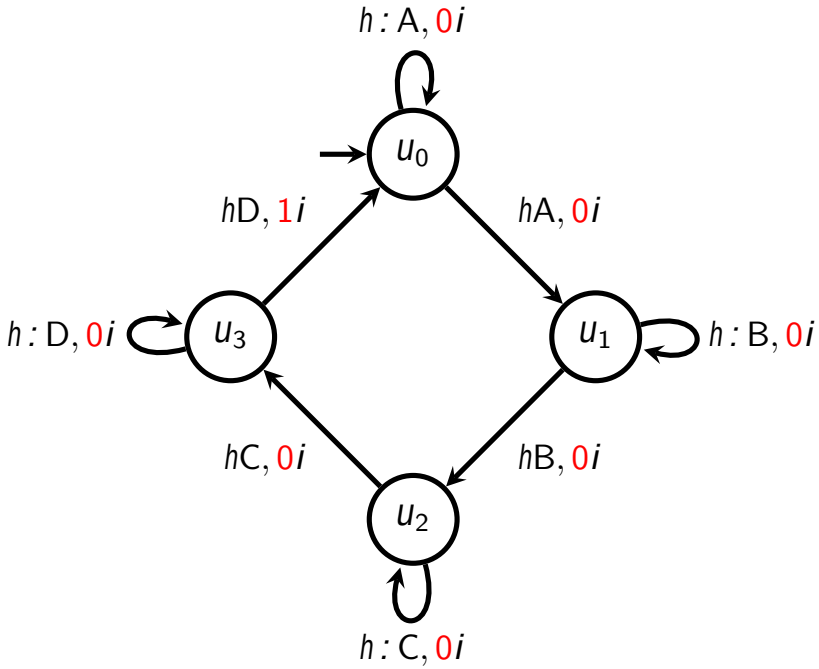
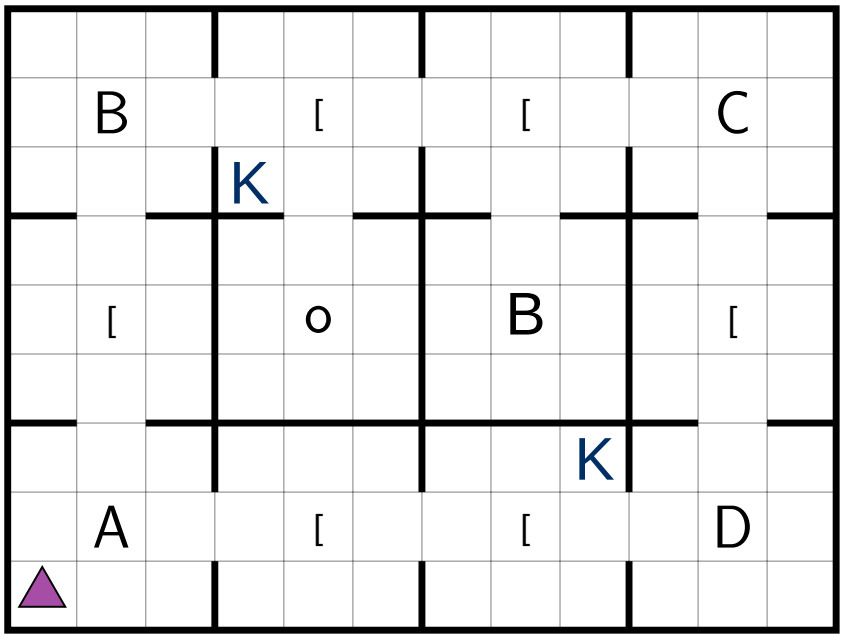
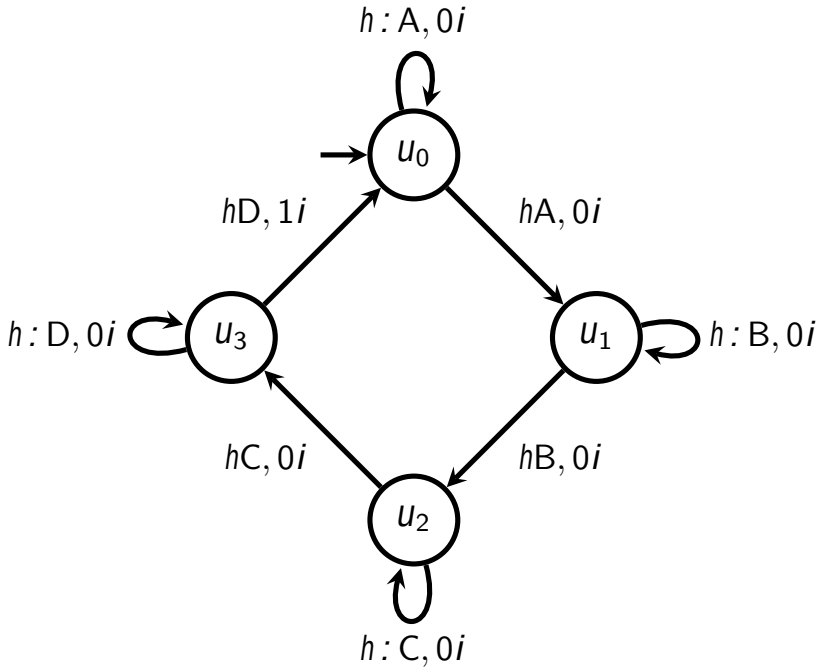


Conditions are over properties of the current state:

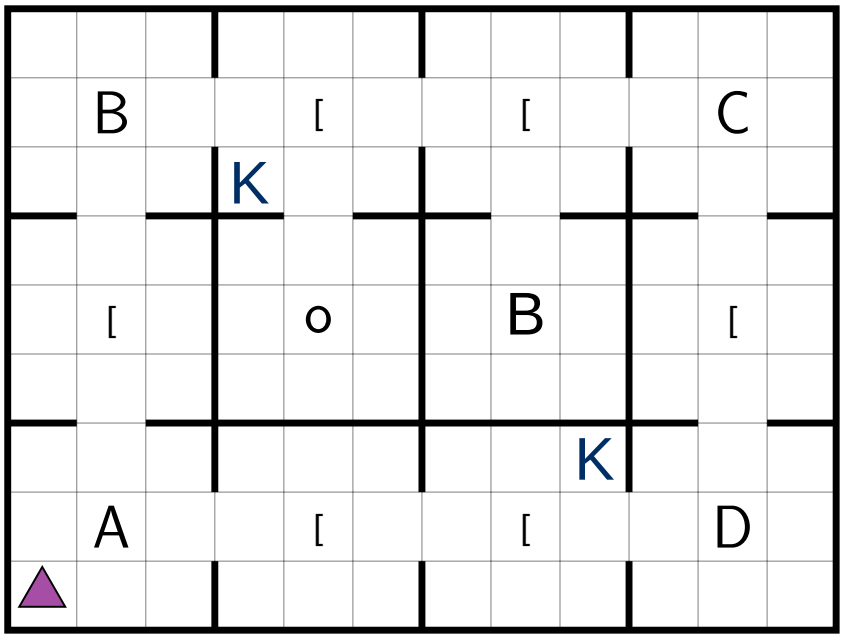
$$P = f\mathrm{K}, \mathrm{B}, o, [, A, B, C, Dg$$

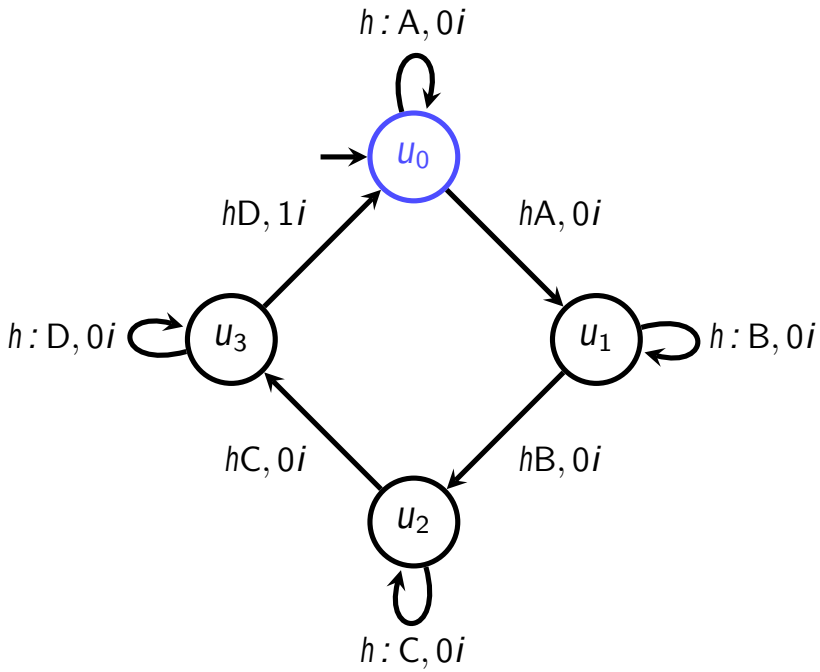
Reward machines in action



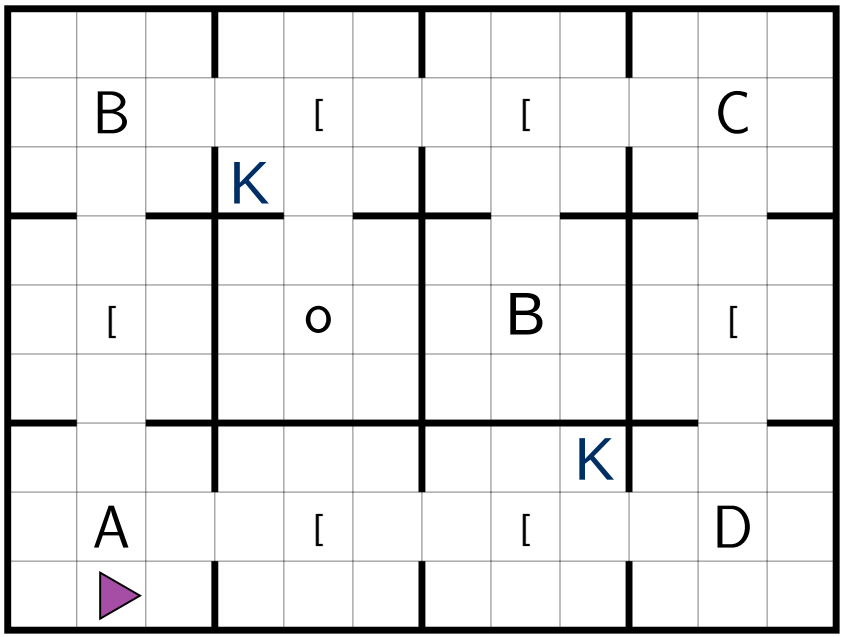


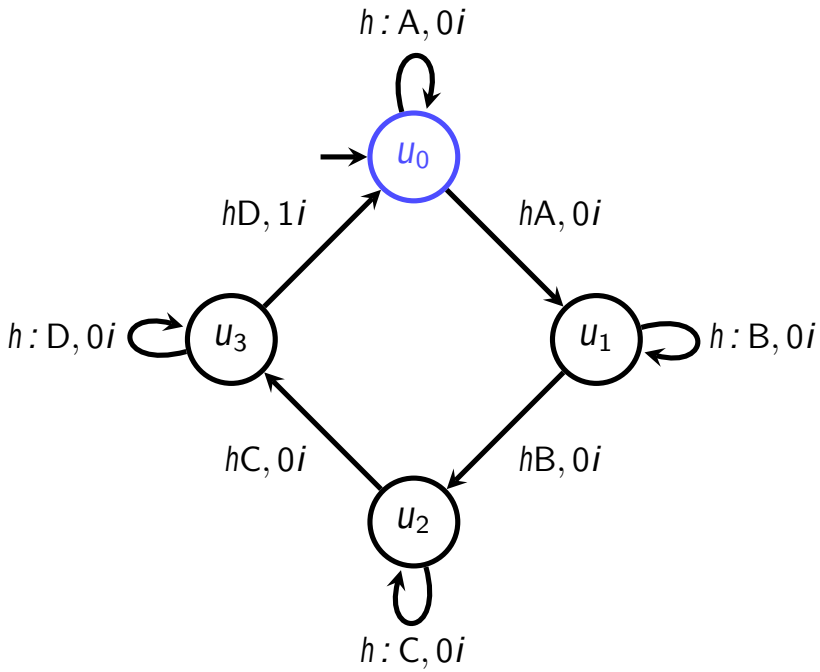
Reward machines in action



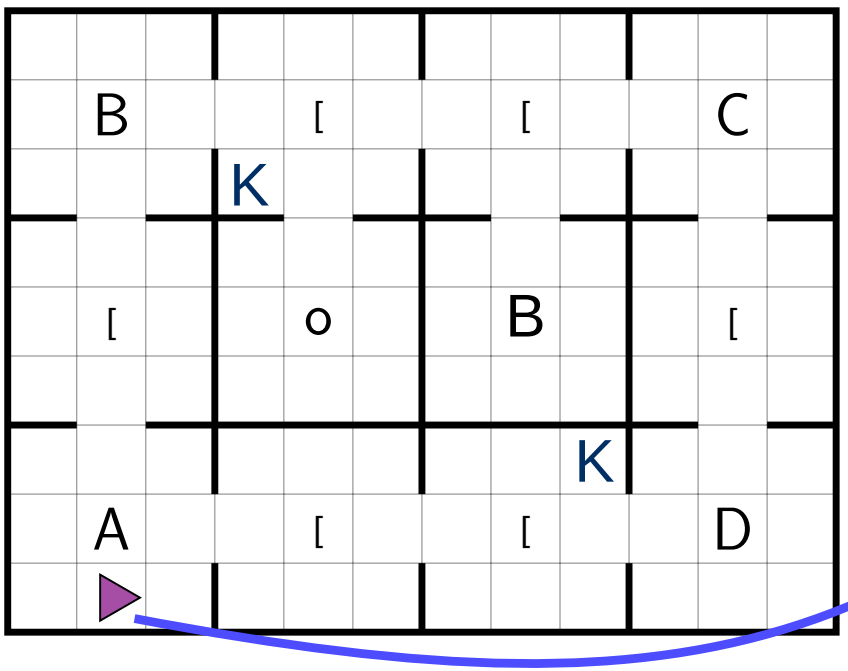


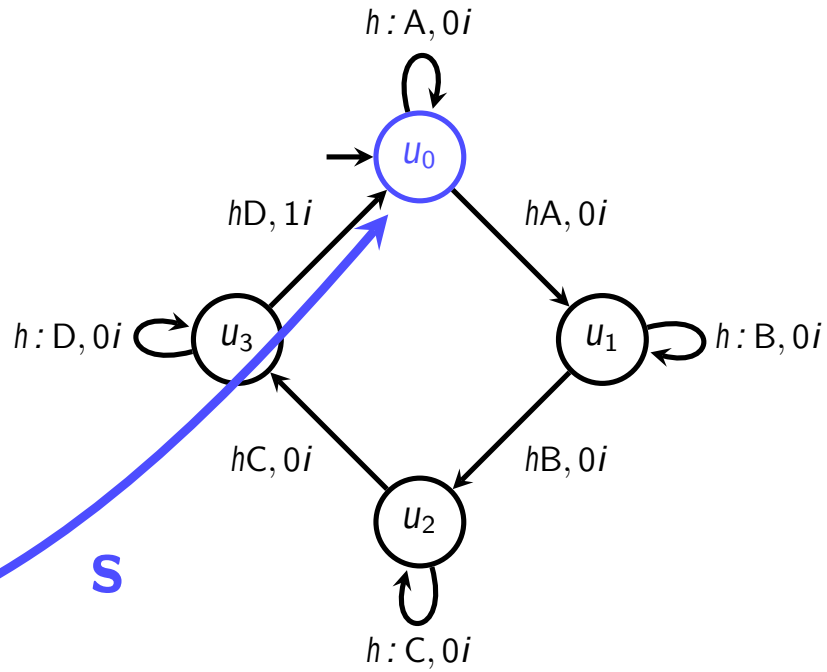
Reward machines in action





Reward machines in action





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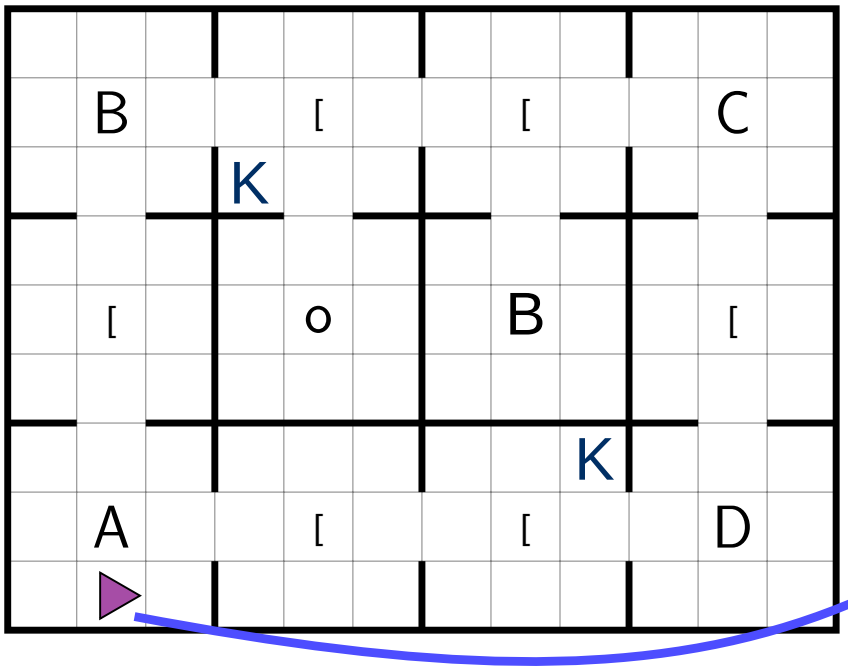
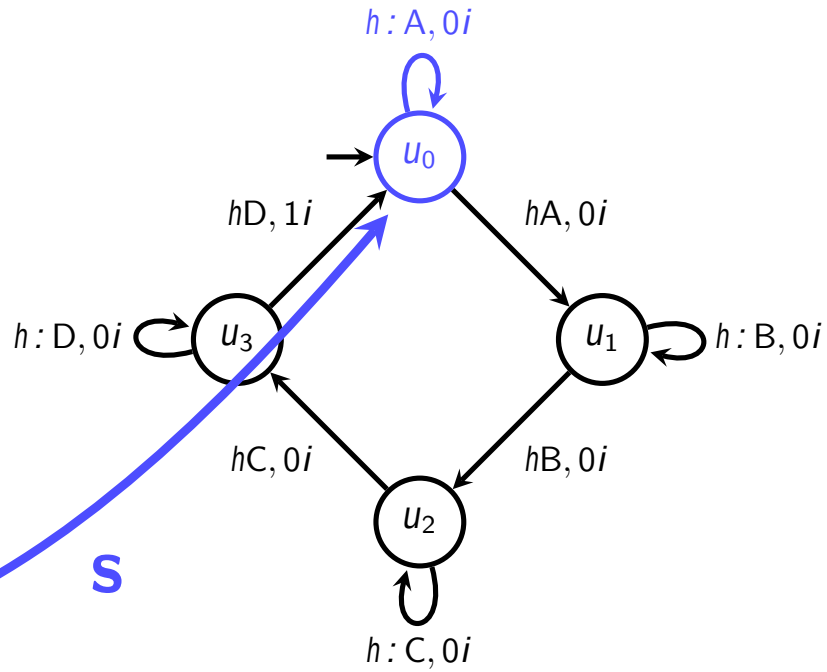
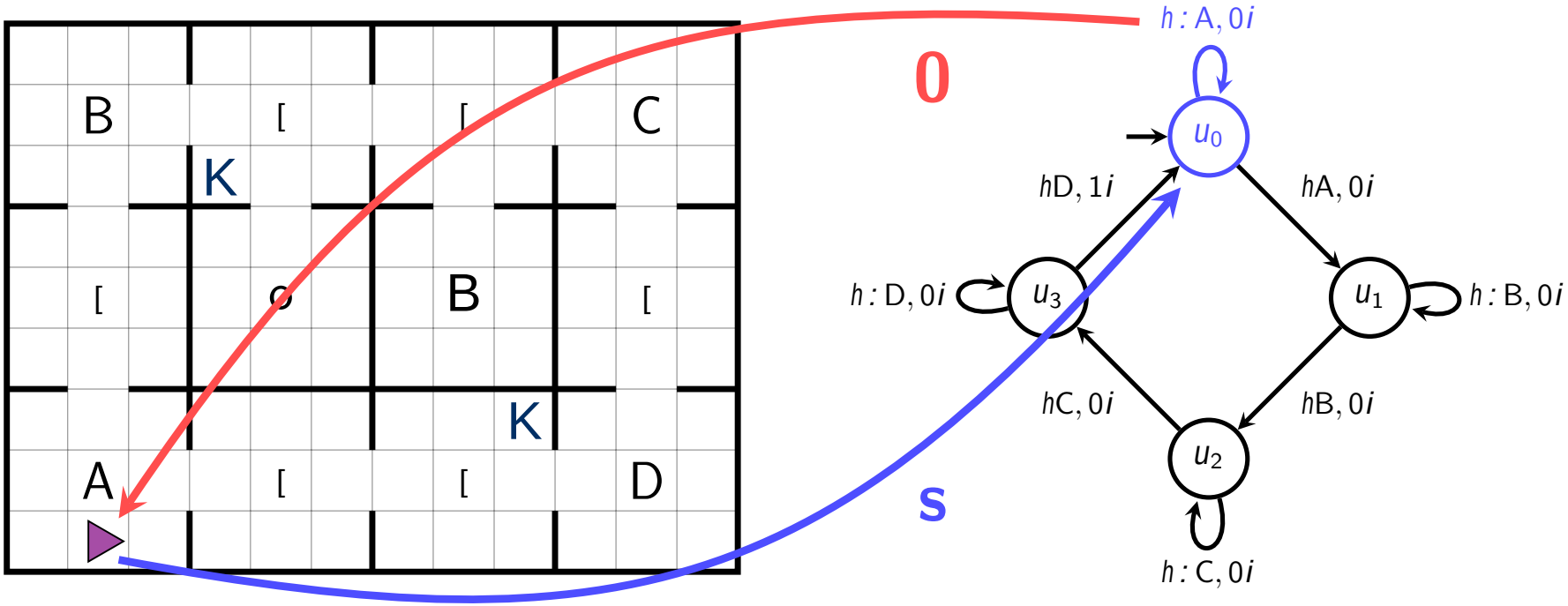
Reward machines in action

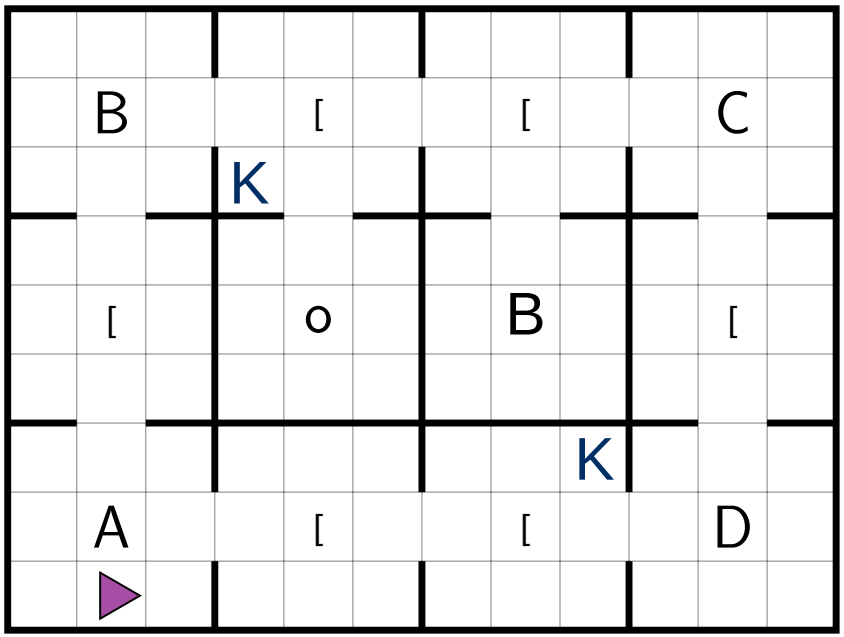


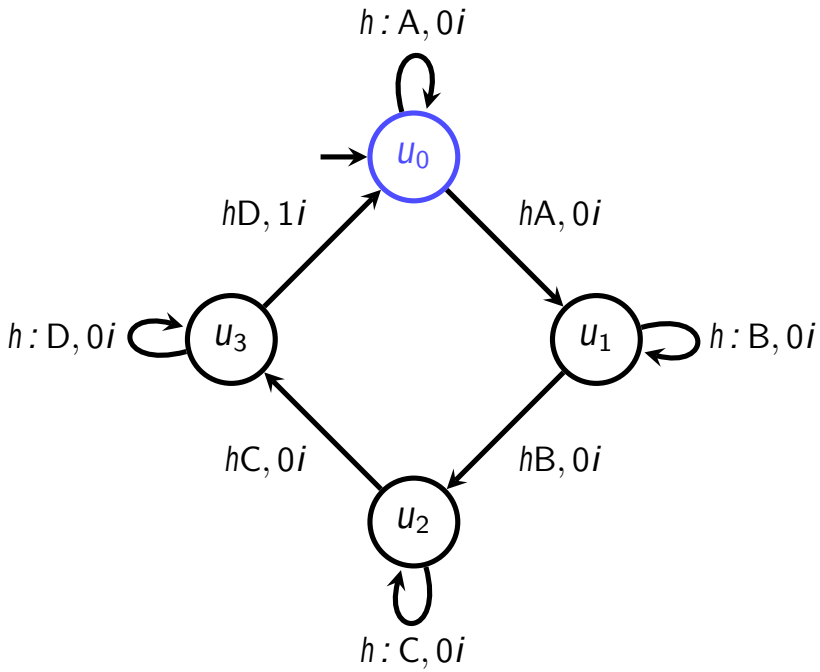


Reward machines in action



Reward machines in action





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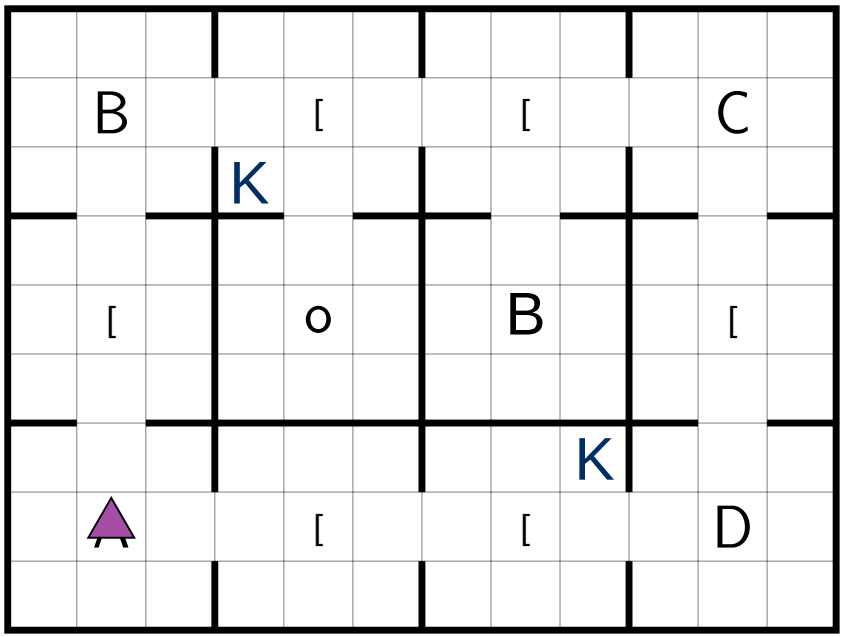

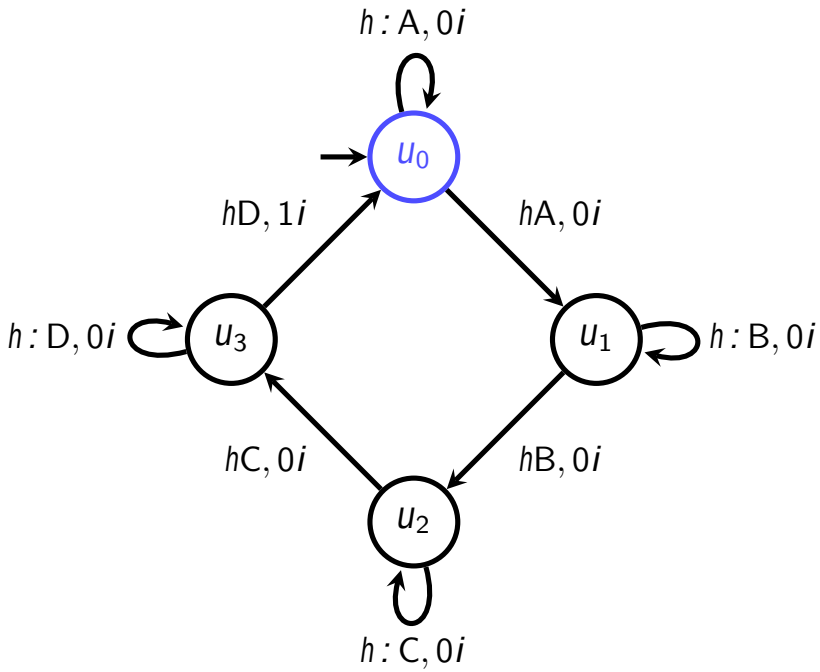

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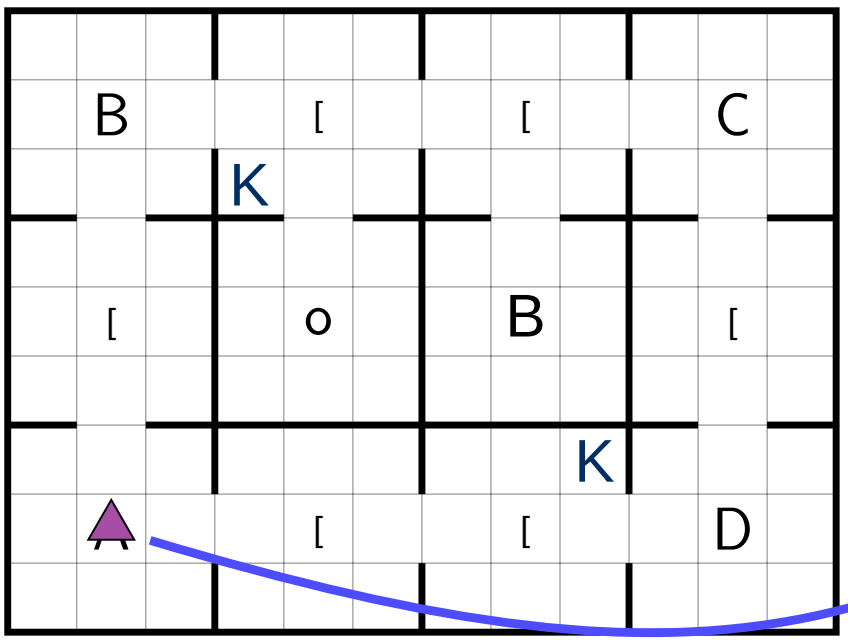

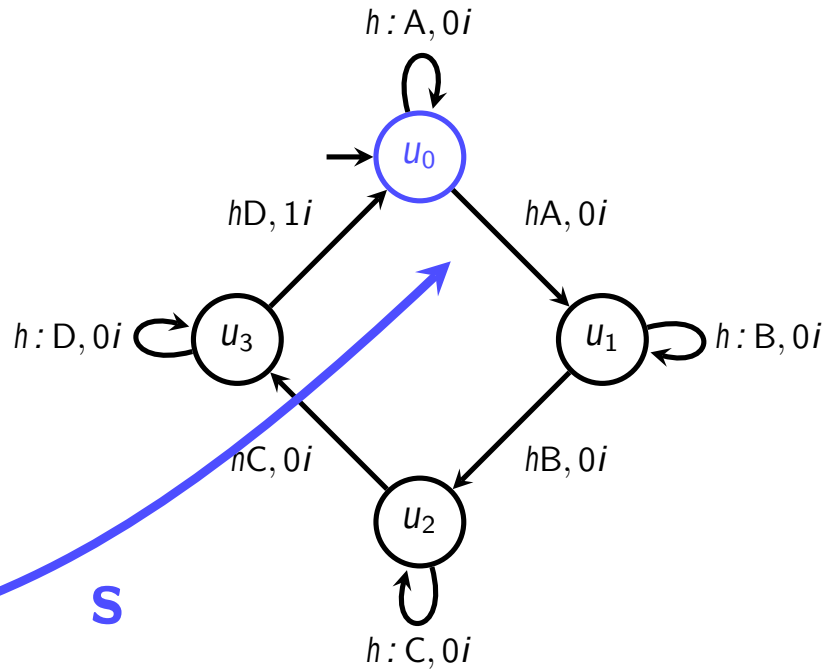

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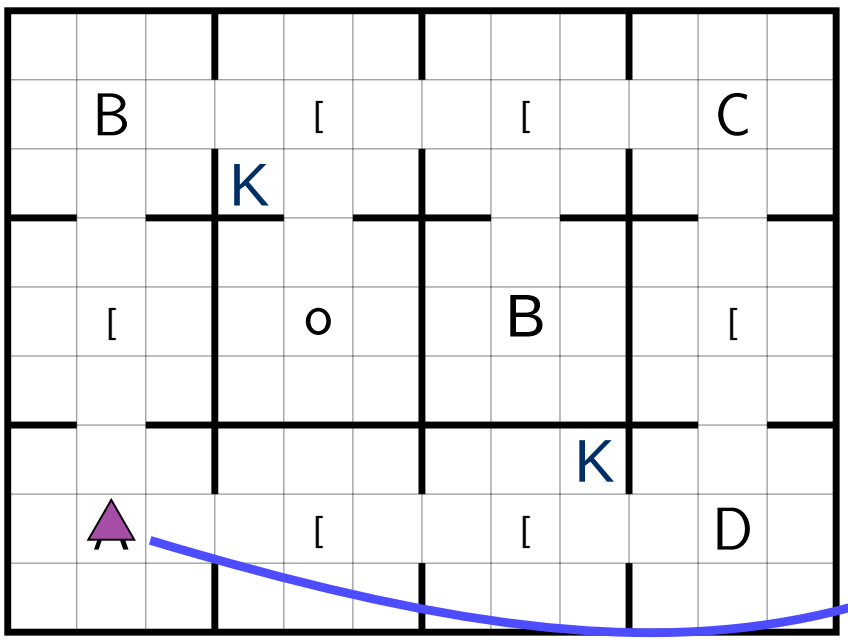
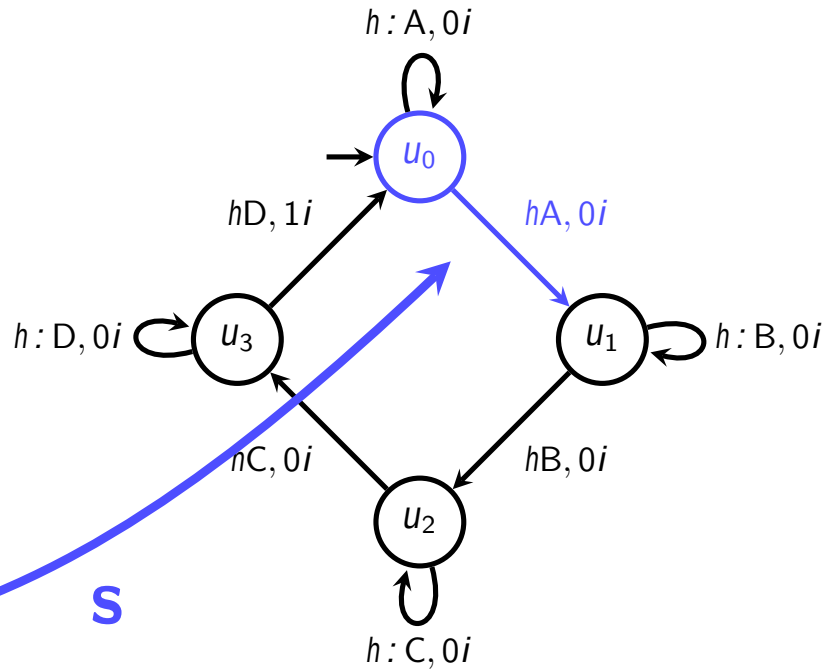
Reward machines in action





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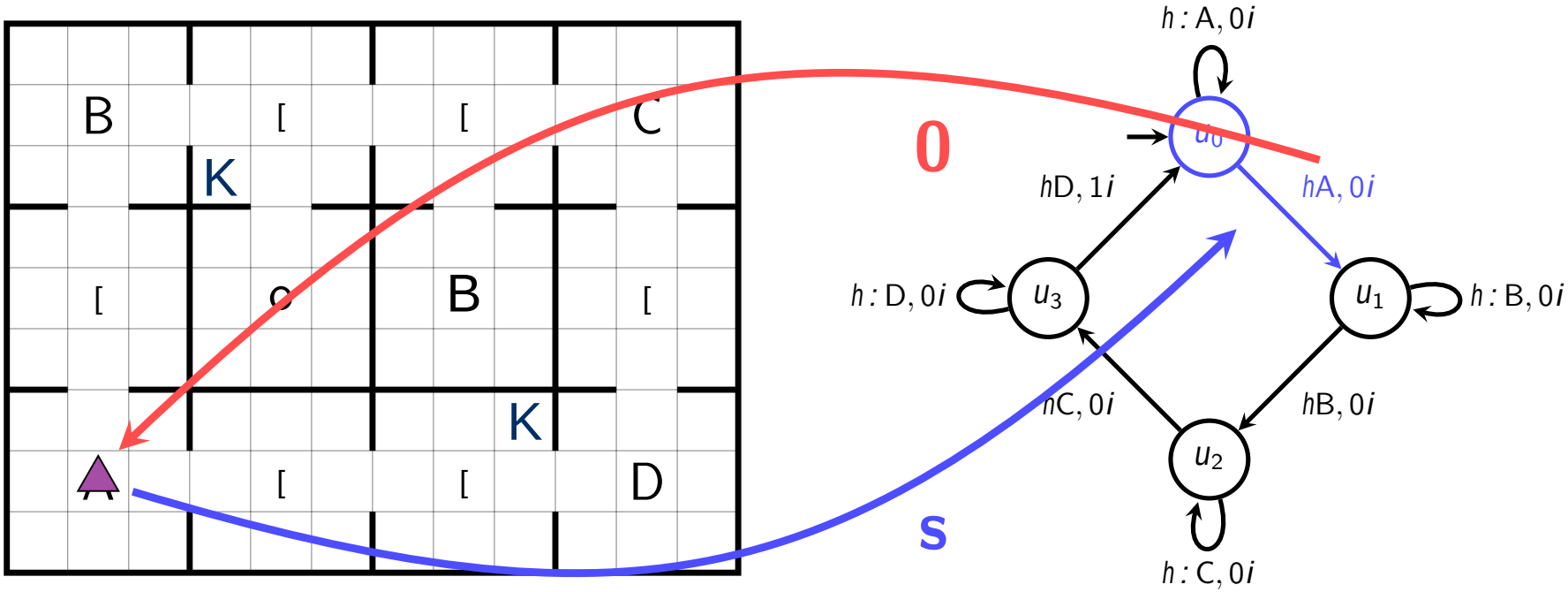
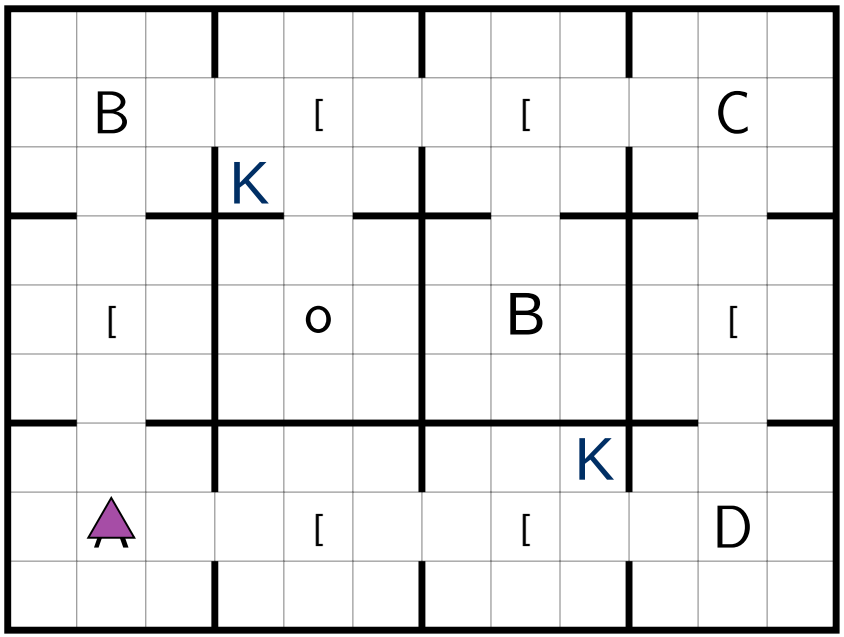
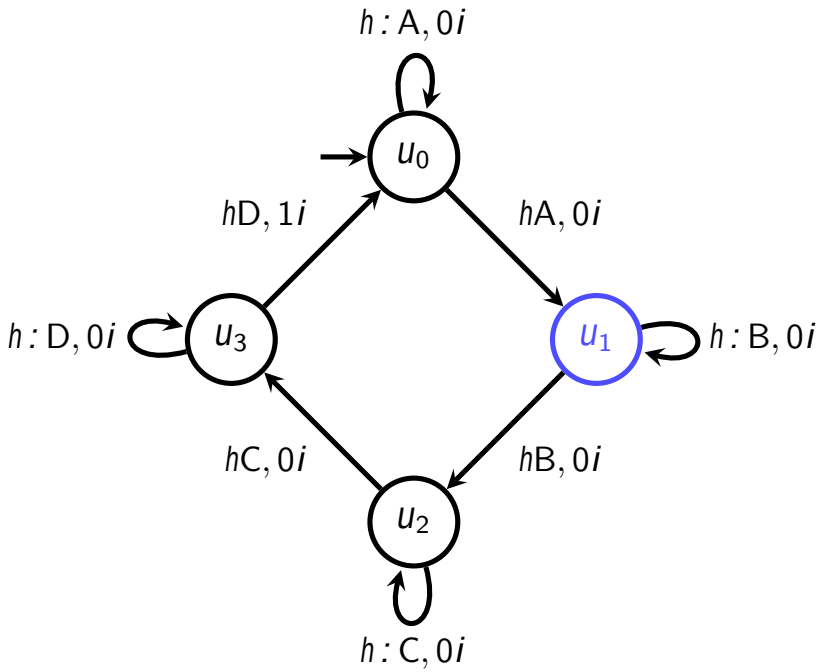
Reward machines in action

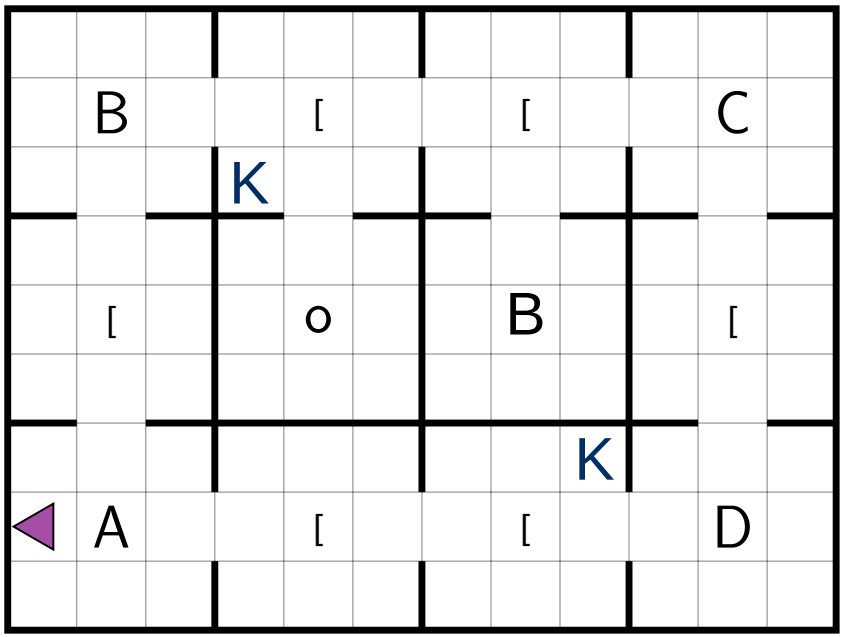


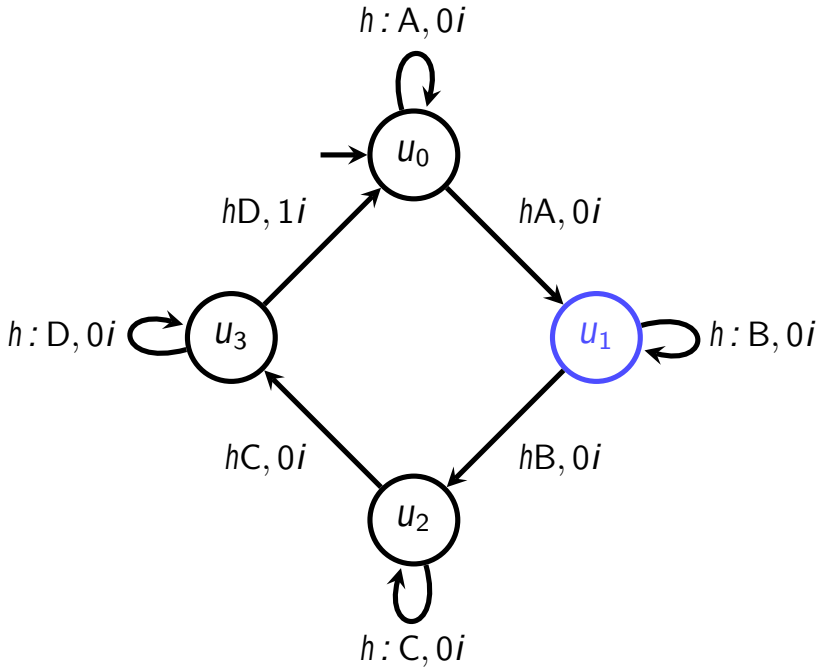
Reward machines in action



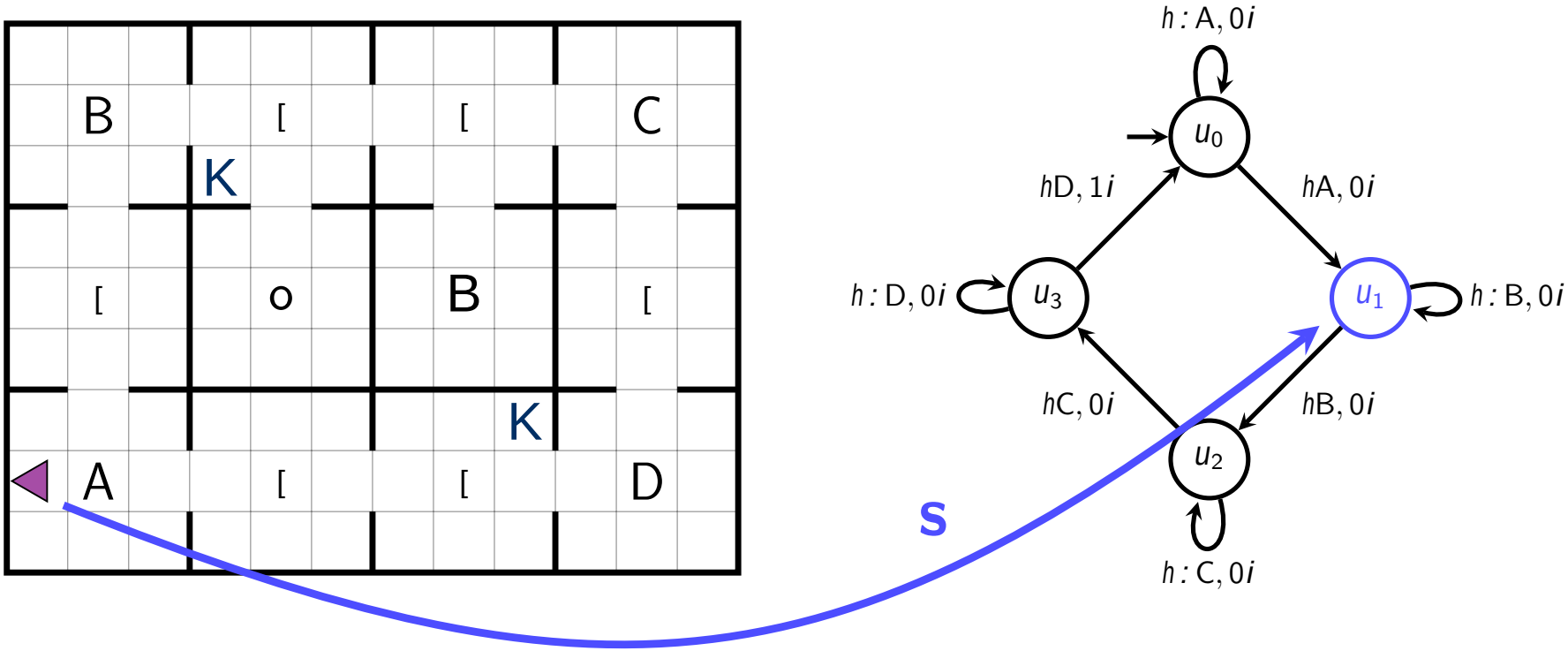


Reward machines in action





Reward machines in action



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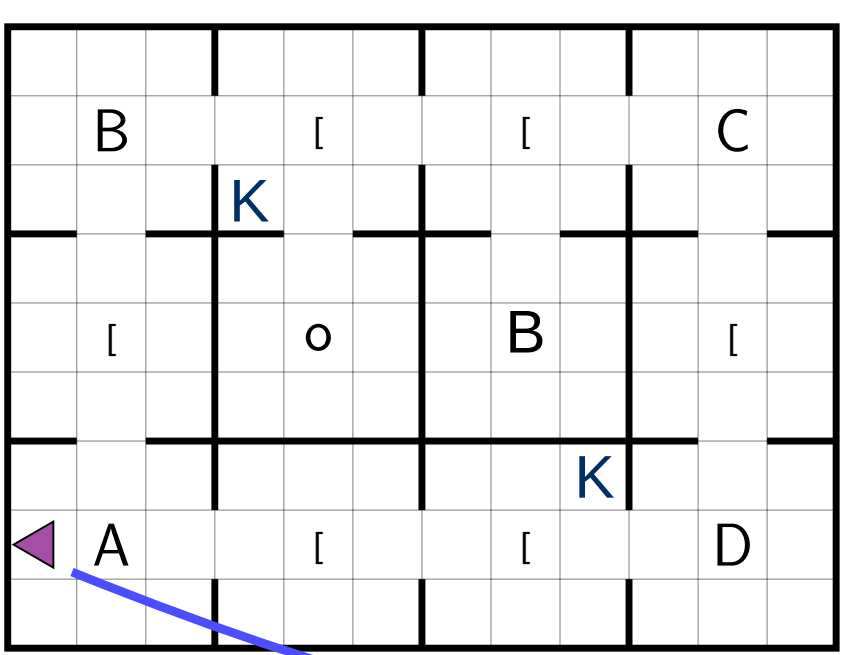

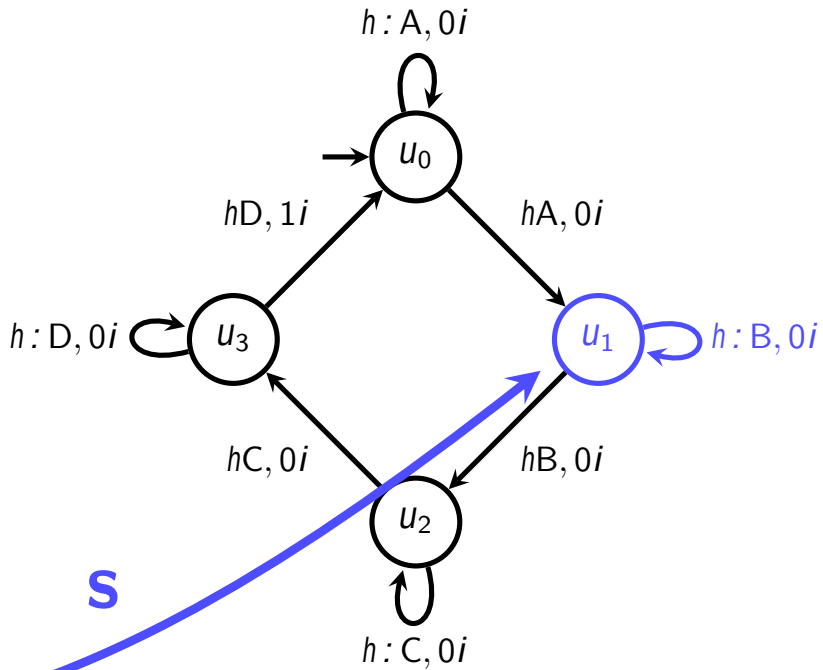

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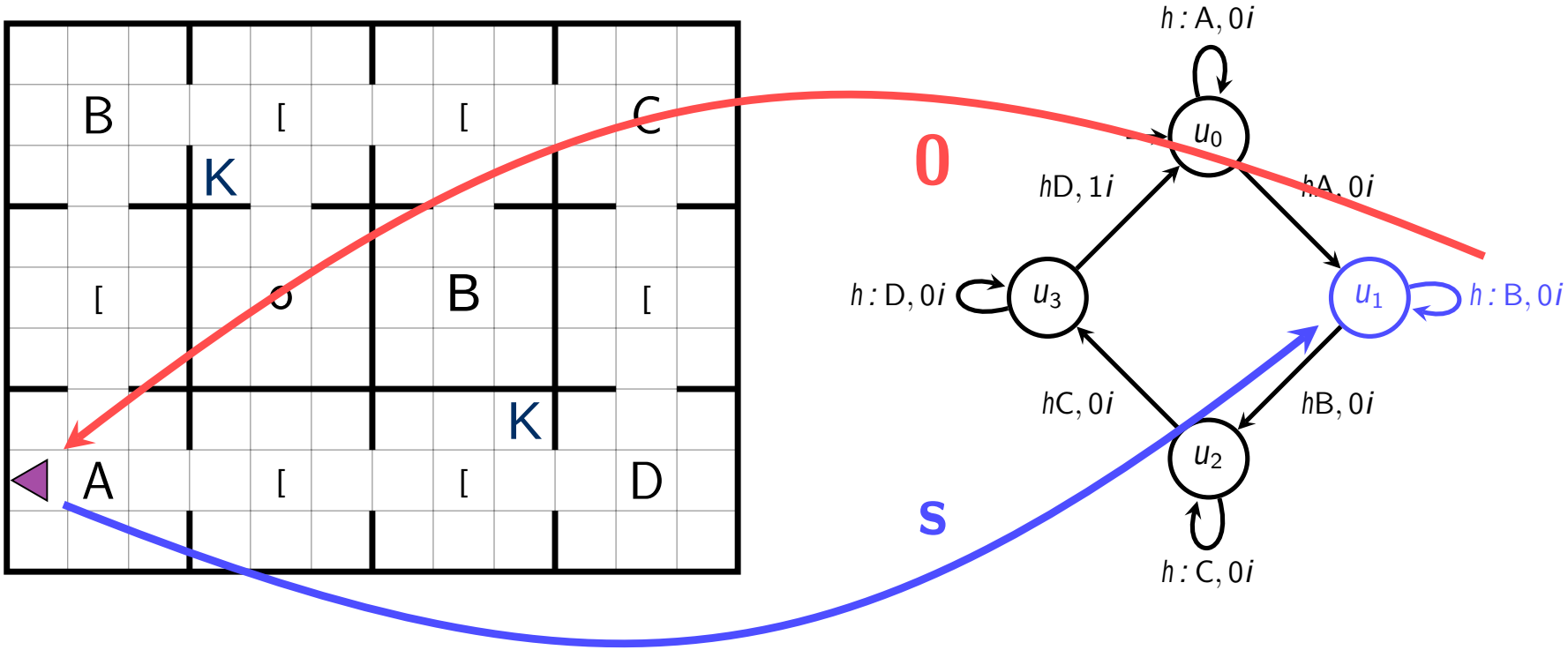

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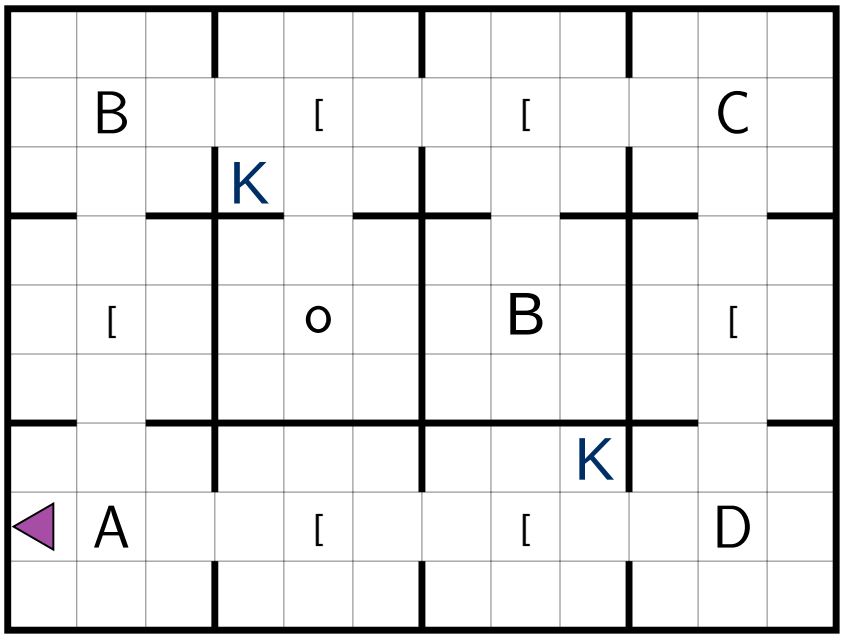

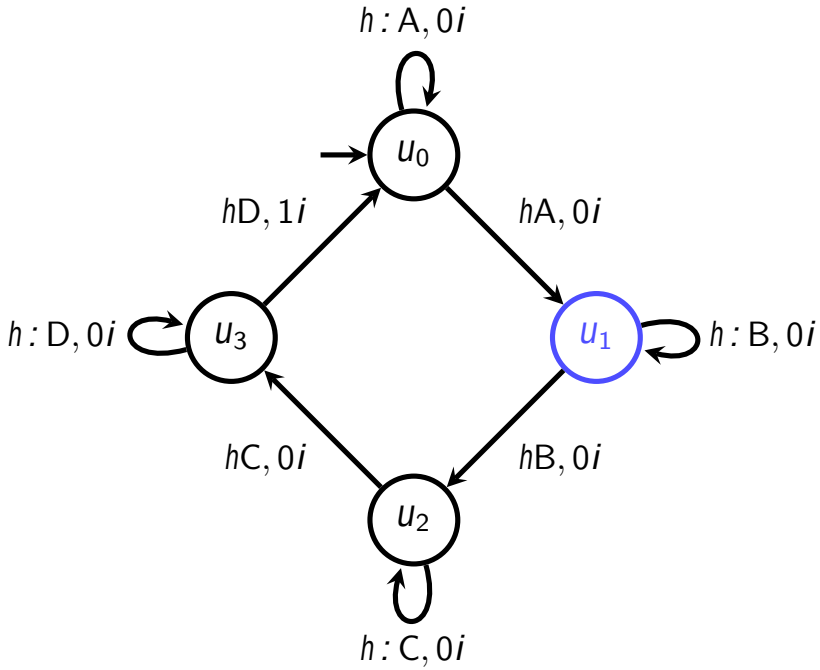

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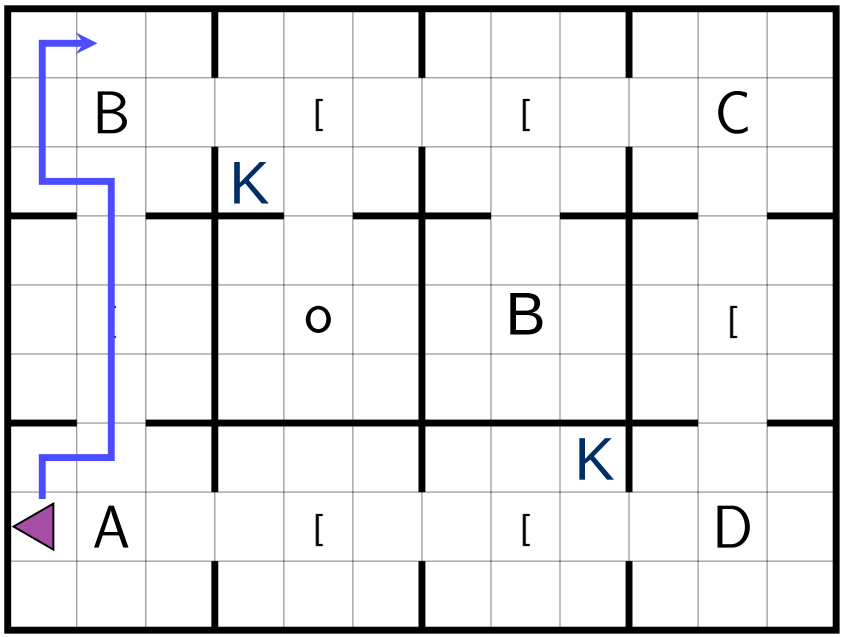

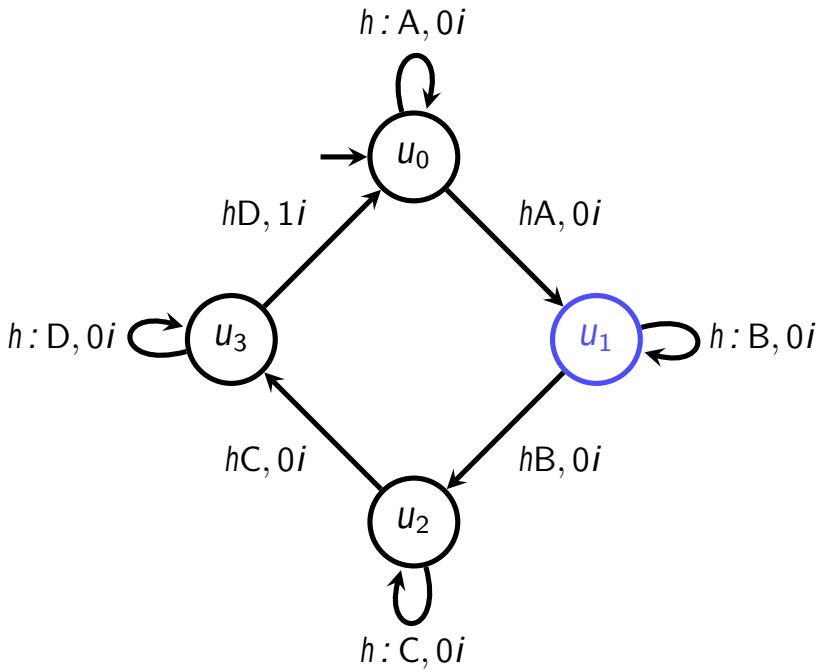

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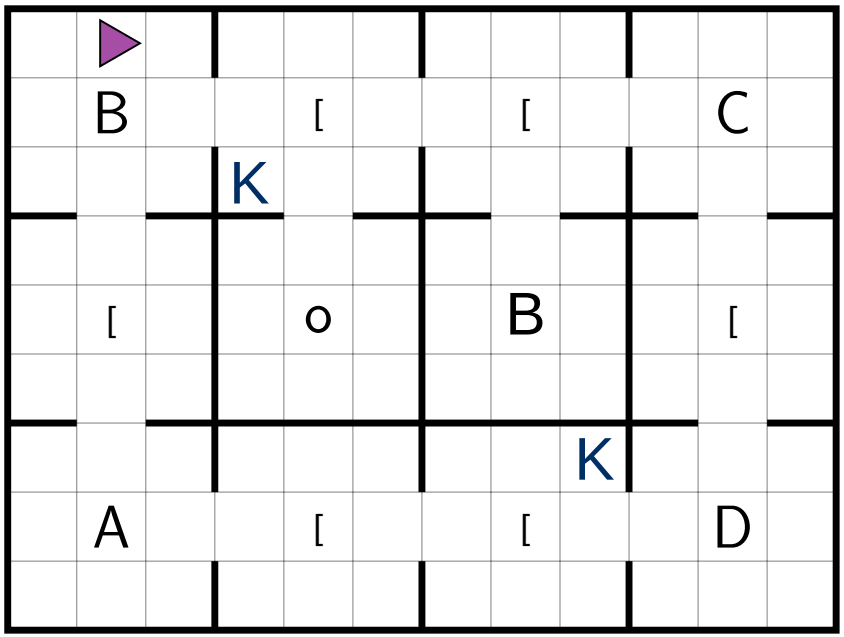

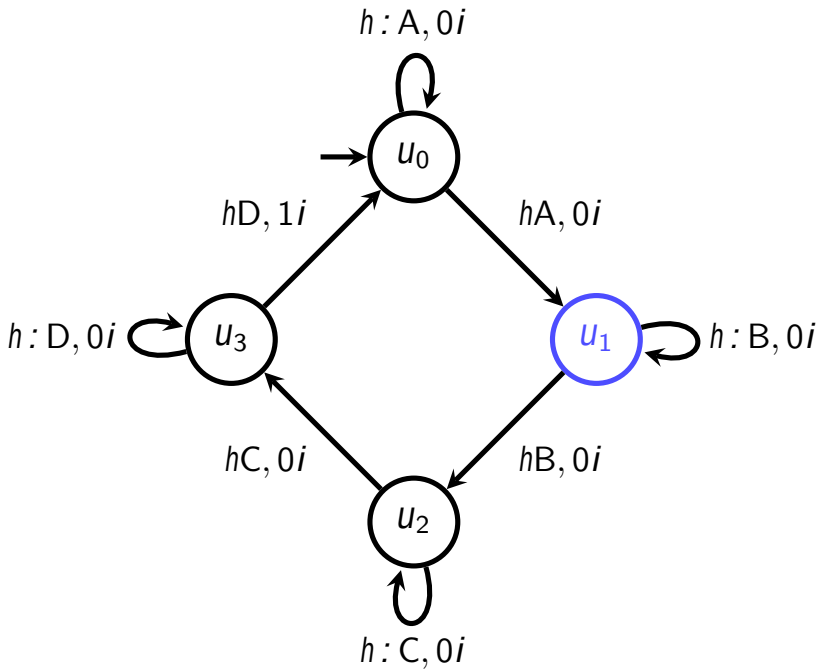

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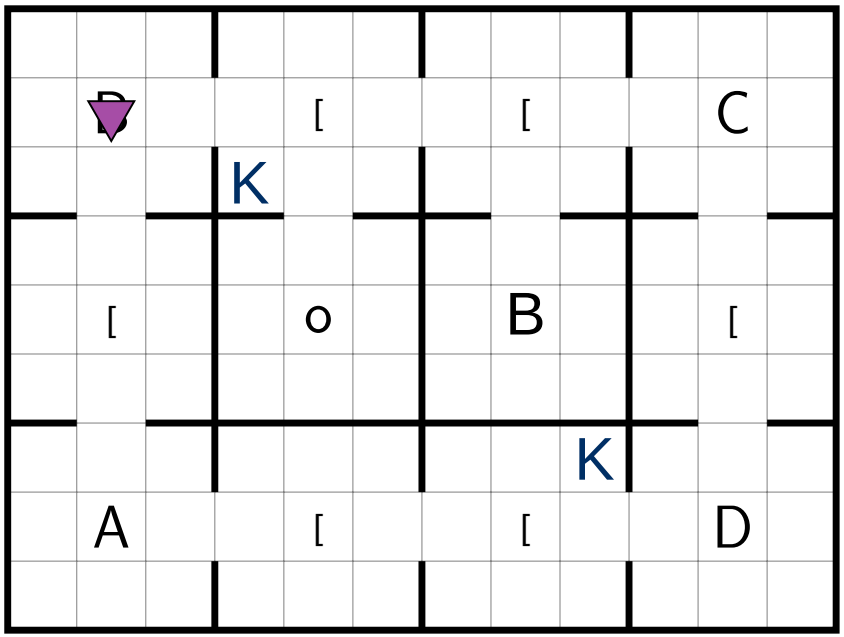

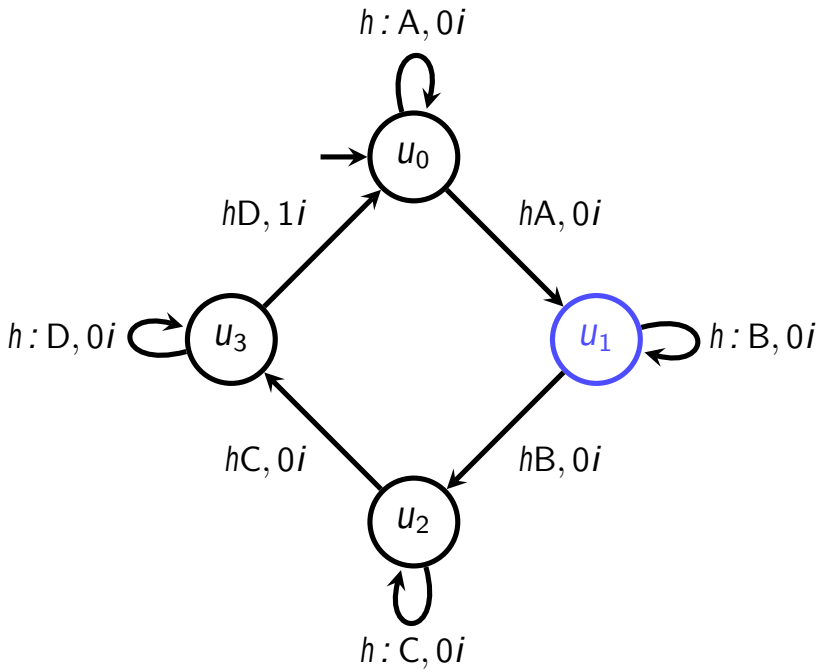

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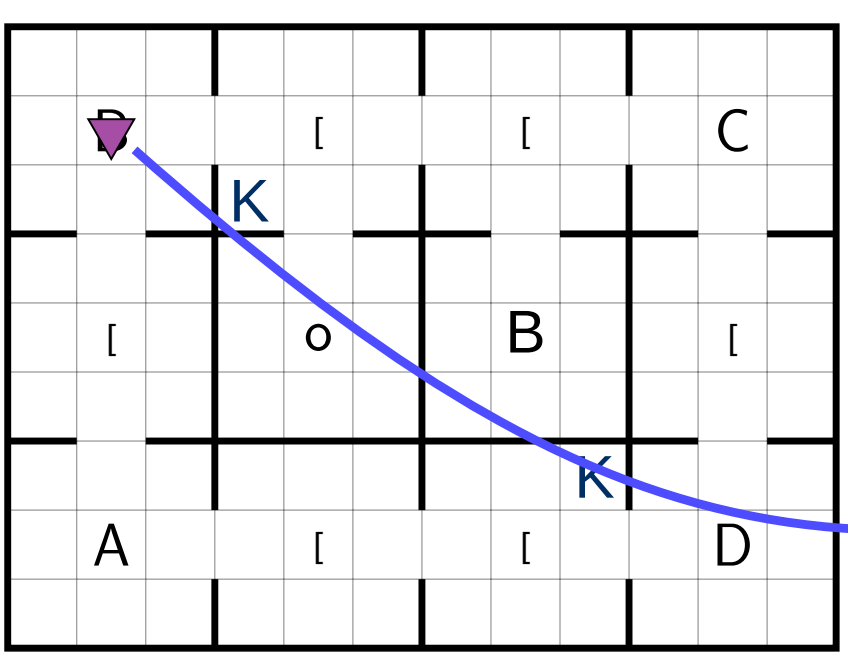

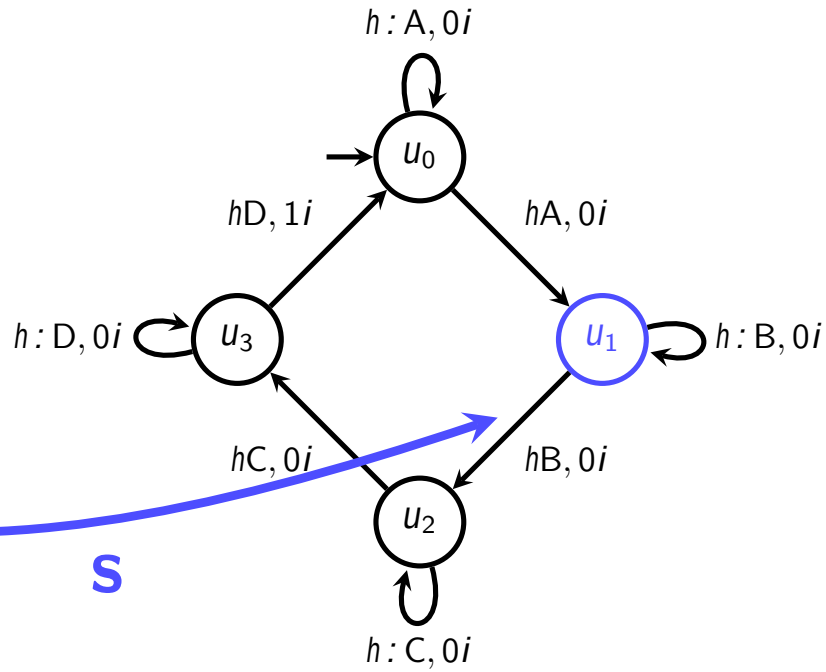

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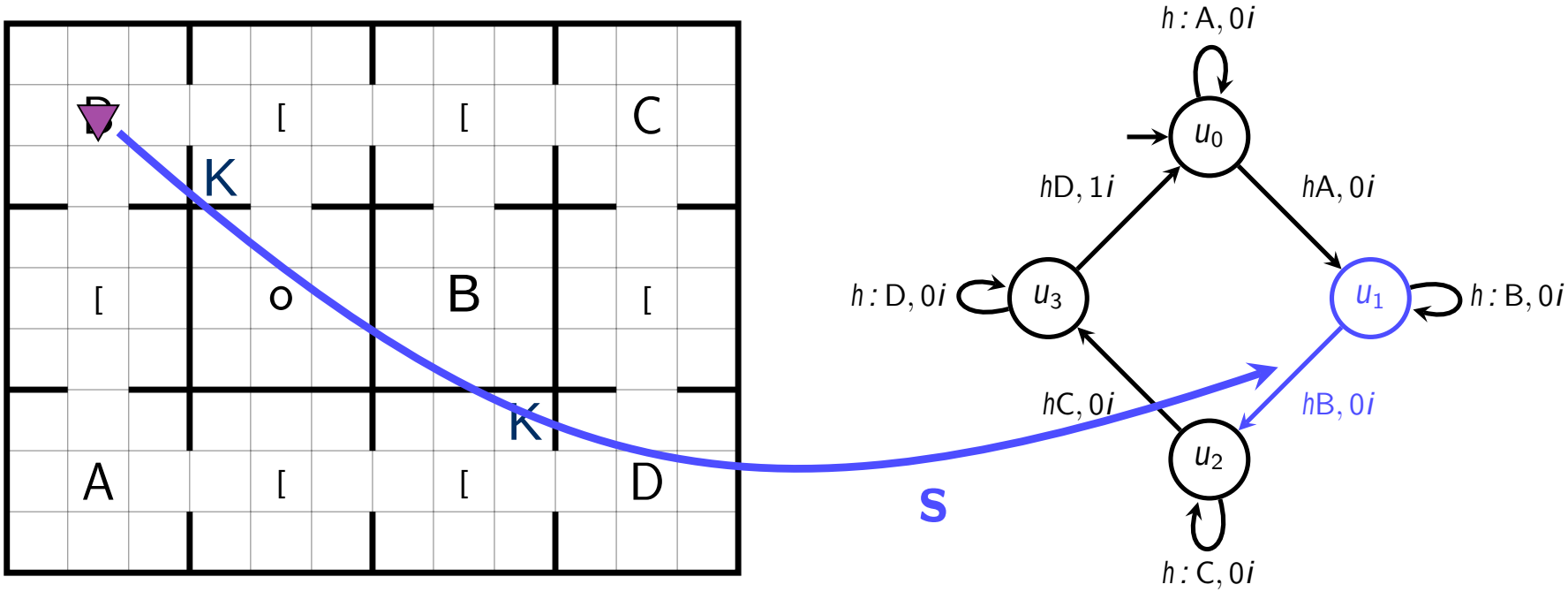
Reward machines in action



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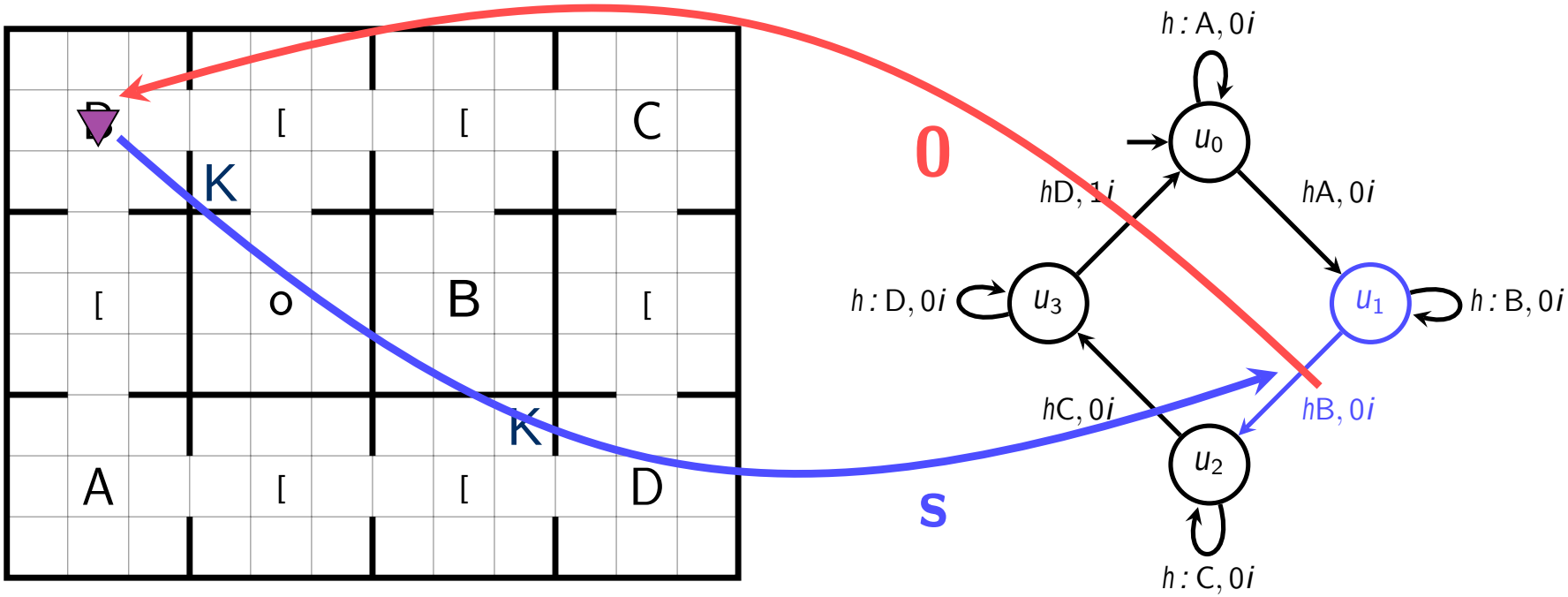

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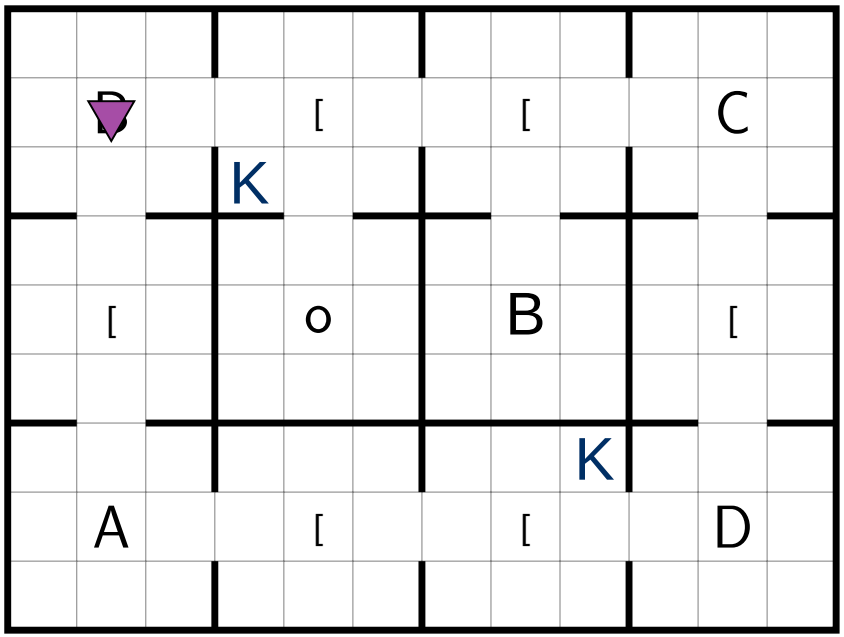
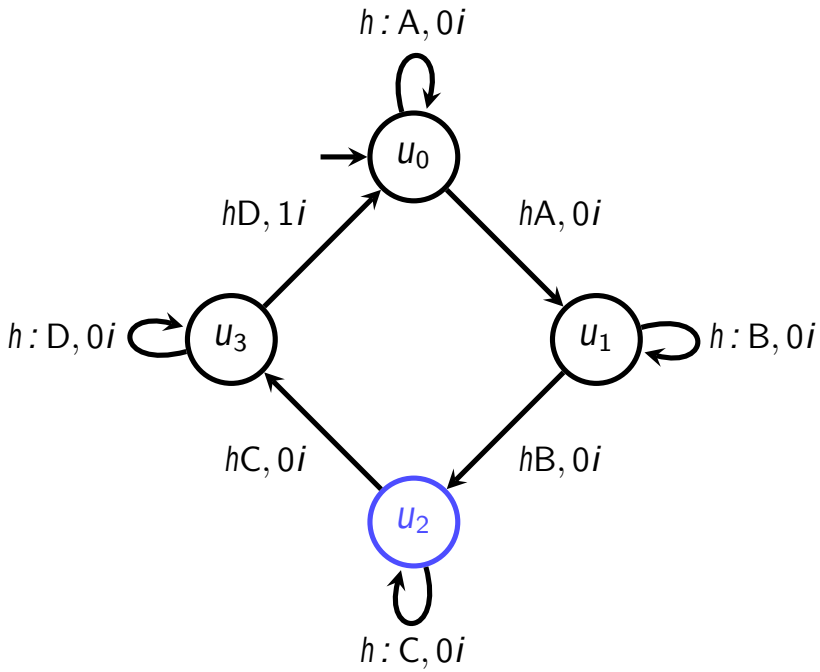
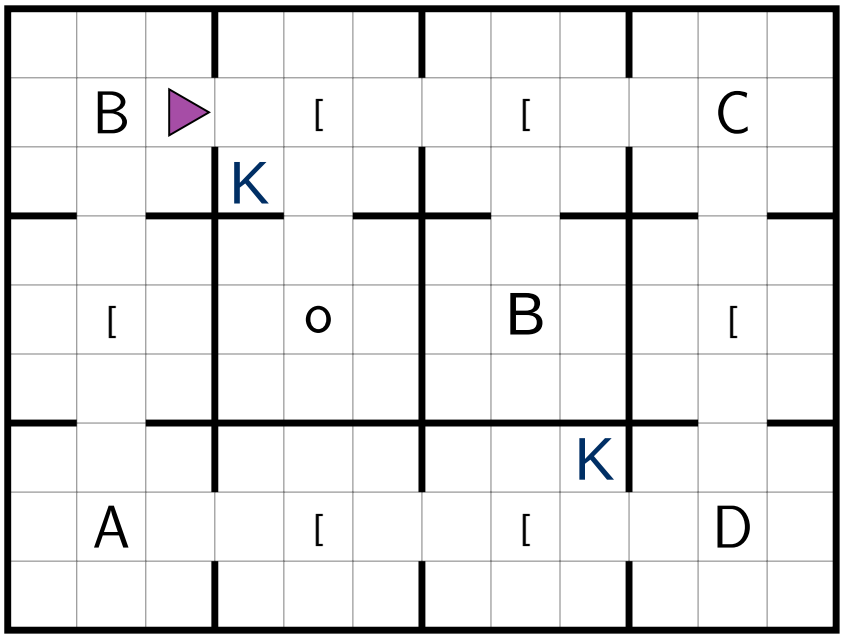
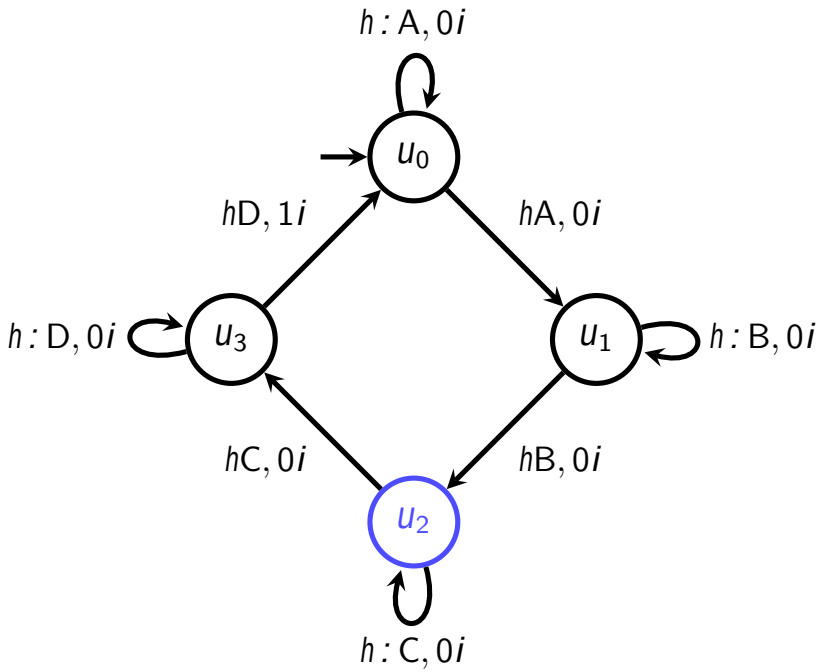




Reward machines in action





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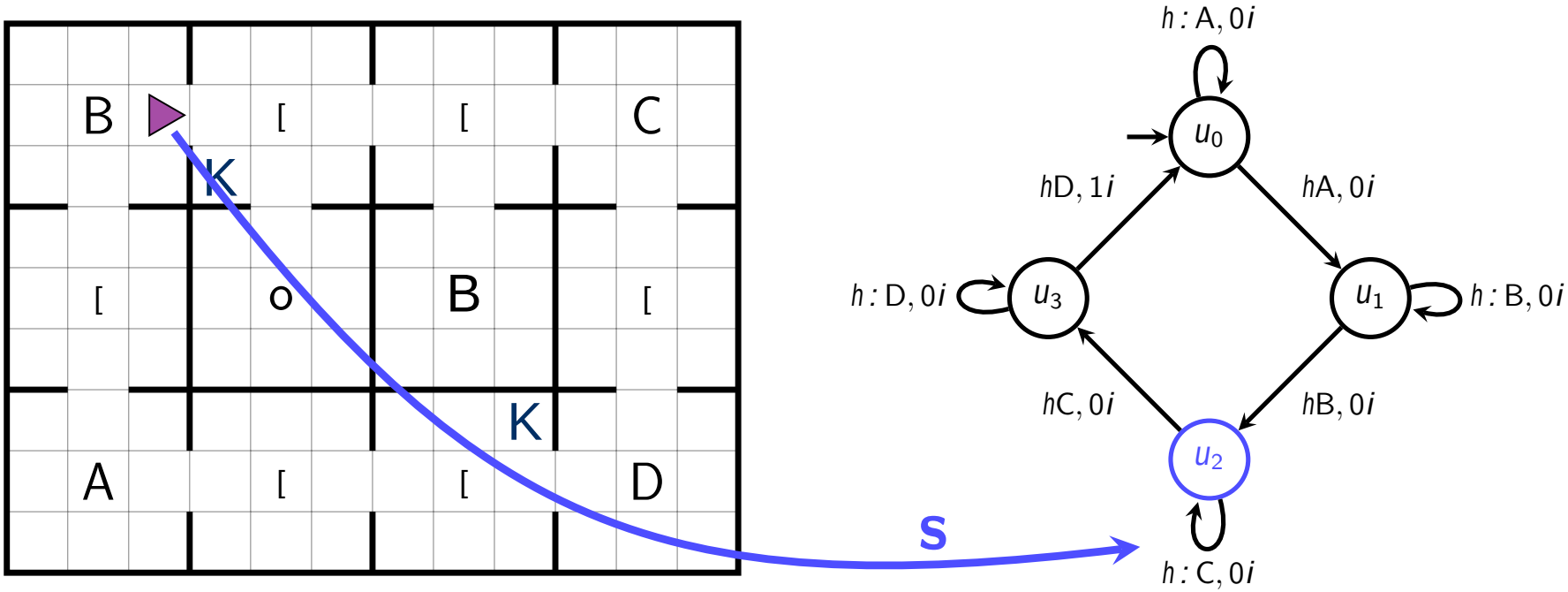
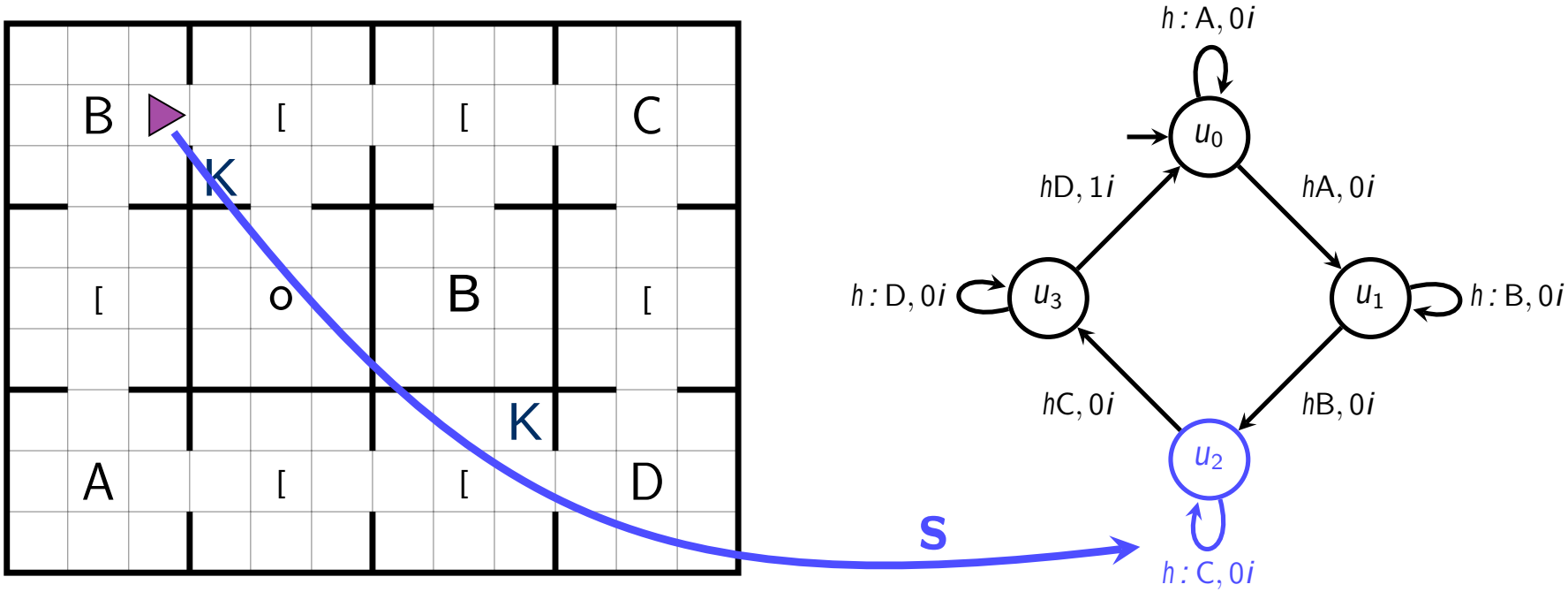


Reward machines in action



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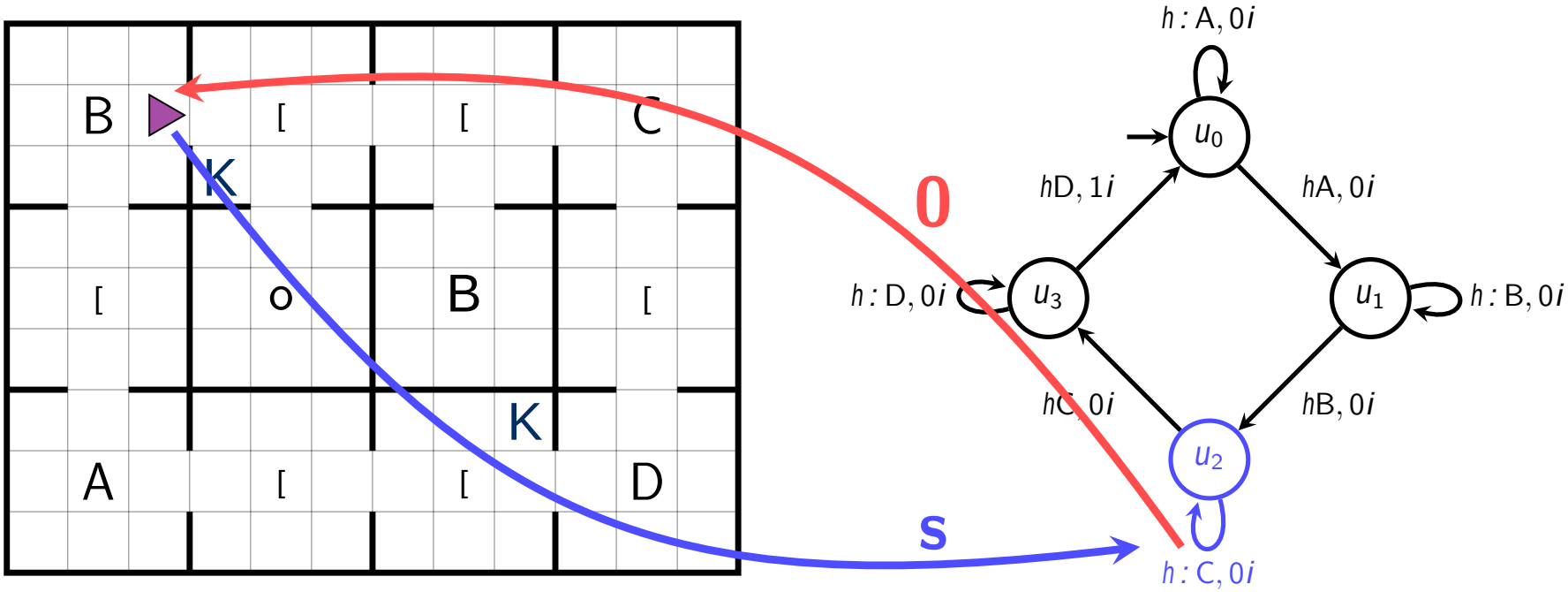

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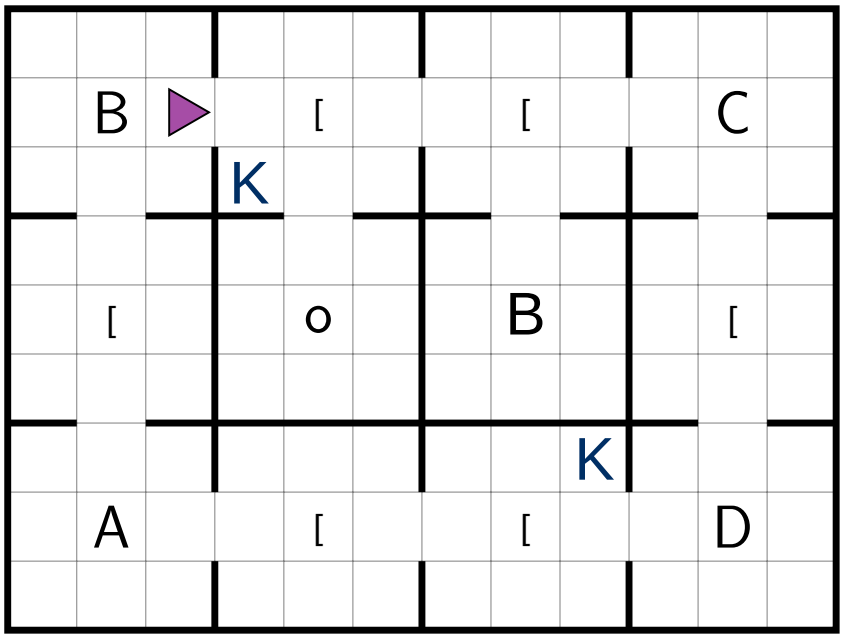

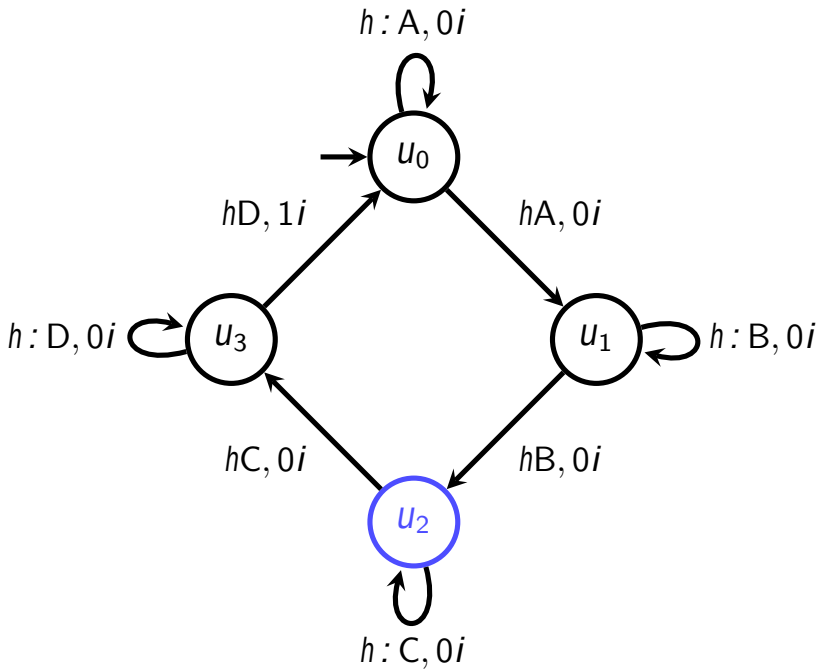

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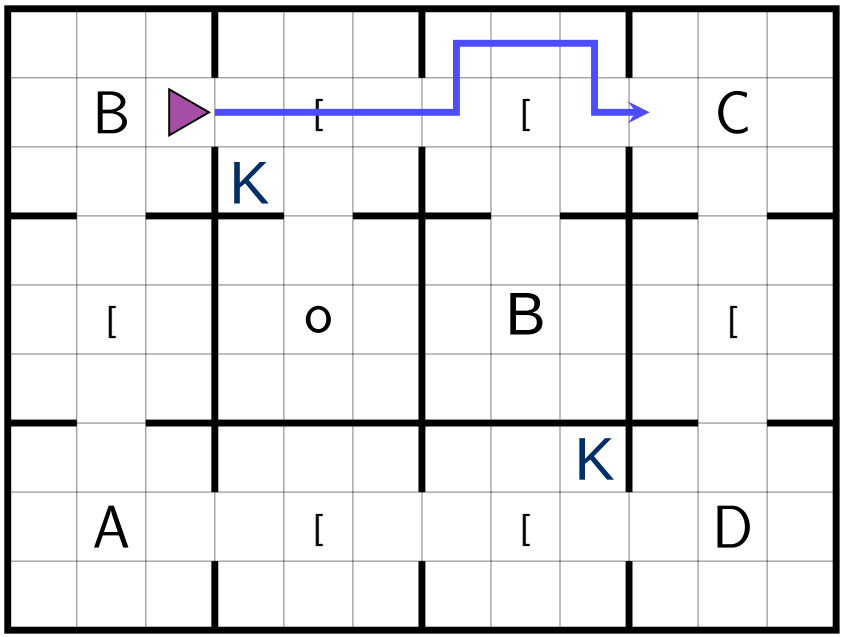

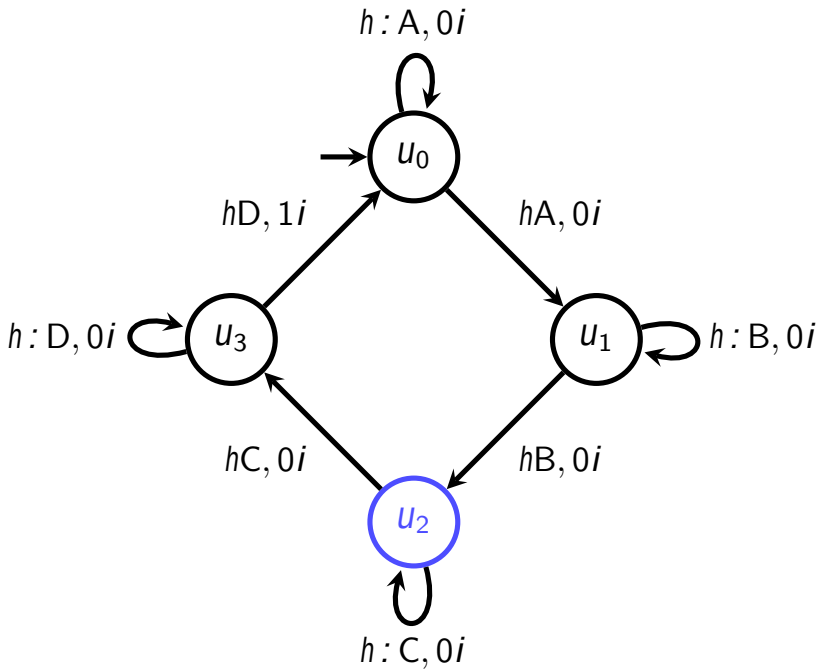

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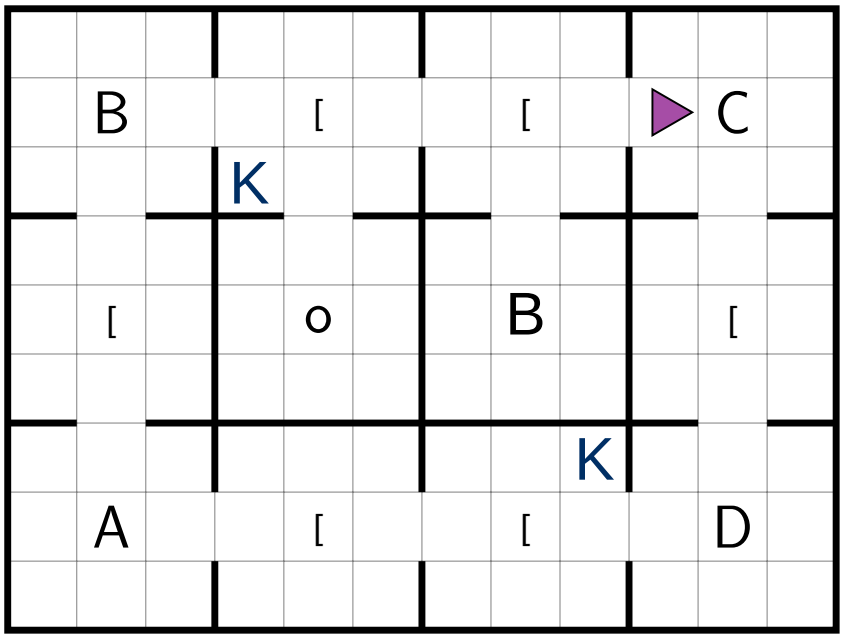

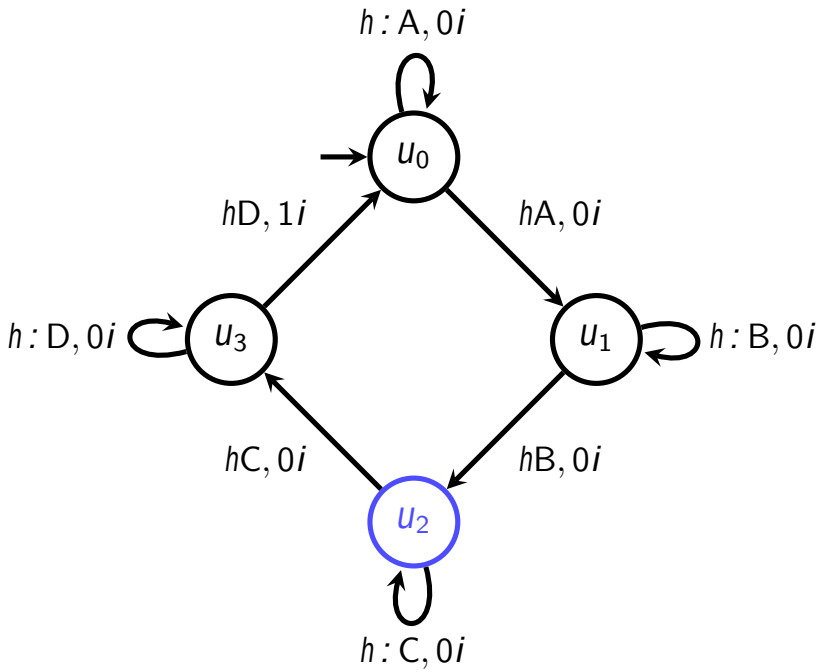

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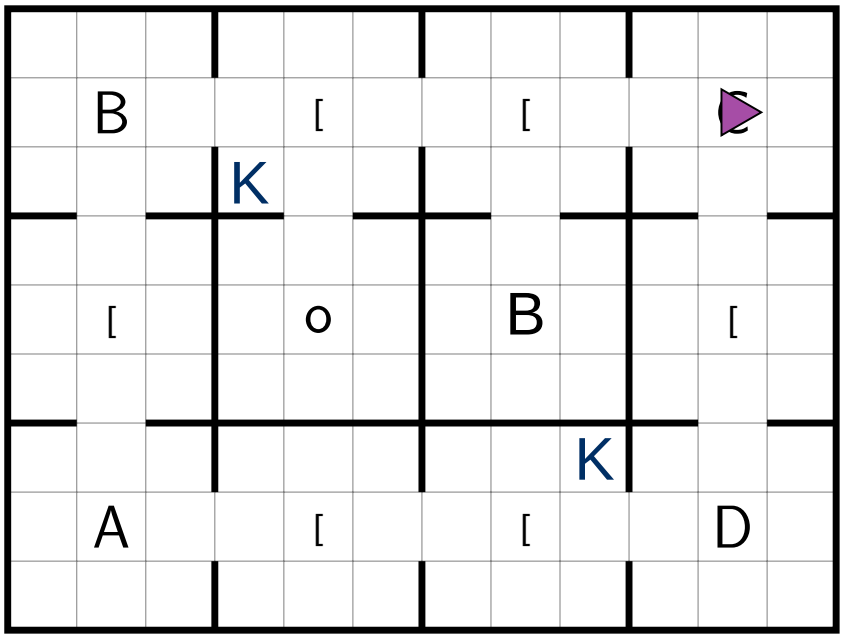

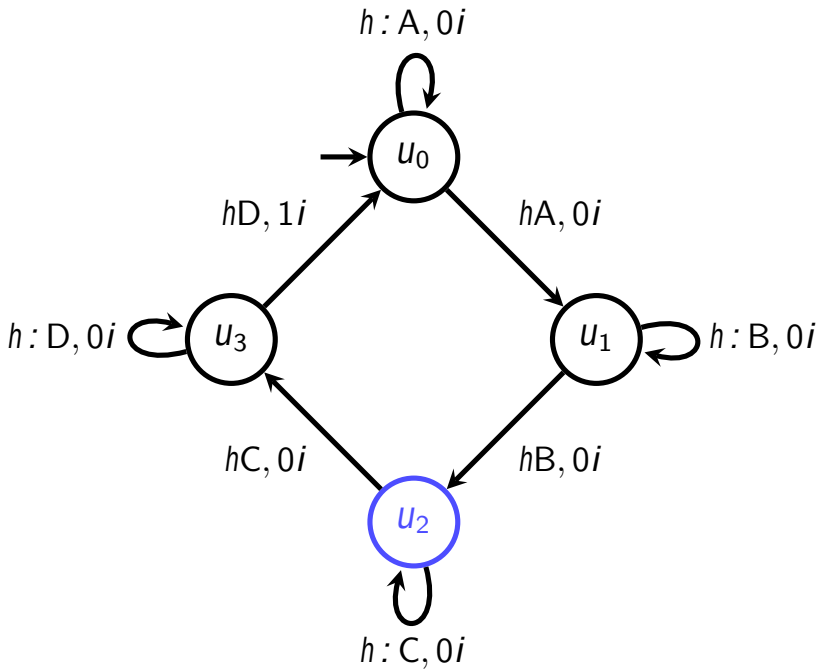

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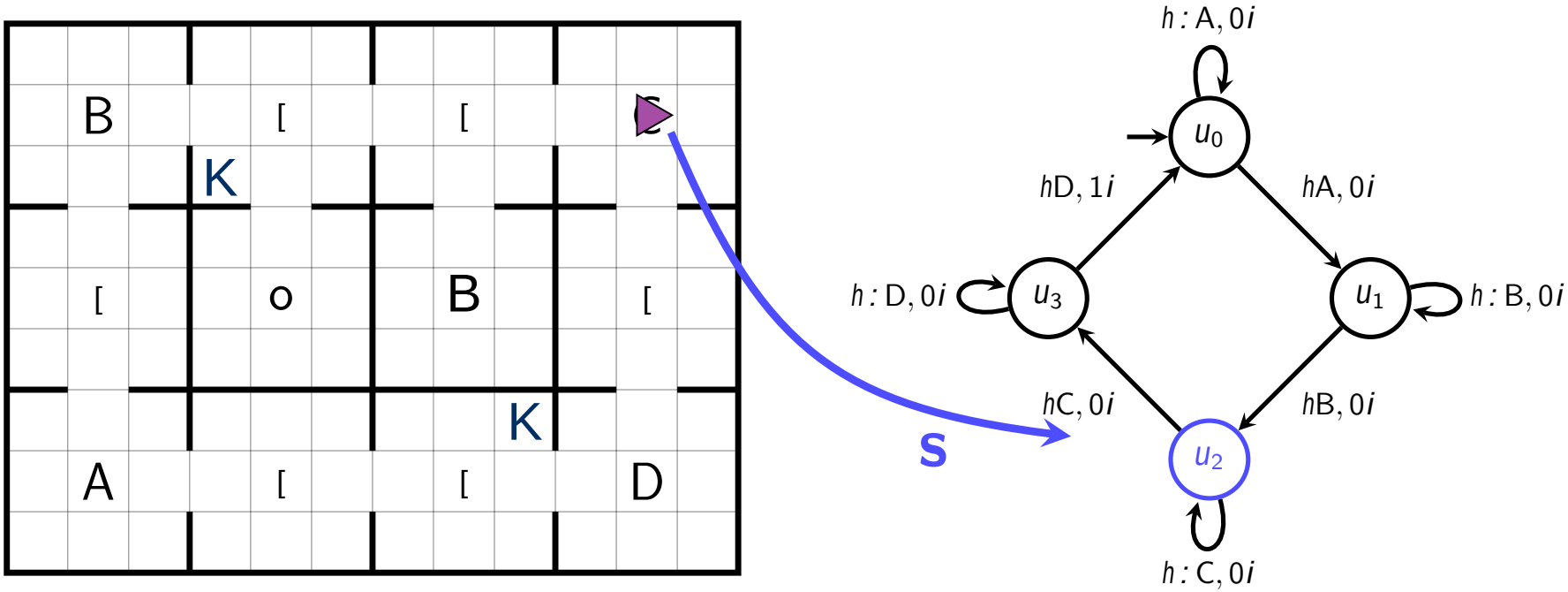

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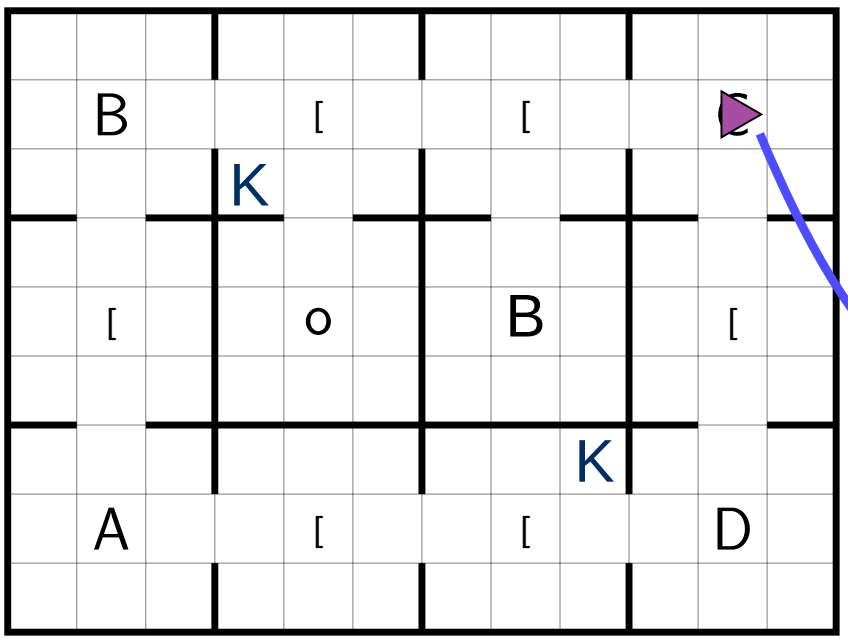

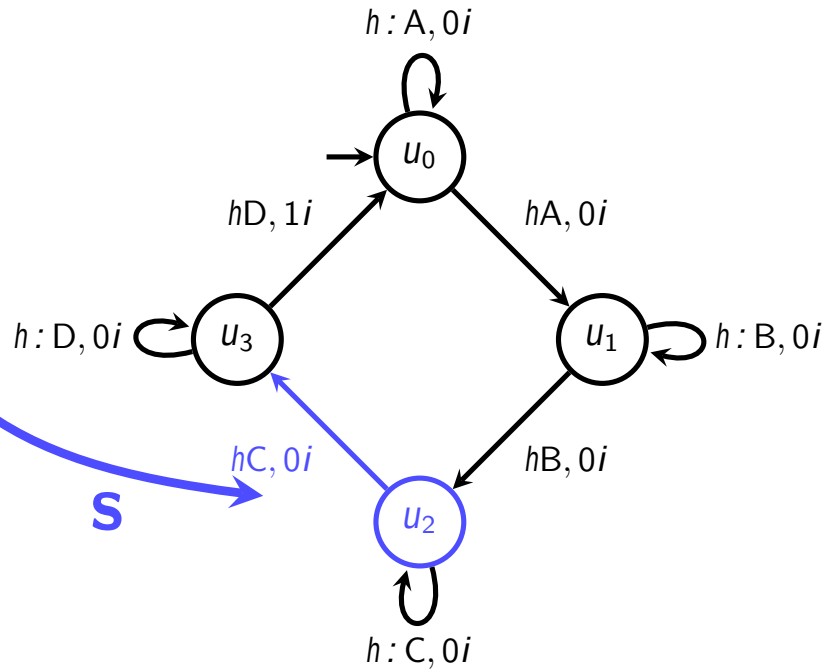

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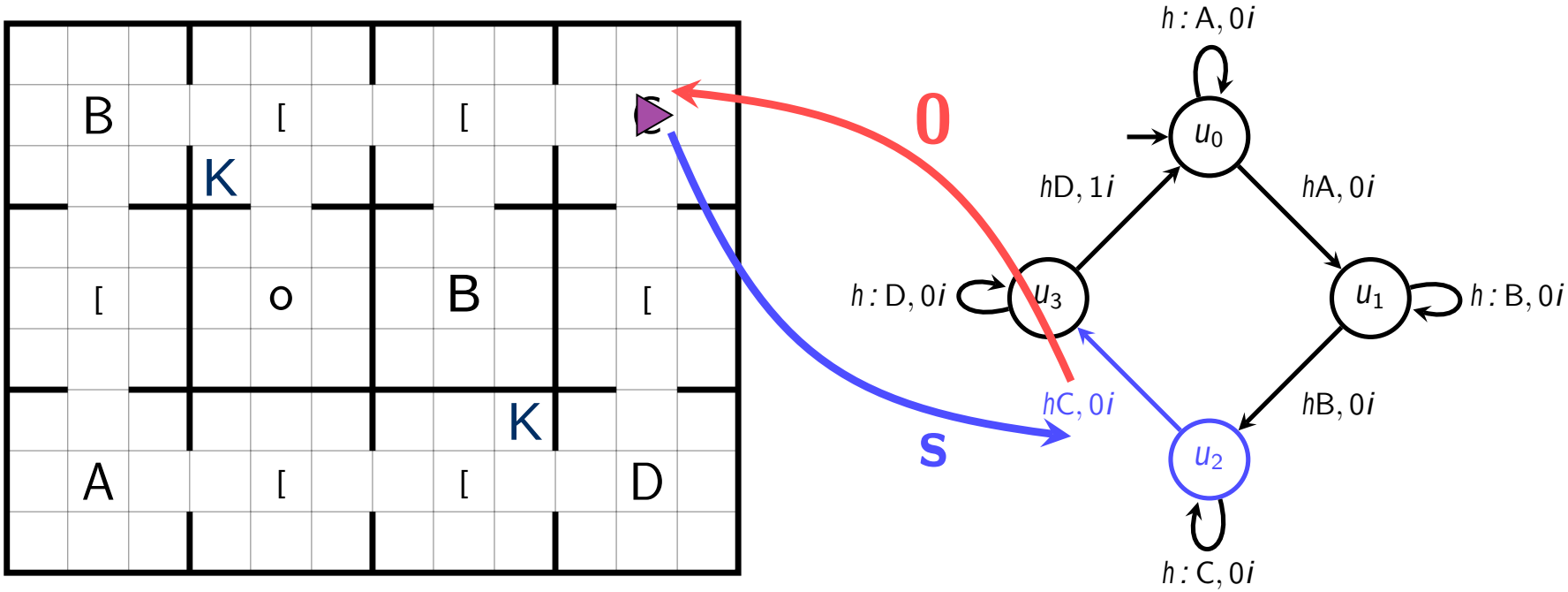
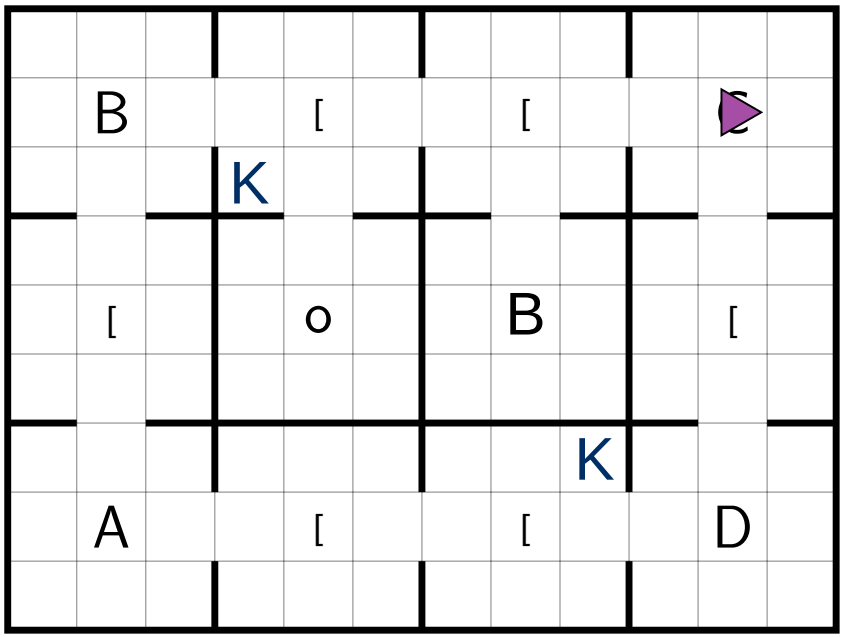
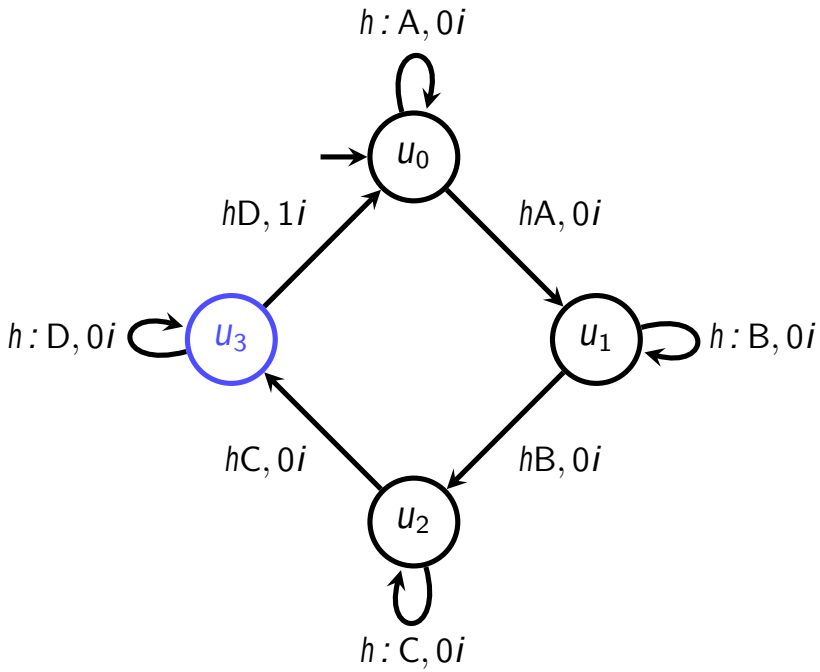


Reward machines in action





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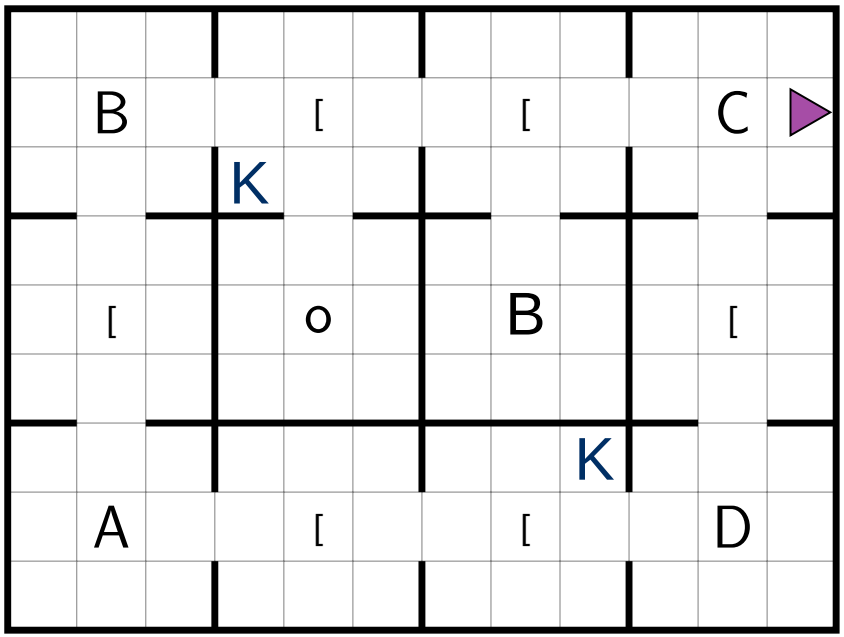

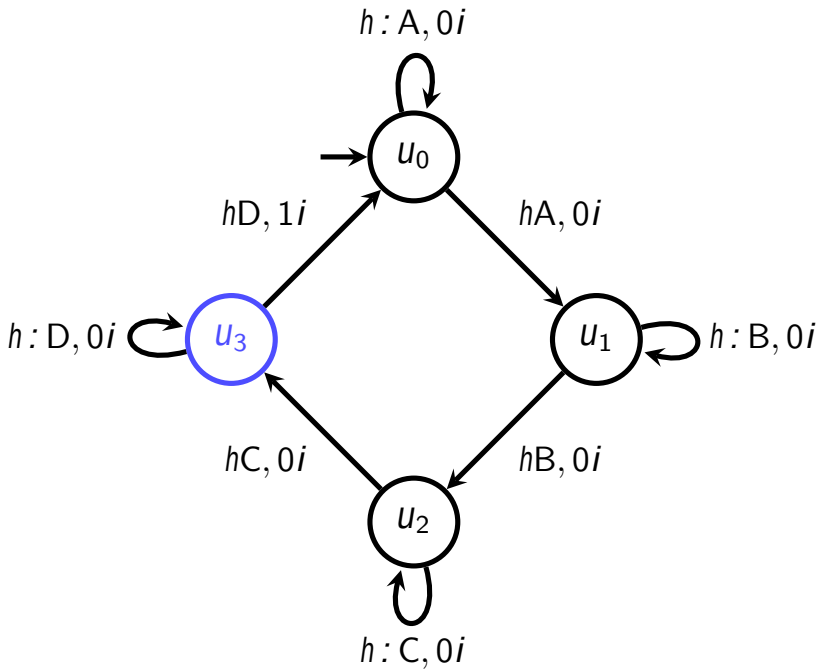

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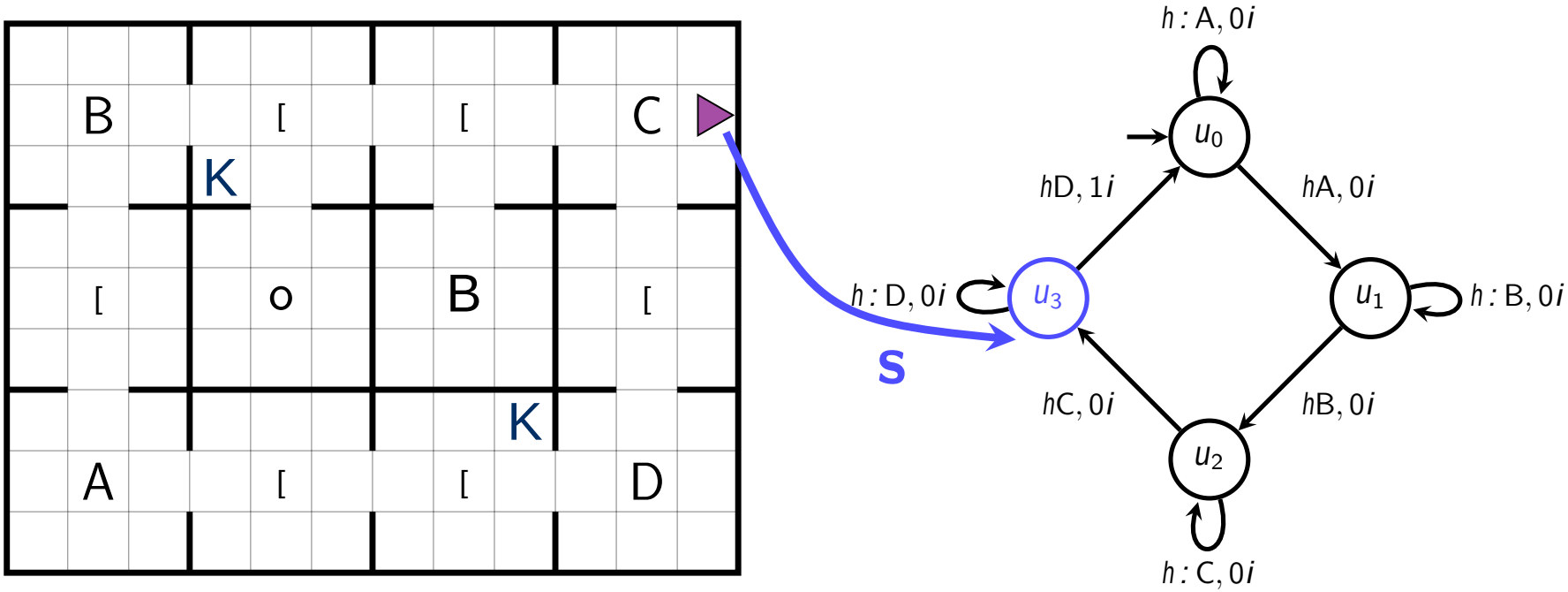

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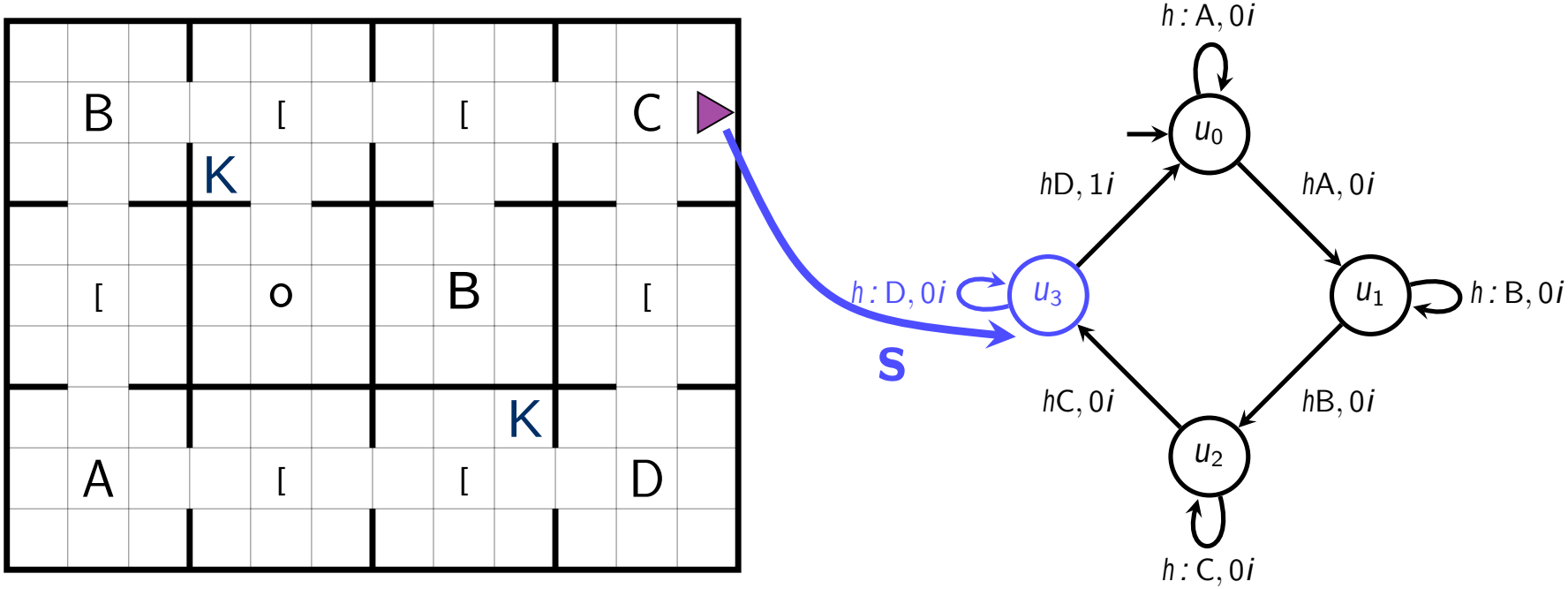

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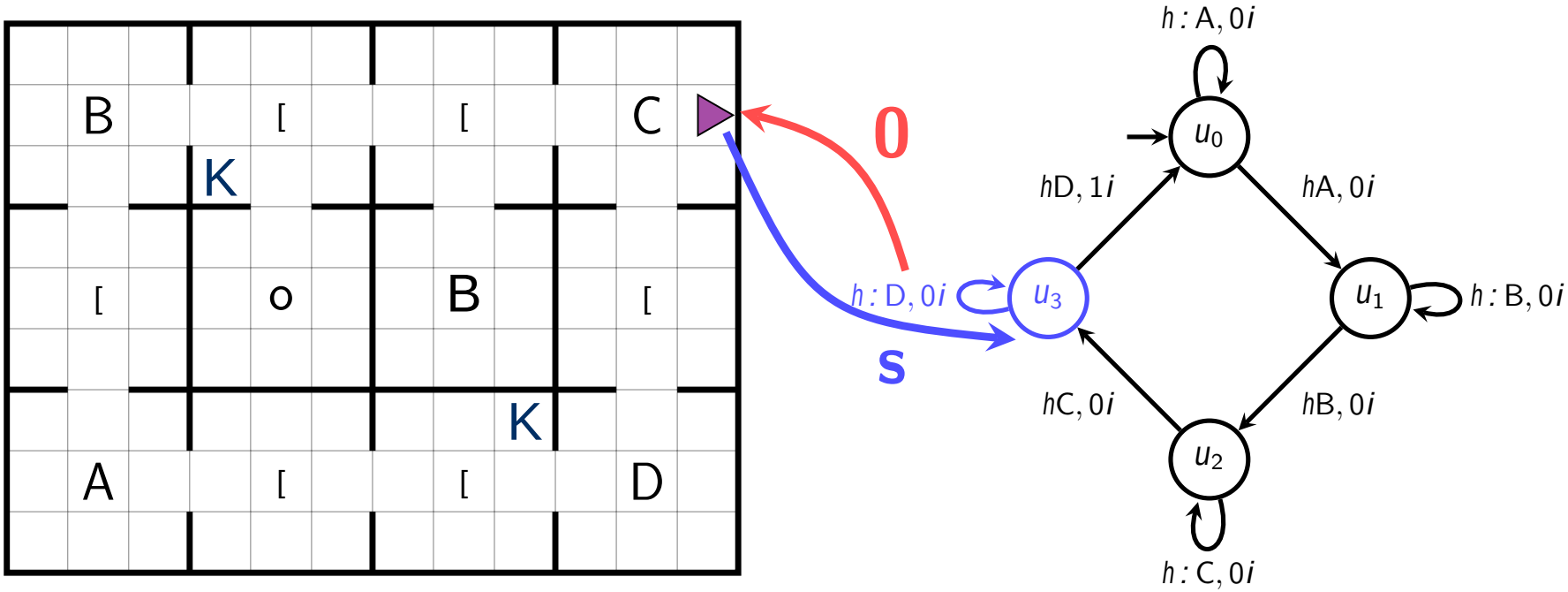

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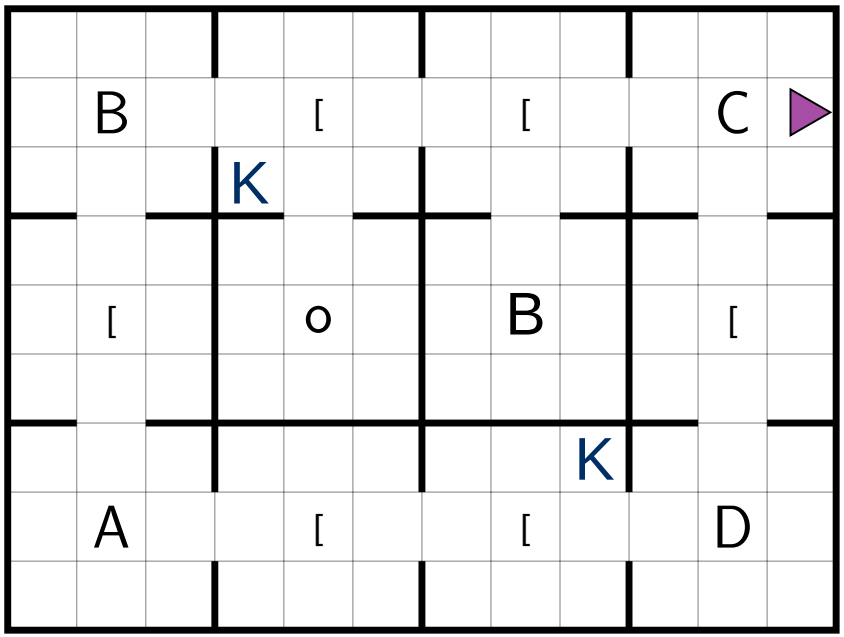

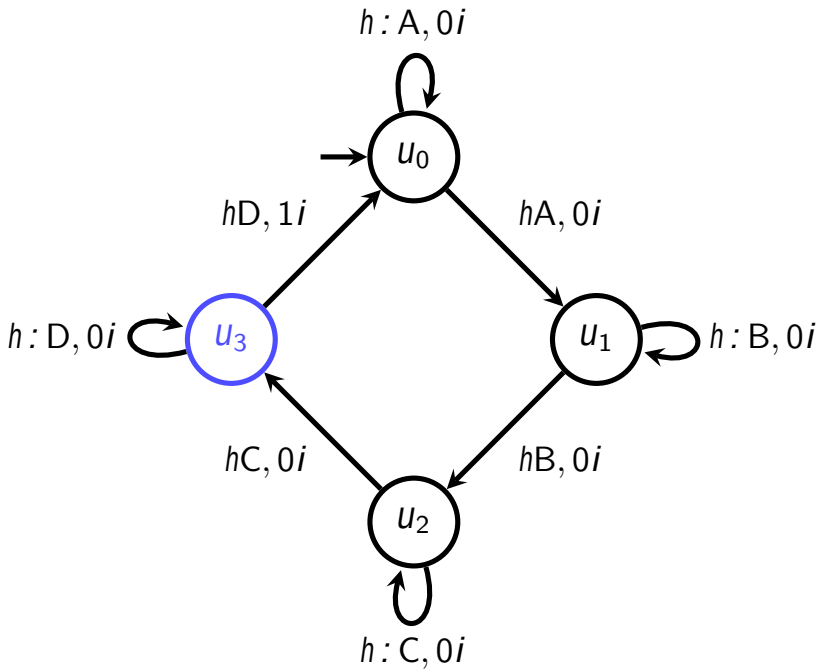

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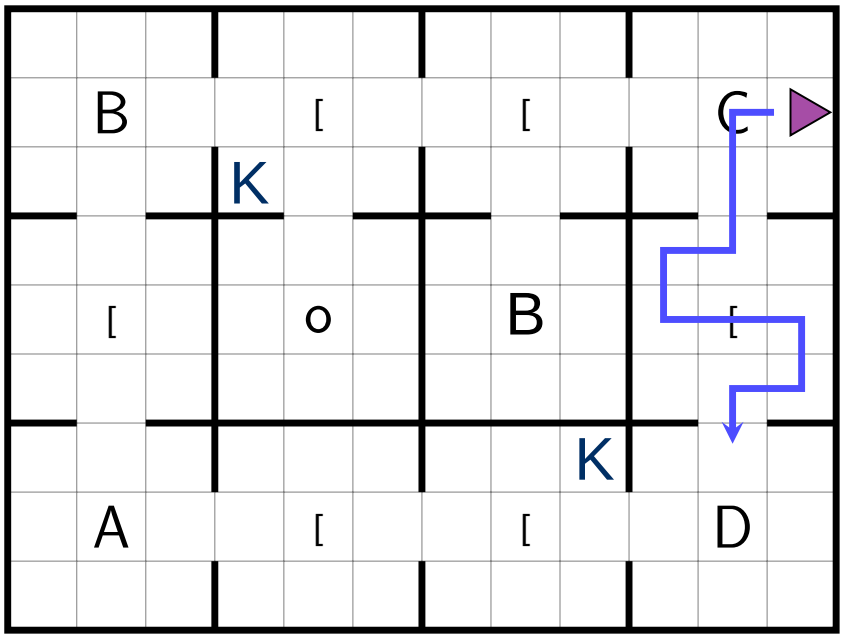

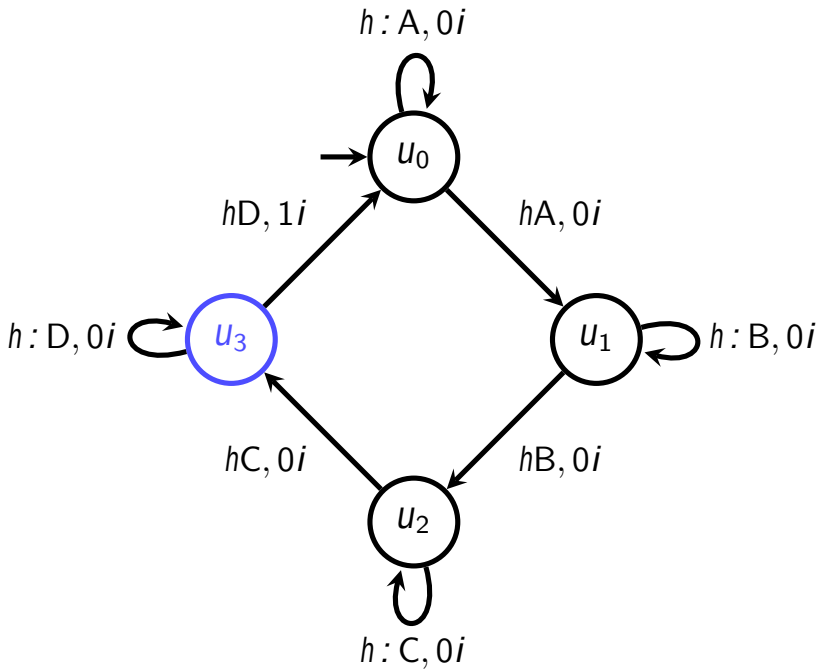

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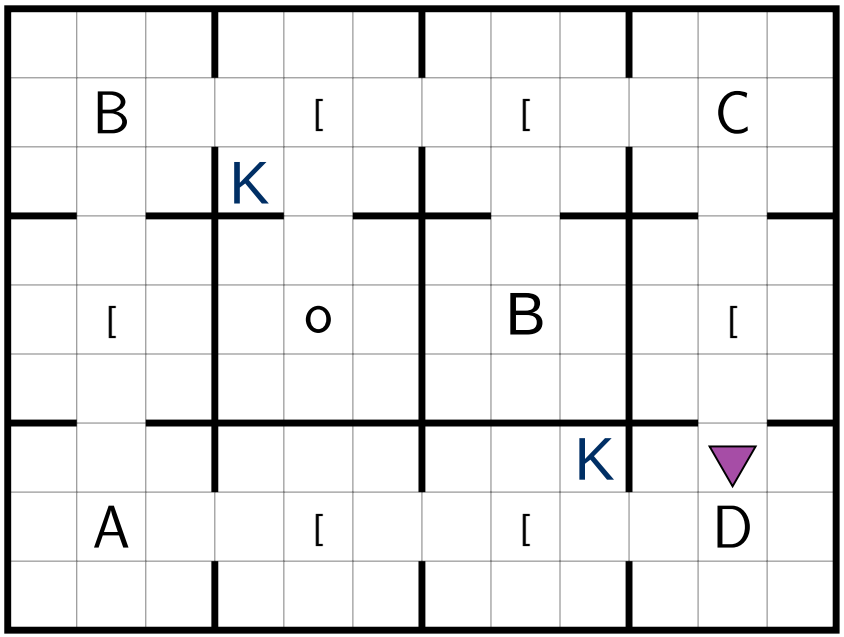

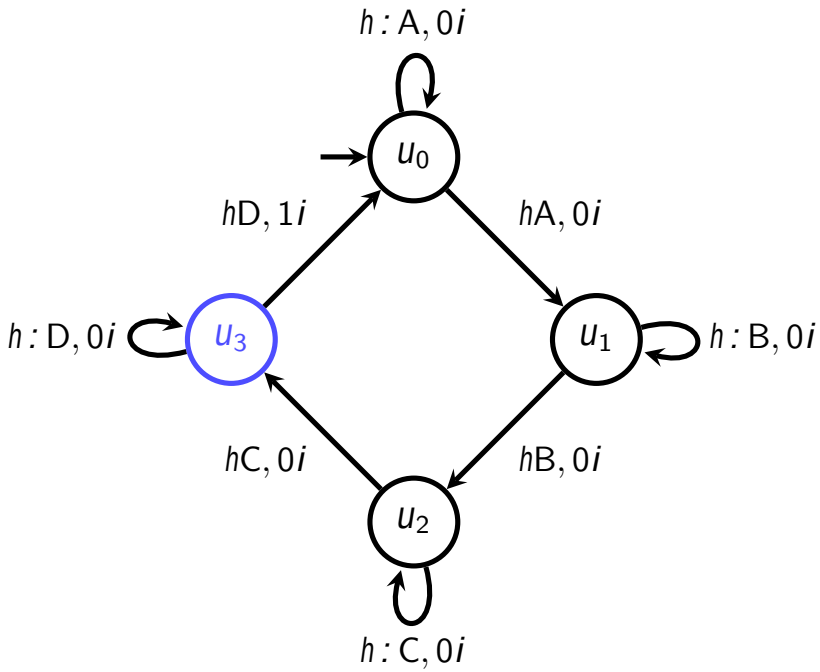

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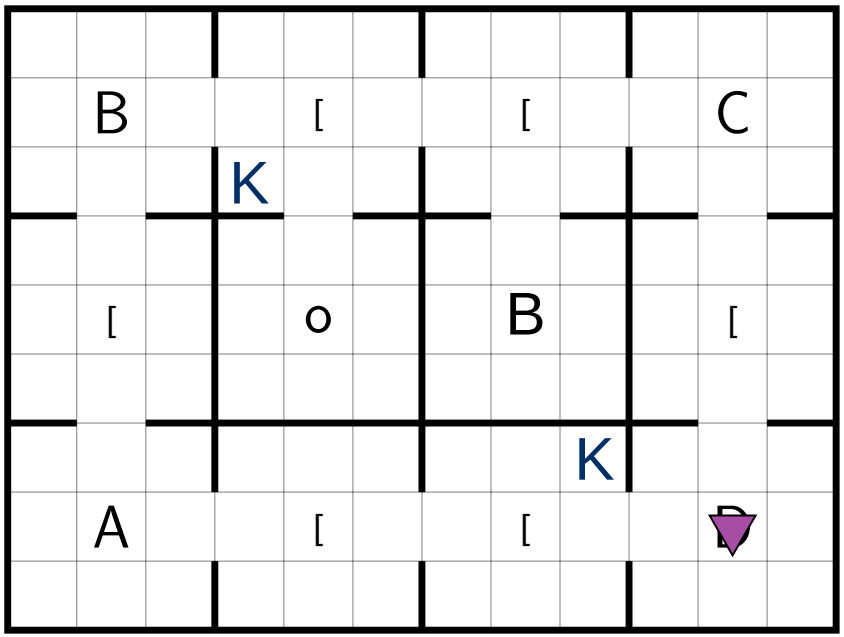

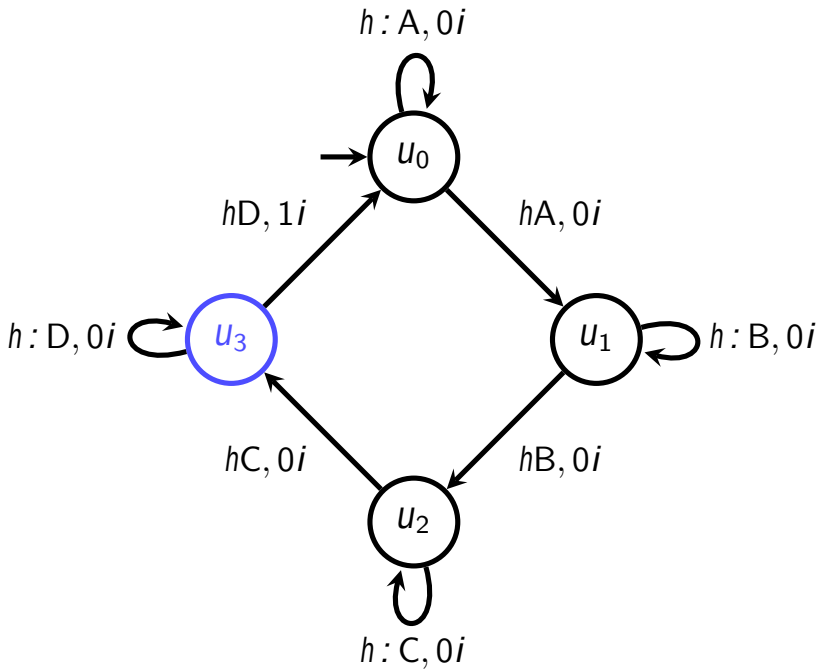

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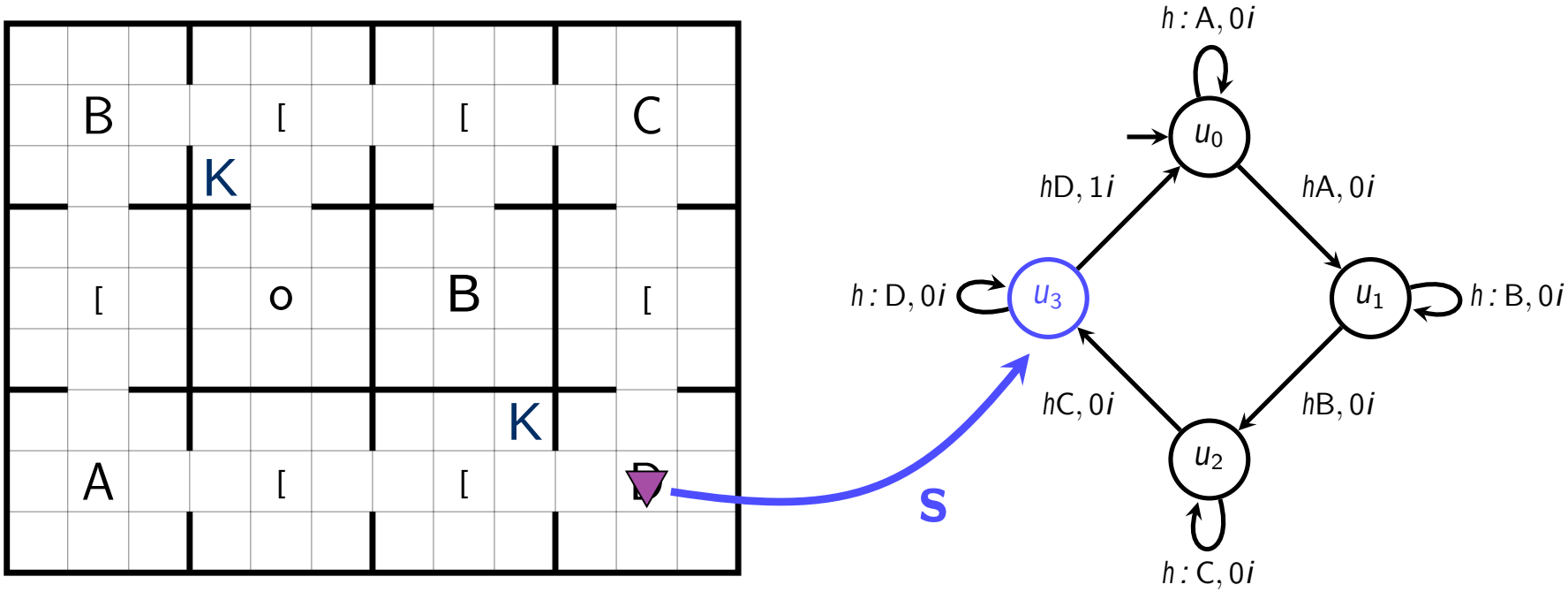

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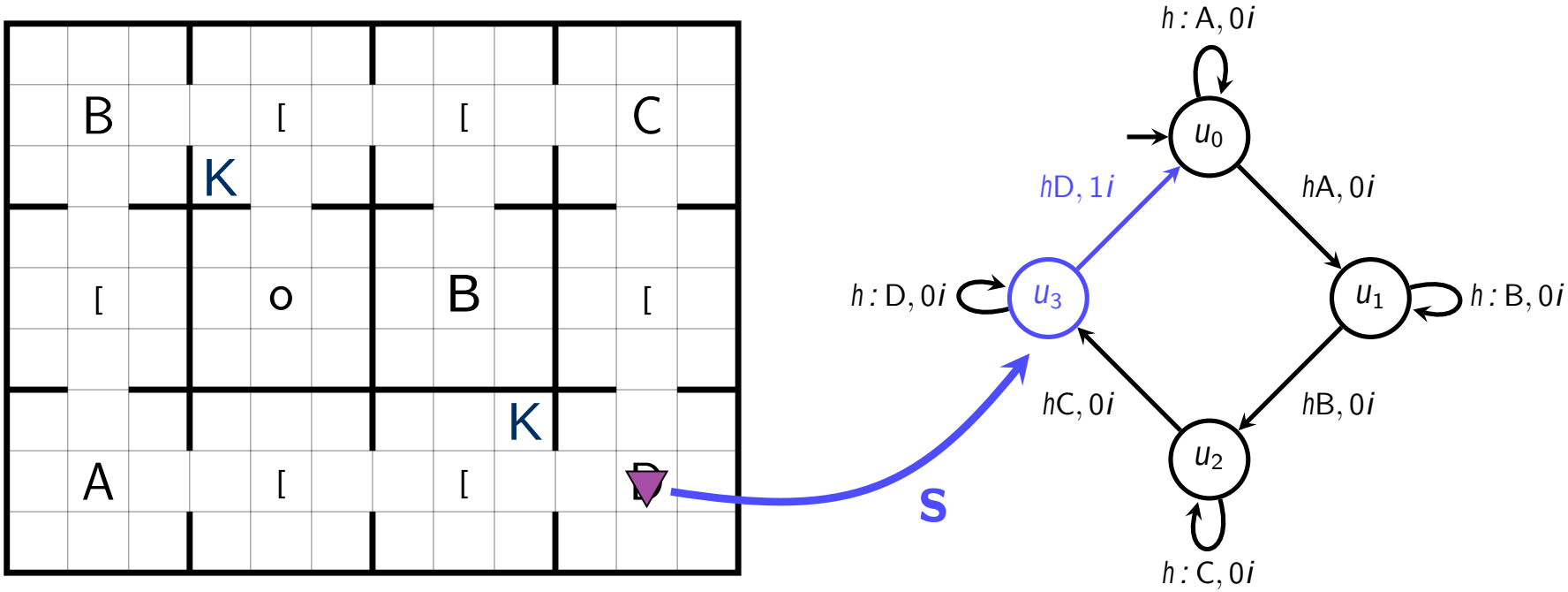

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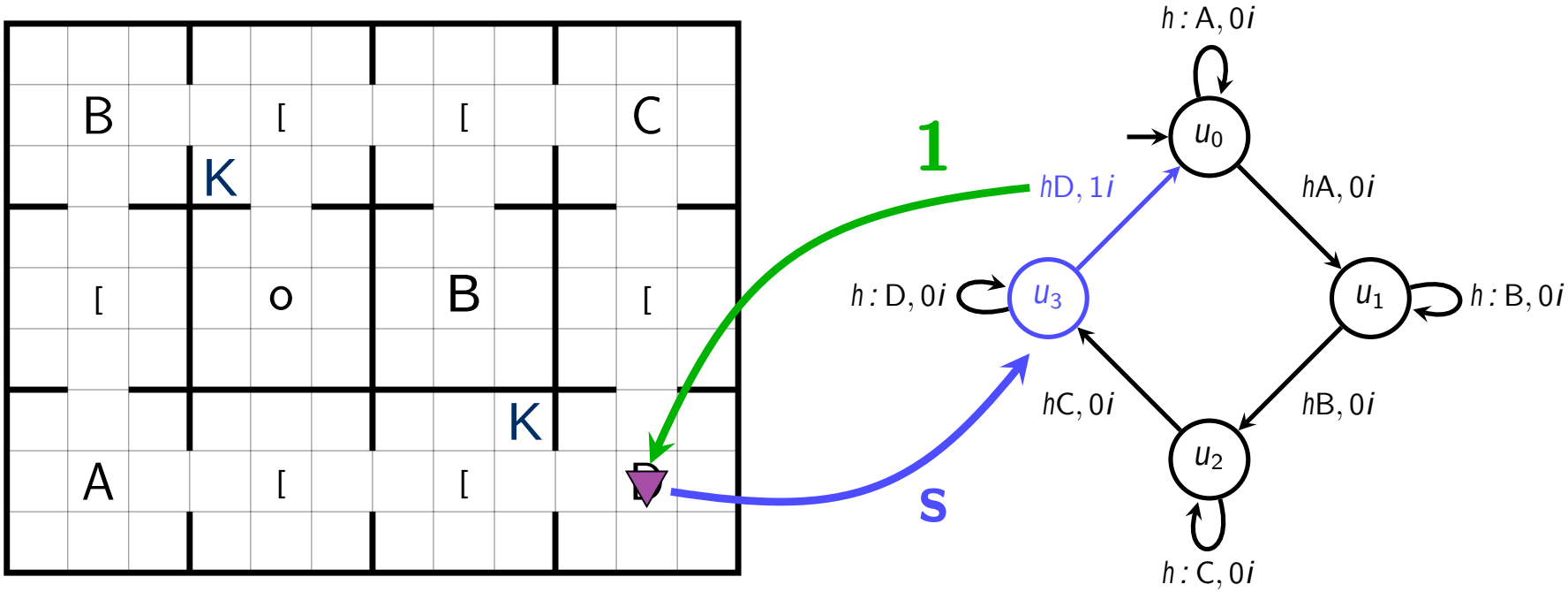

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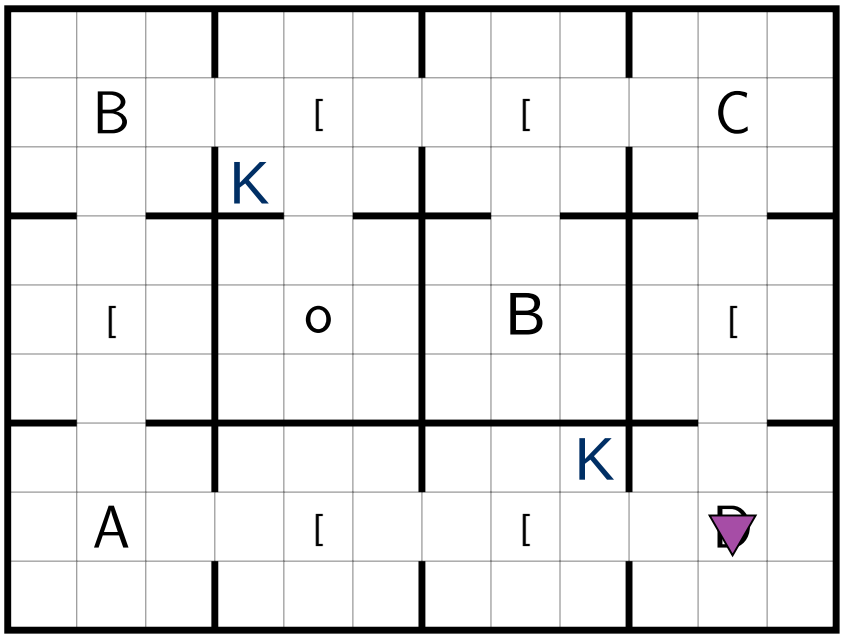

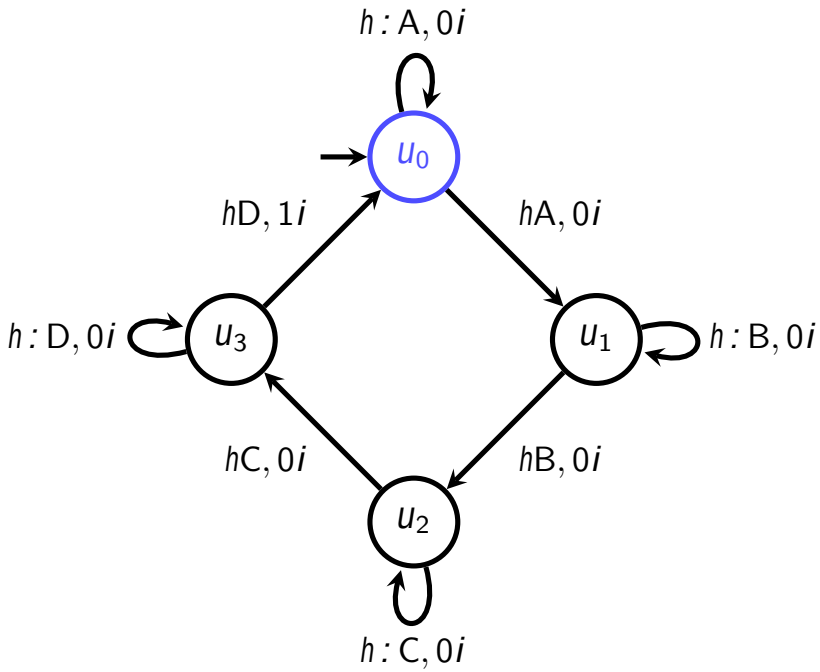

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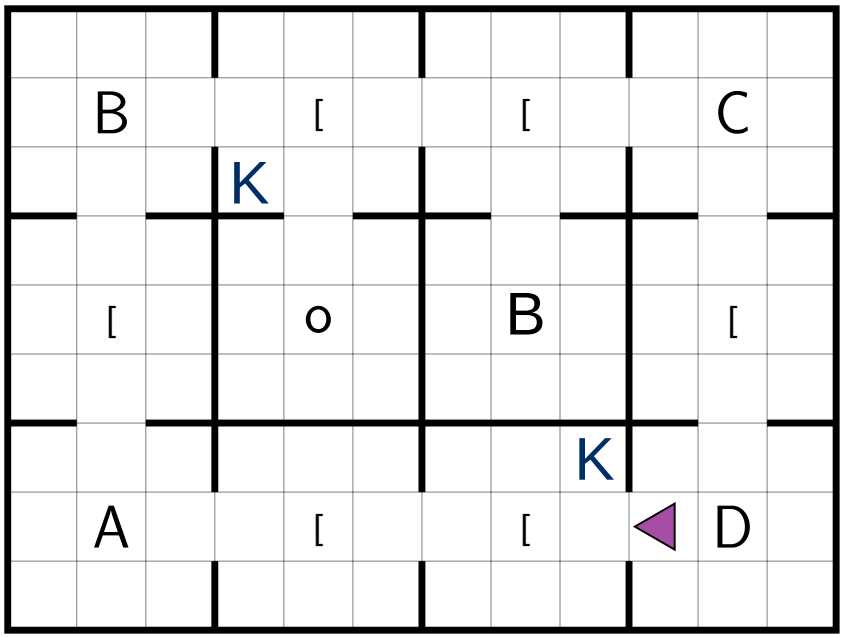

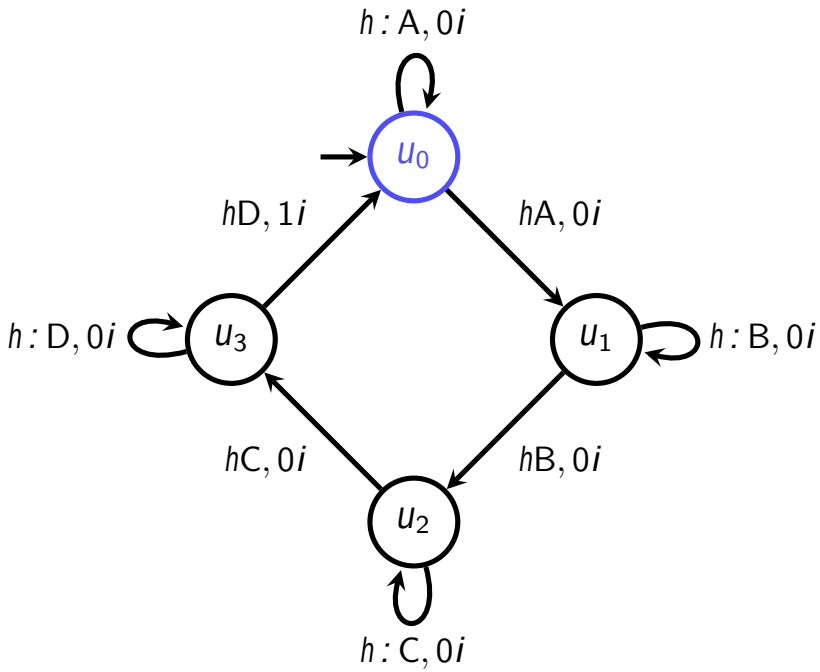

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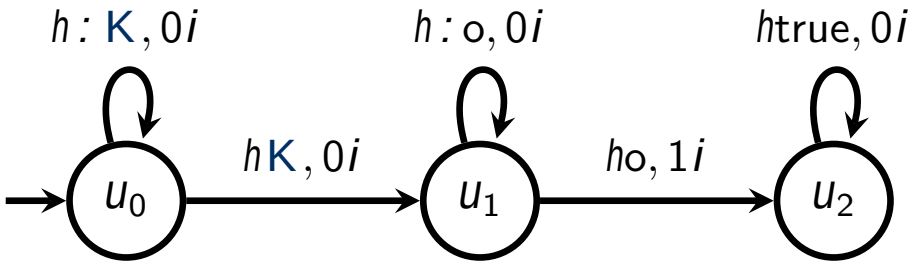

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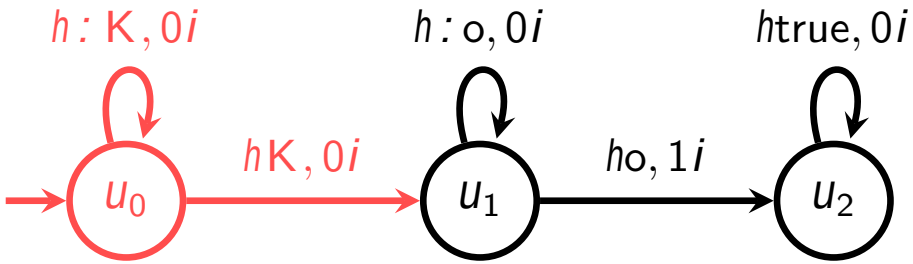

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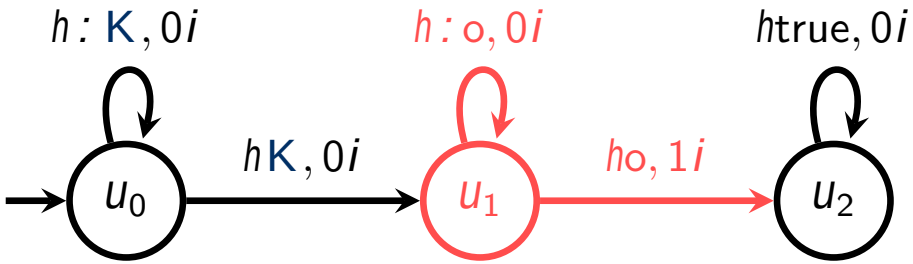

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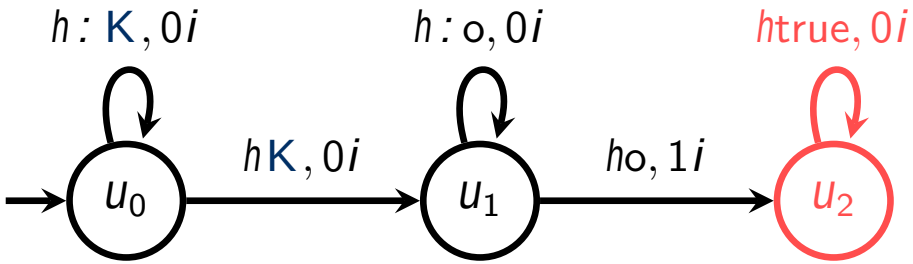

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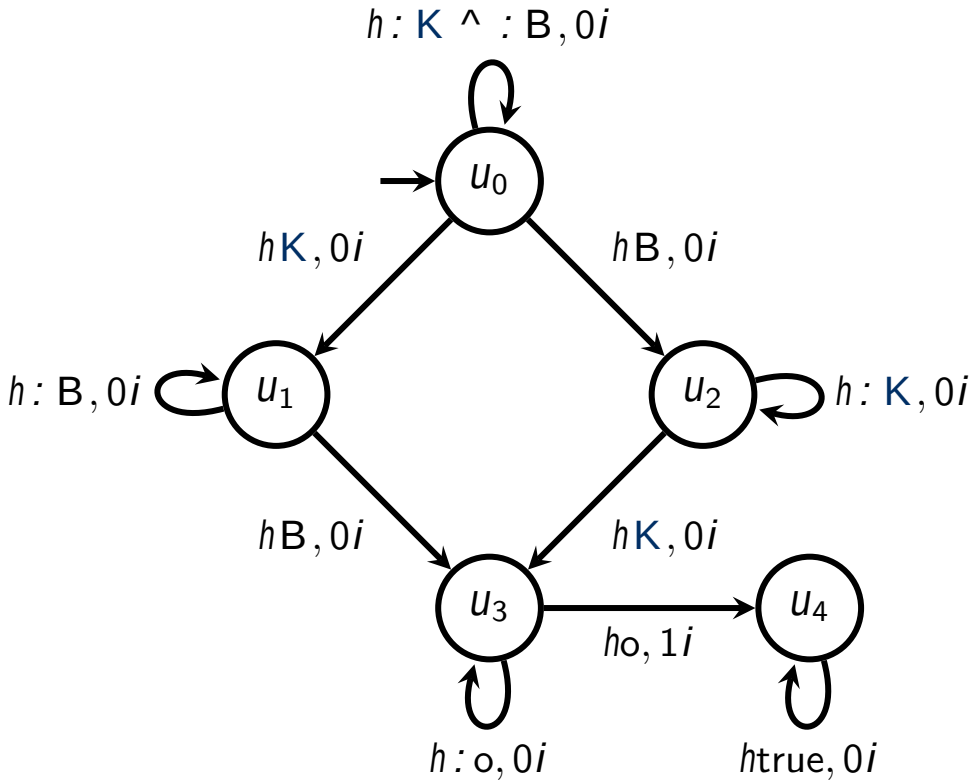

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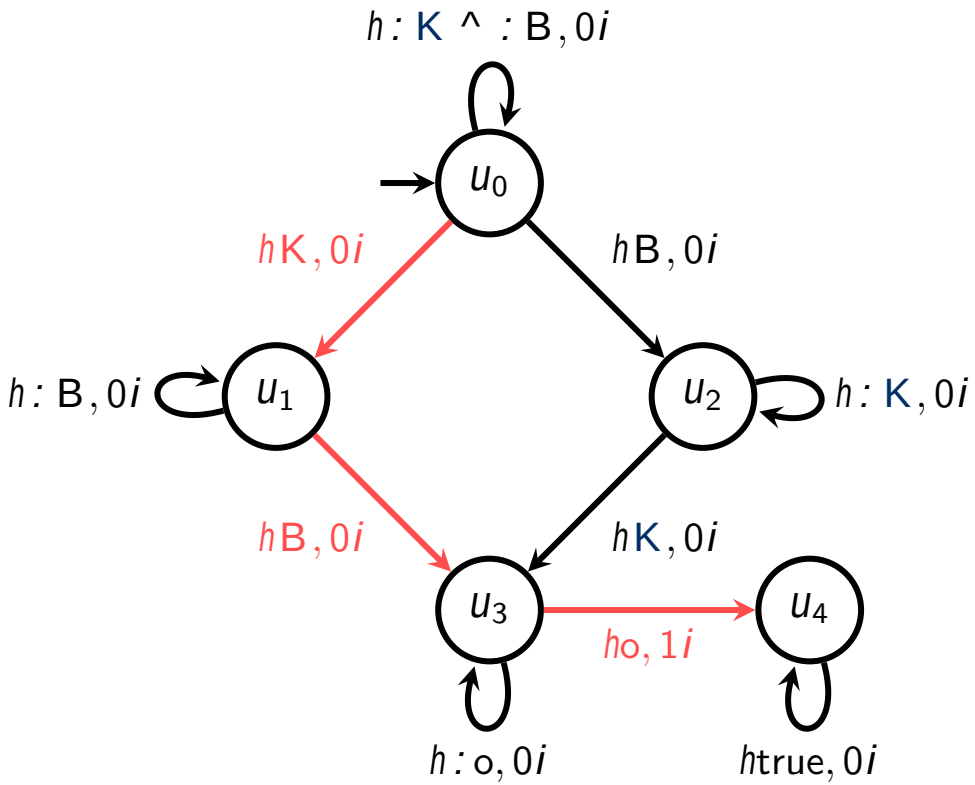

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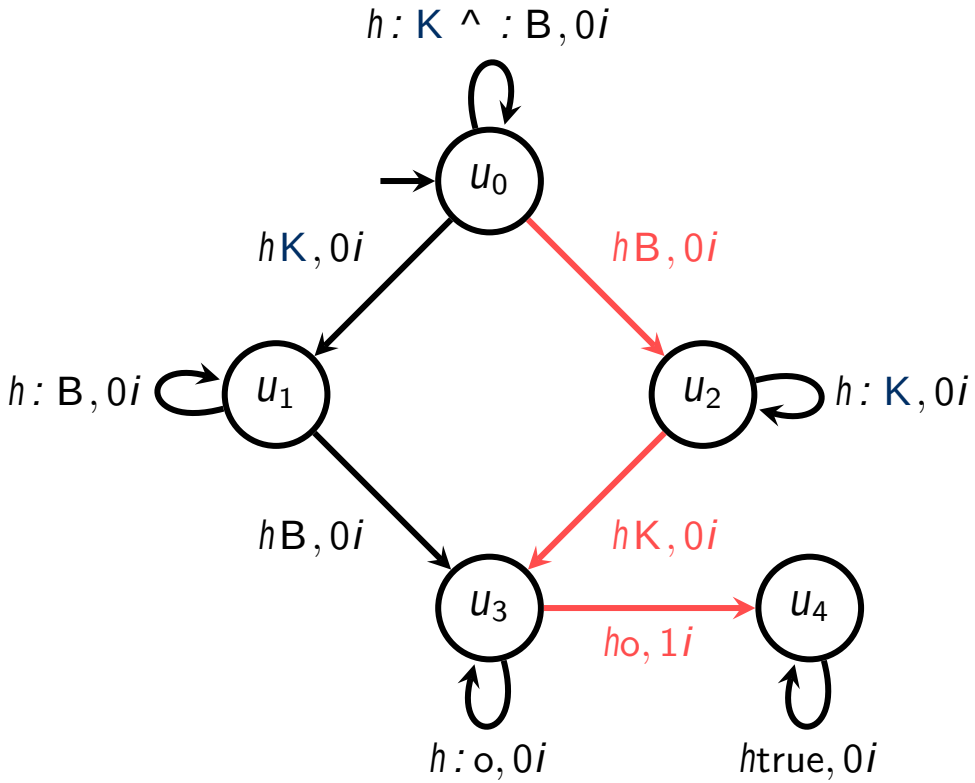

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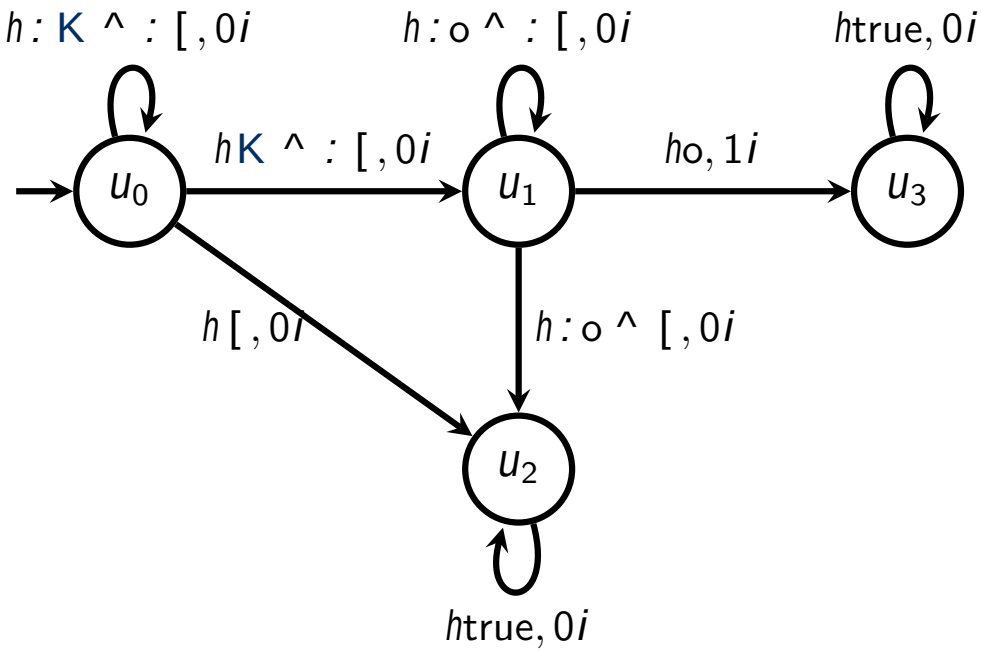

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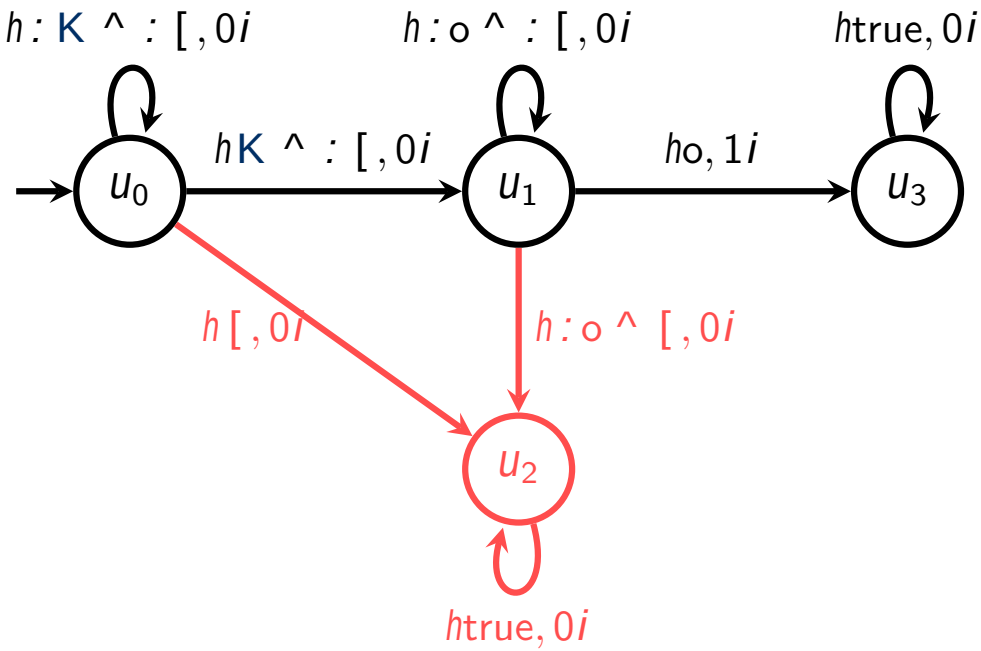

Outline

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Exploiting reward machines' structure

We explored 4 ideas.

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Baselines:

- Q-Learning over a cross-product MDP (q-learning).
- Hierarchical RL based on options (HRL).
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Our approach:

- Q-learning for Reward Machines (QRM).

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Reward machines might define non-Markovian rewards.

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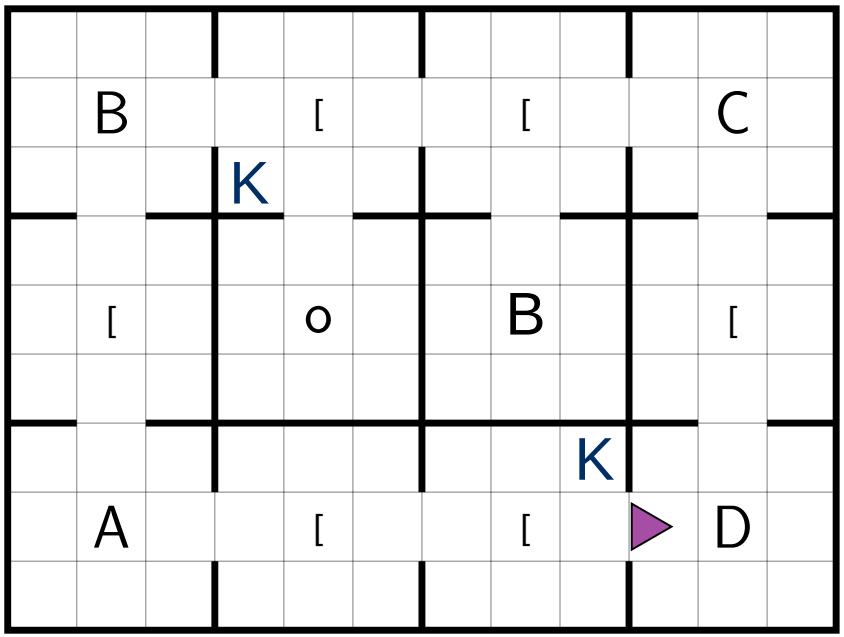

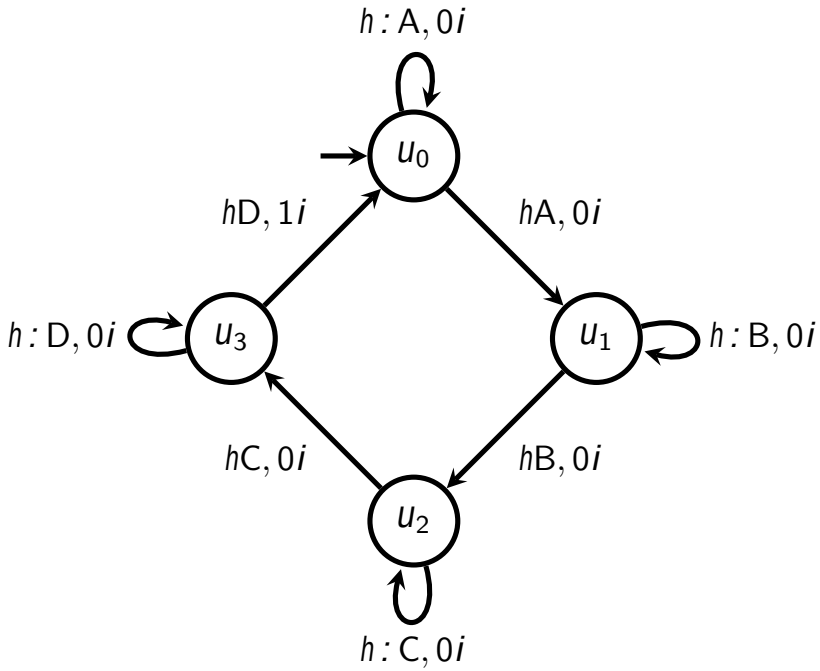

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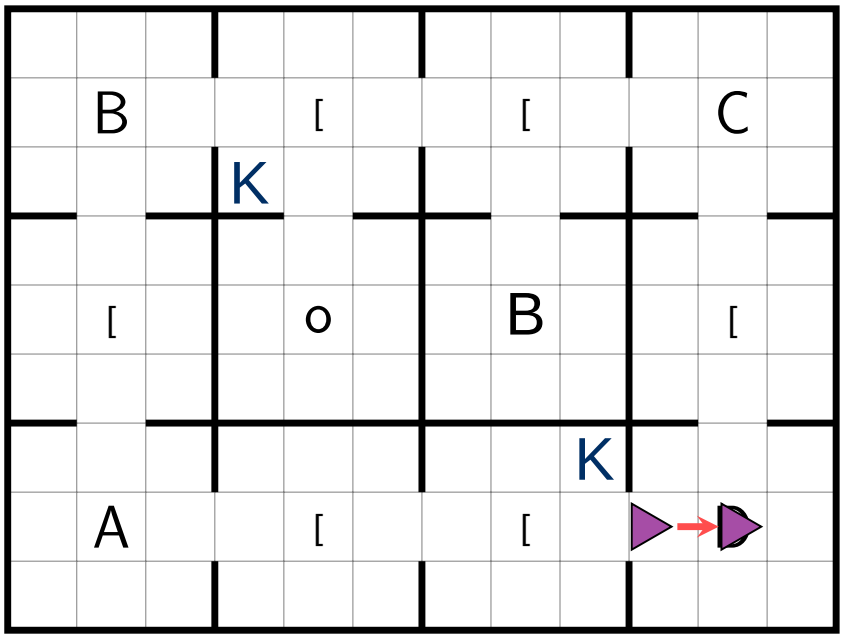

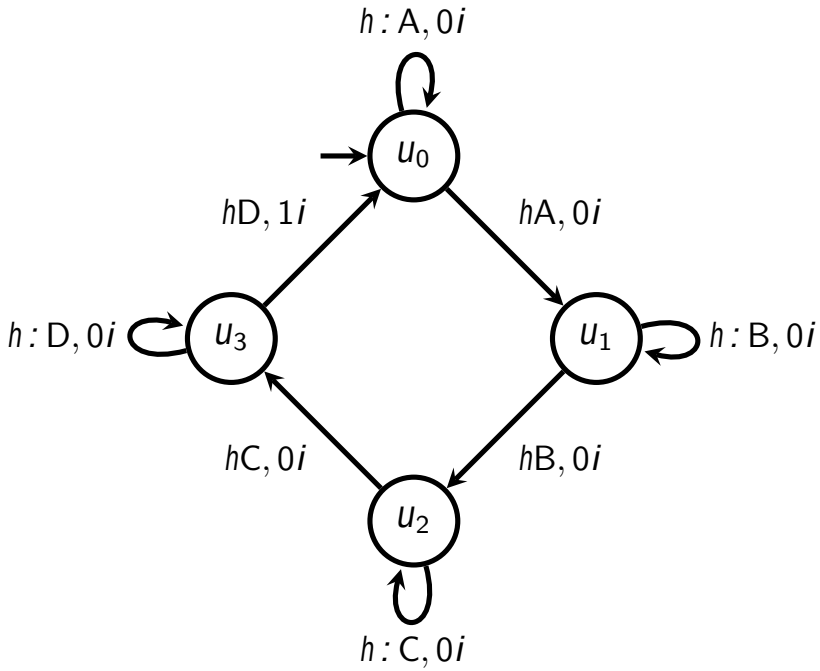

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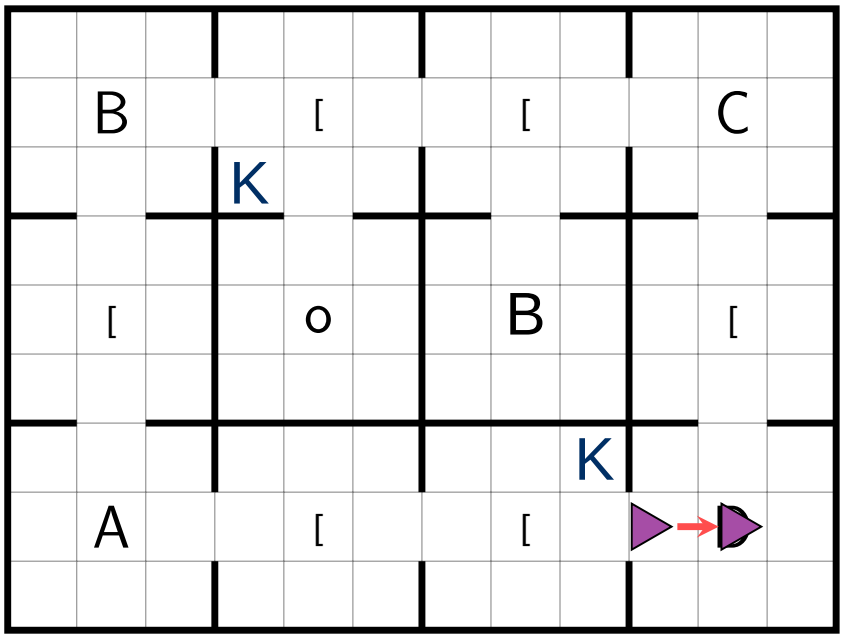

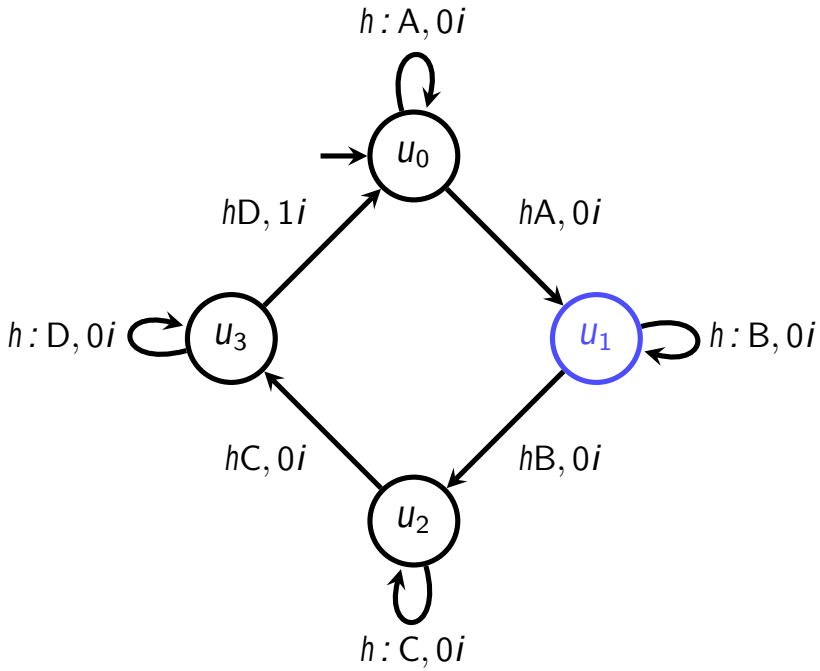

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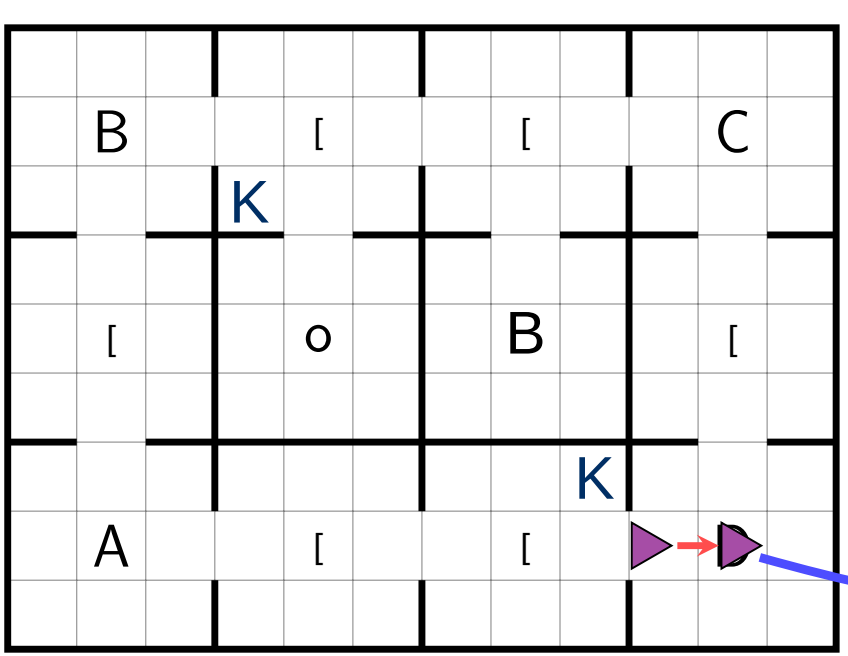

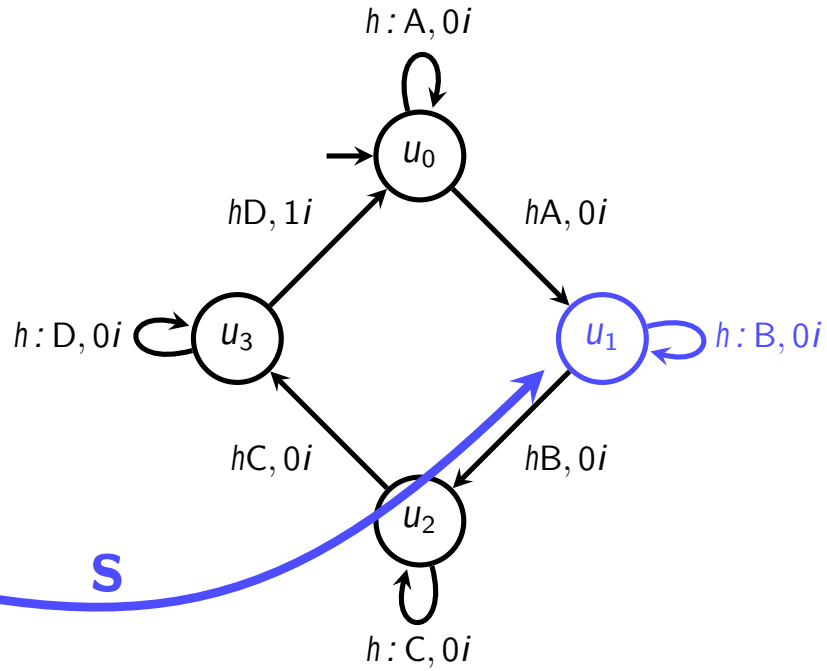

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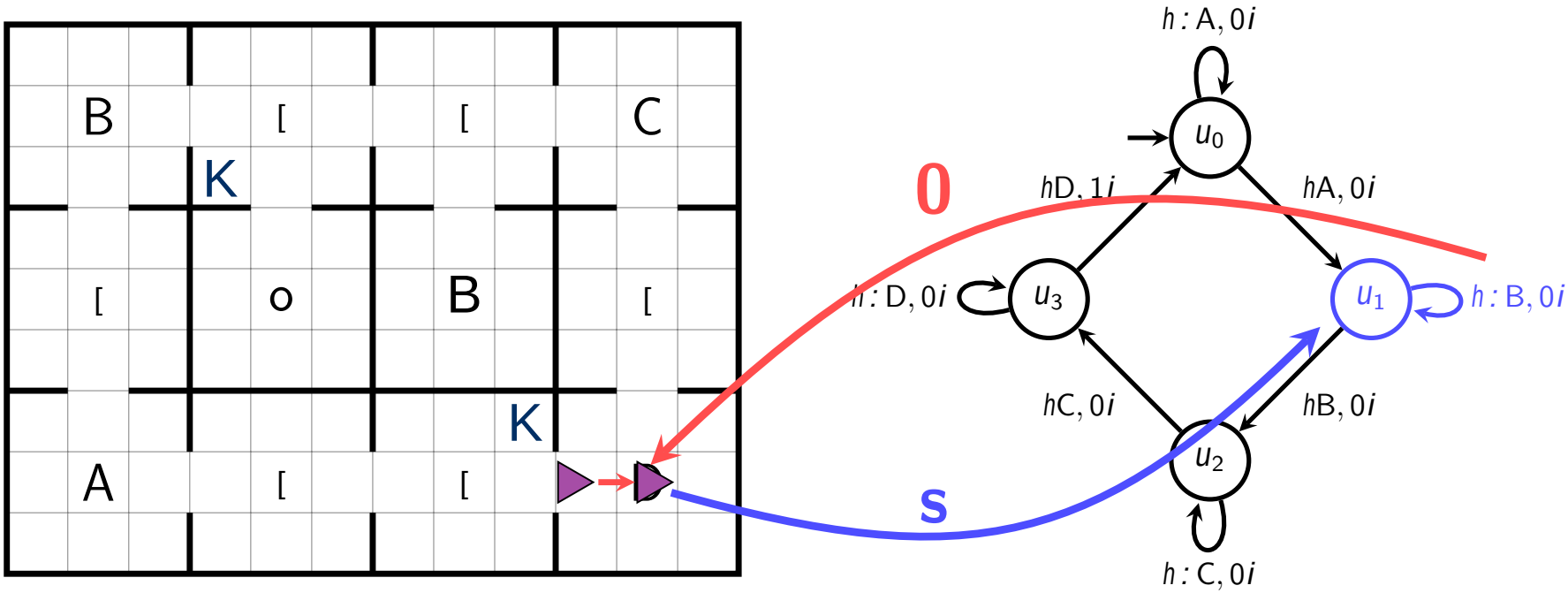

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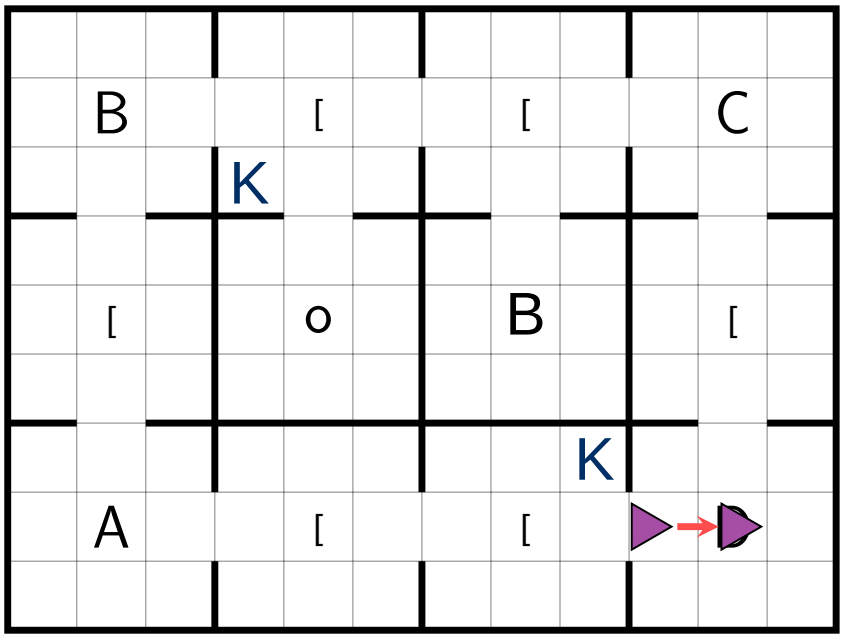

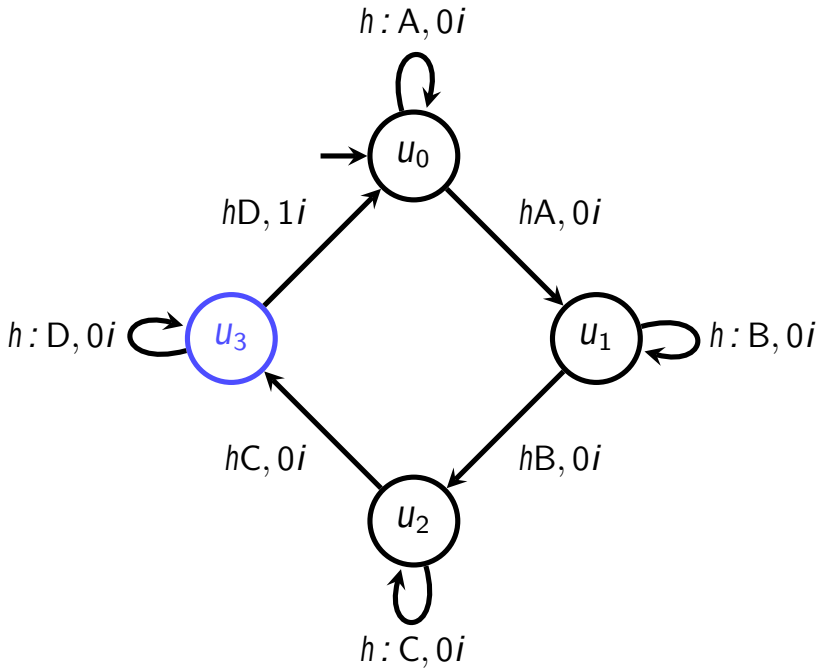

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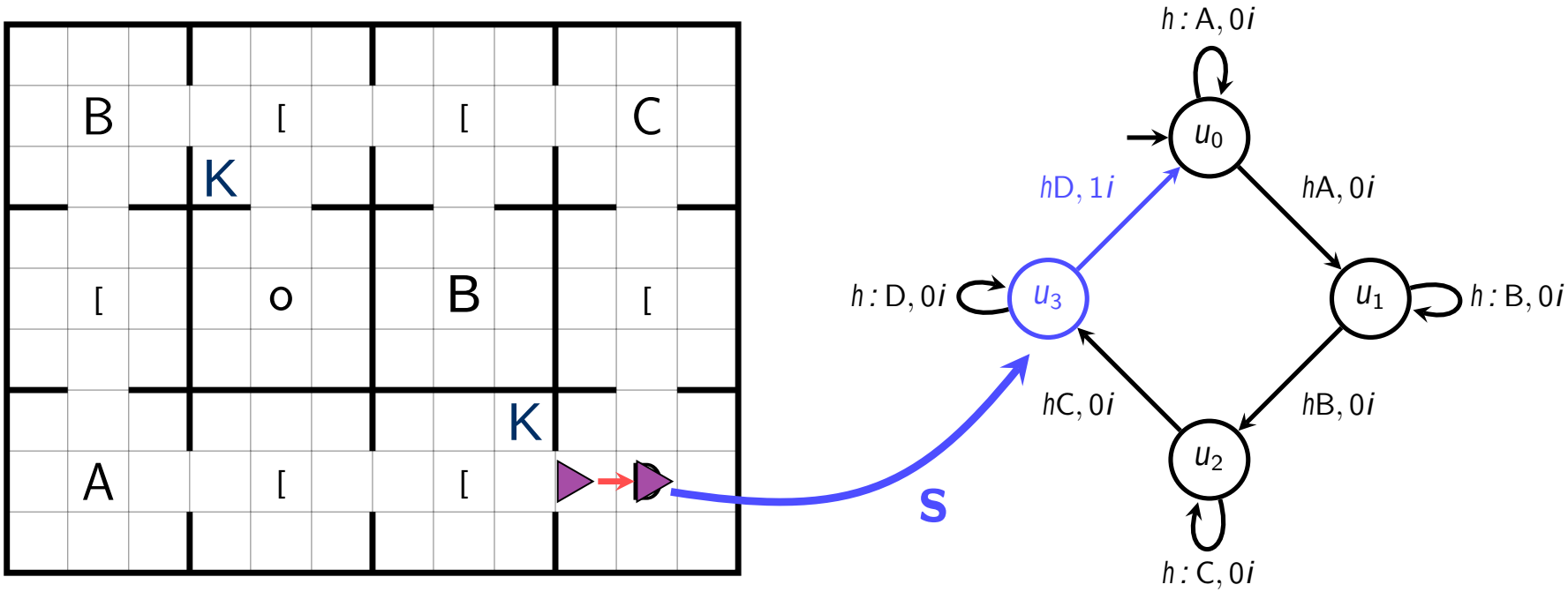

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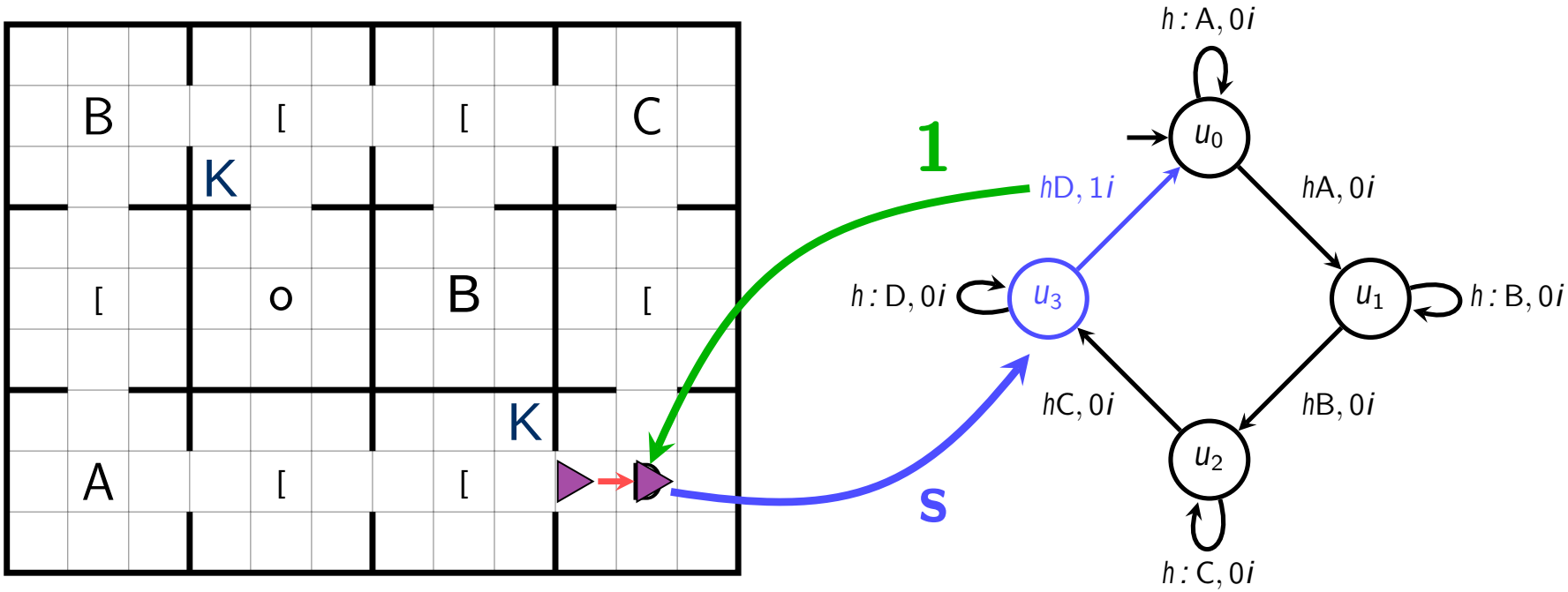

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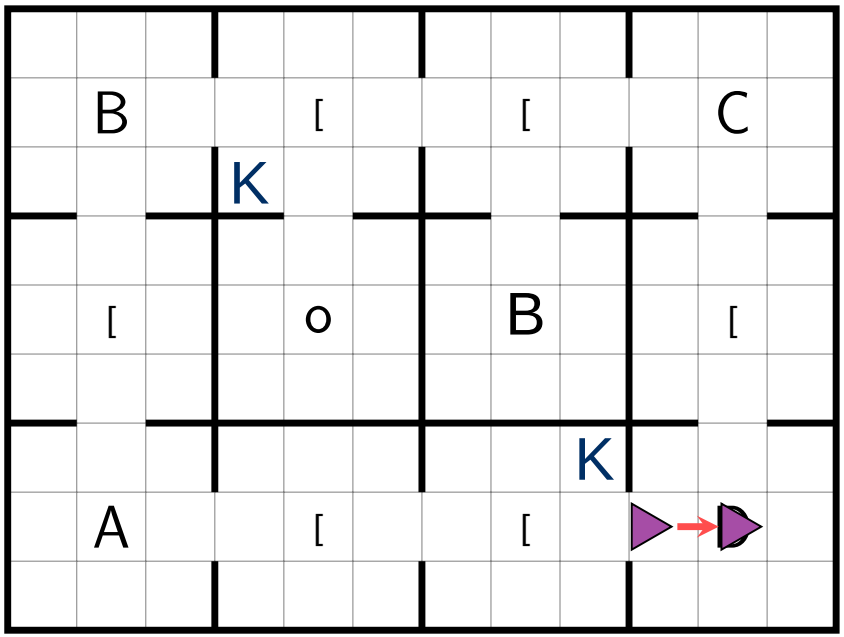

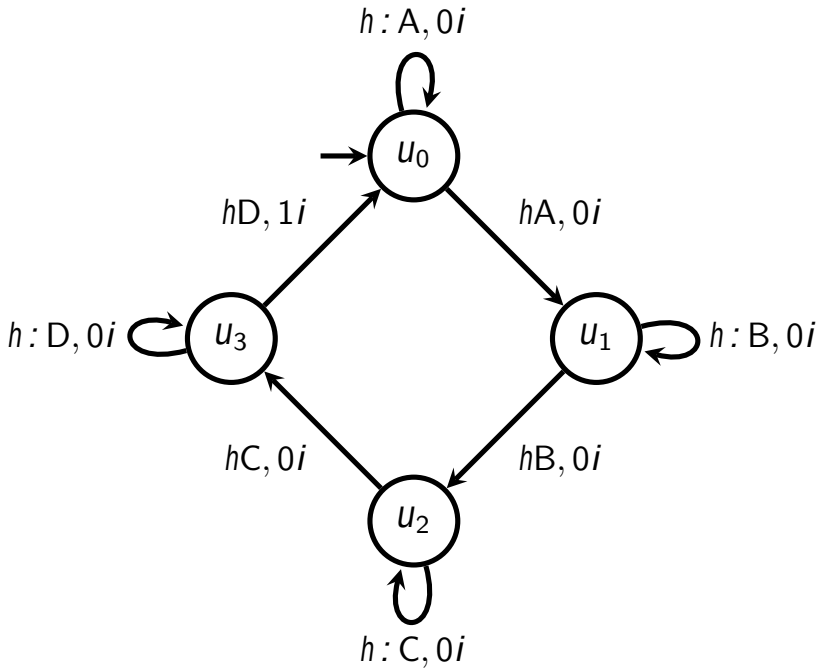

Solution (q-learning baseline)

Include the RM state to the agent's state representation.
Learn policies using standard q-learning.

Hierarchical RL baseline

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Learn meta-controller over a set of options (macro-actions).
Define one option per proposition in the RM's transitions.
Optimize π_i to satisfy i optimally.

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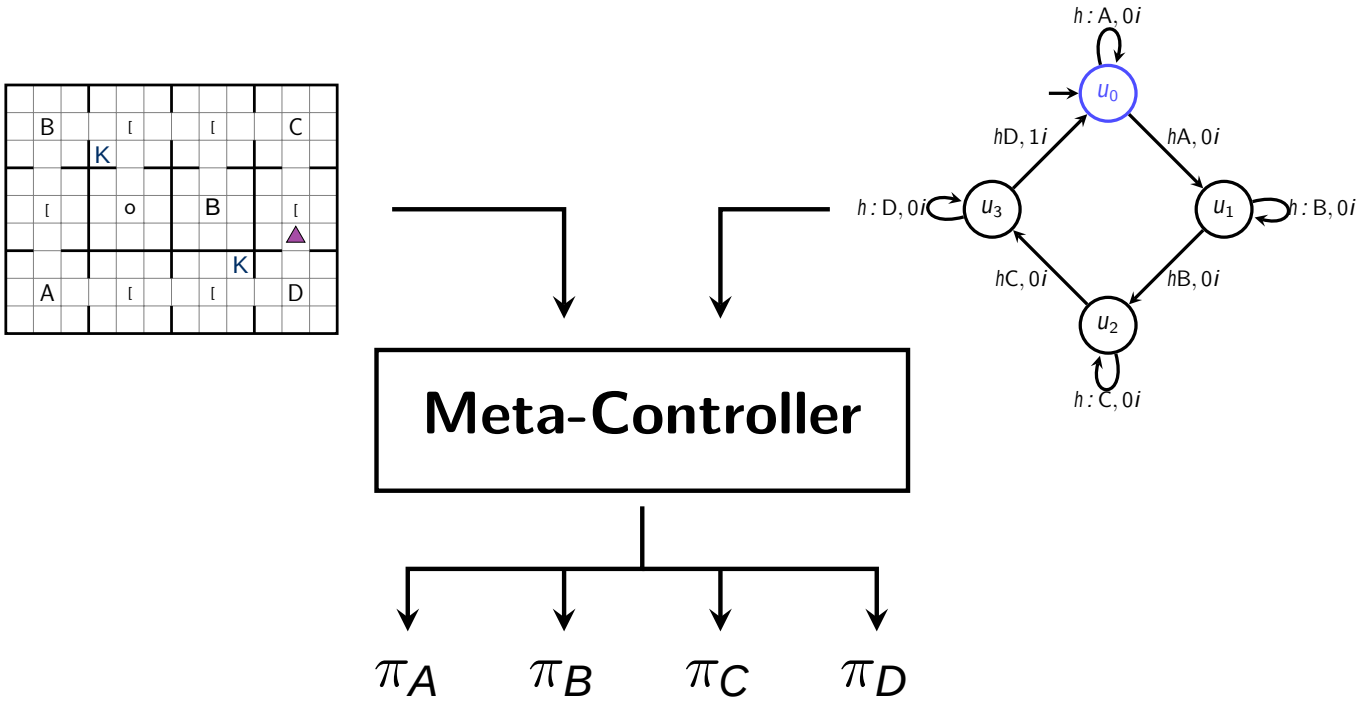

Hierarchical RL with RM pruning baseline

HRL-RM baseline

Prune useless options using the current reward machine state.

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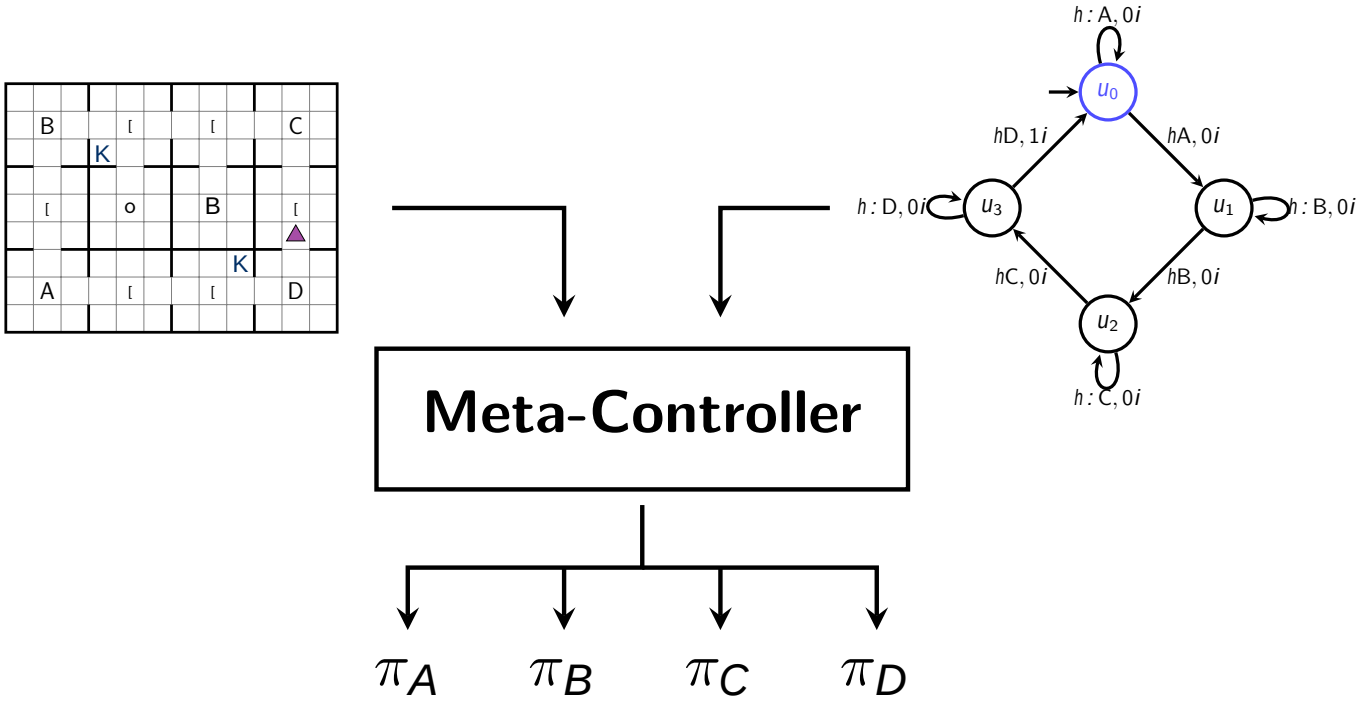

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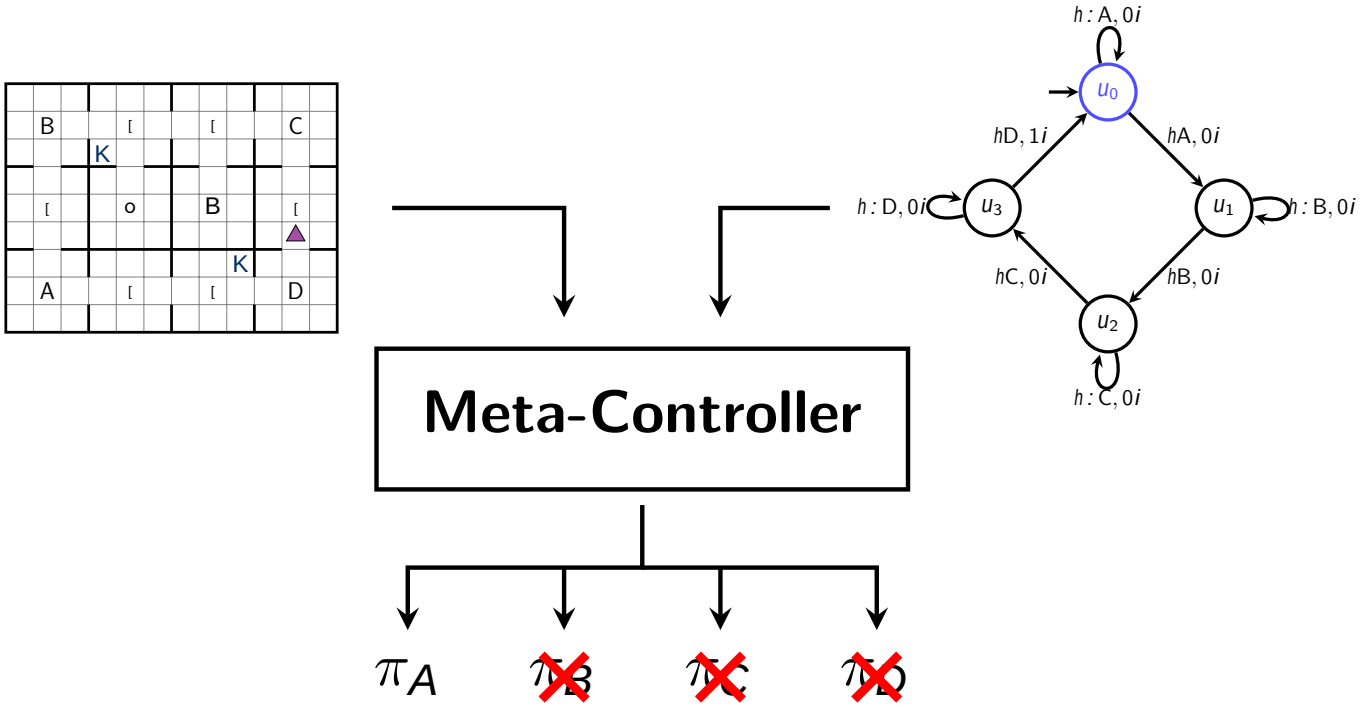

Hierarchical RL might converge to suboptimal policies

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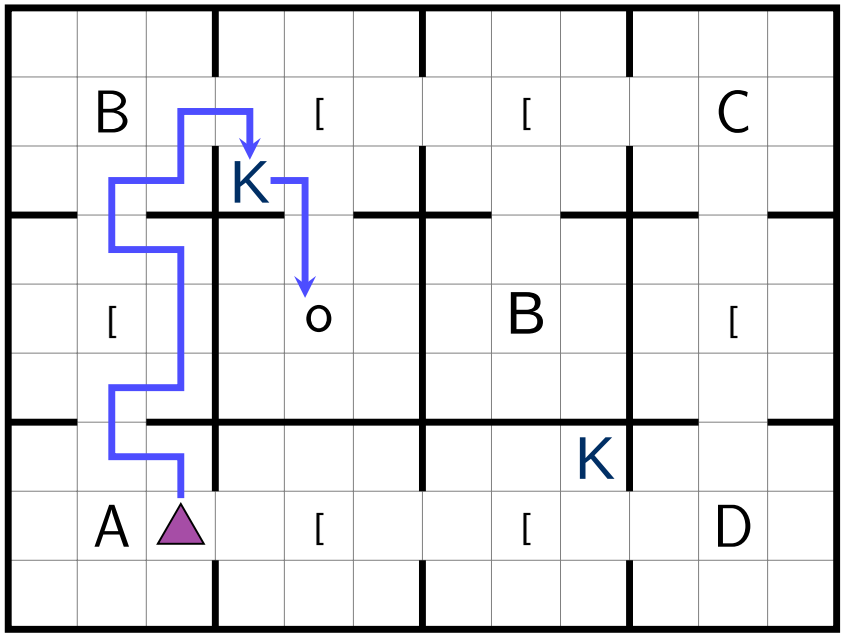

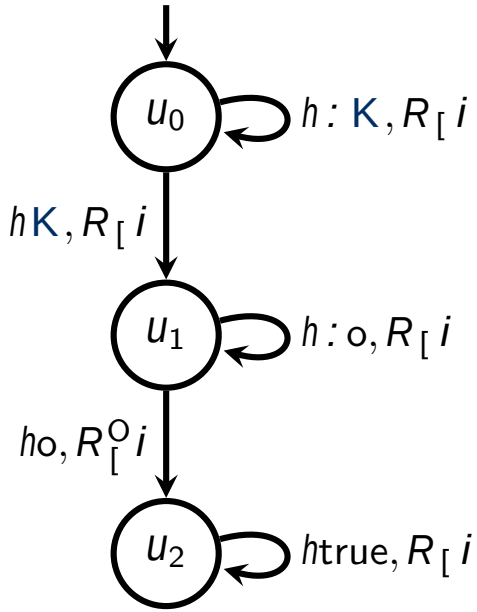

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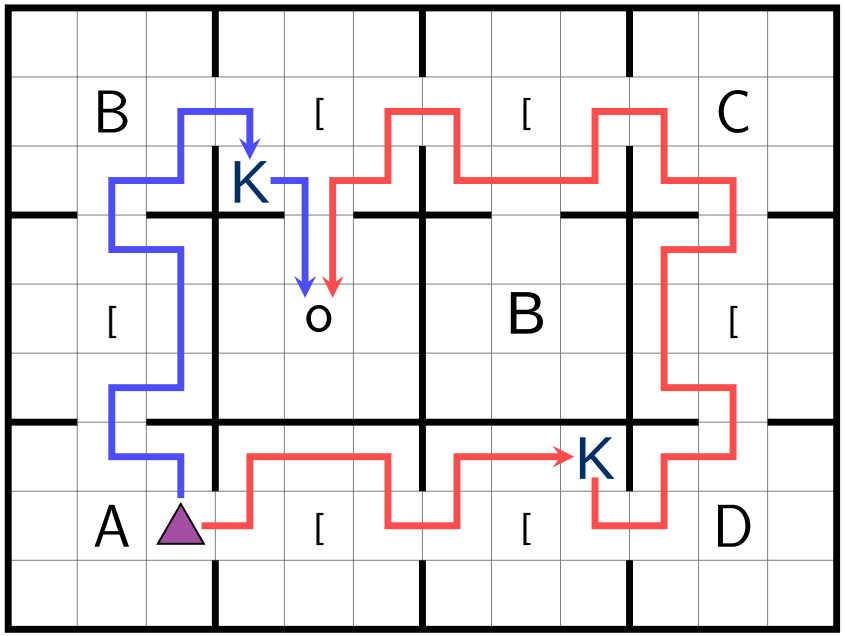

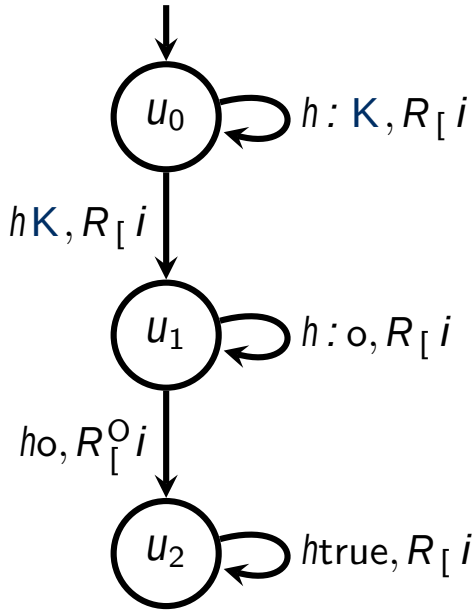

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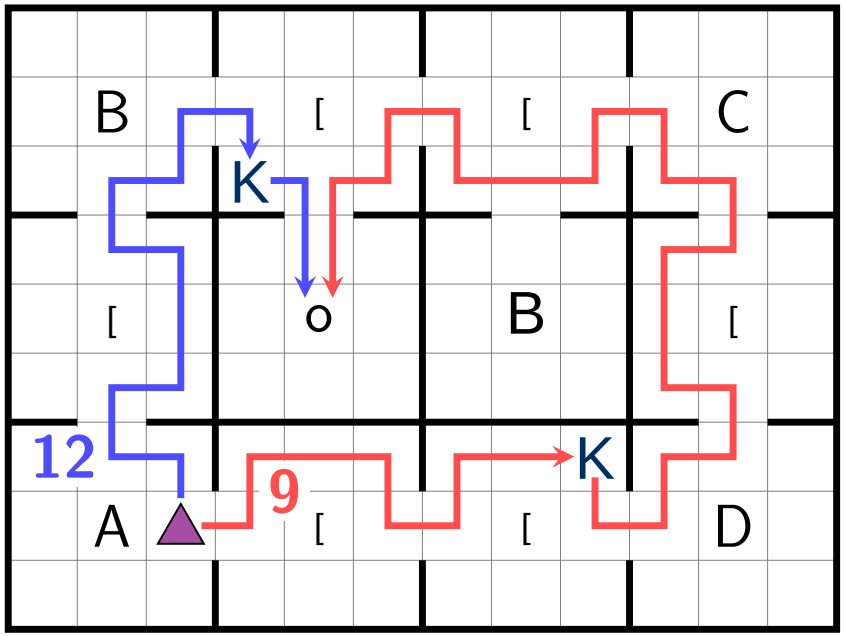
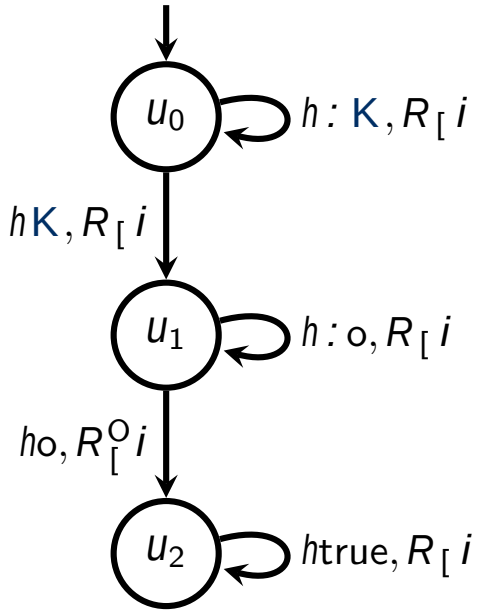
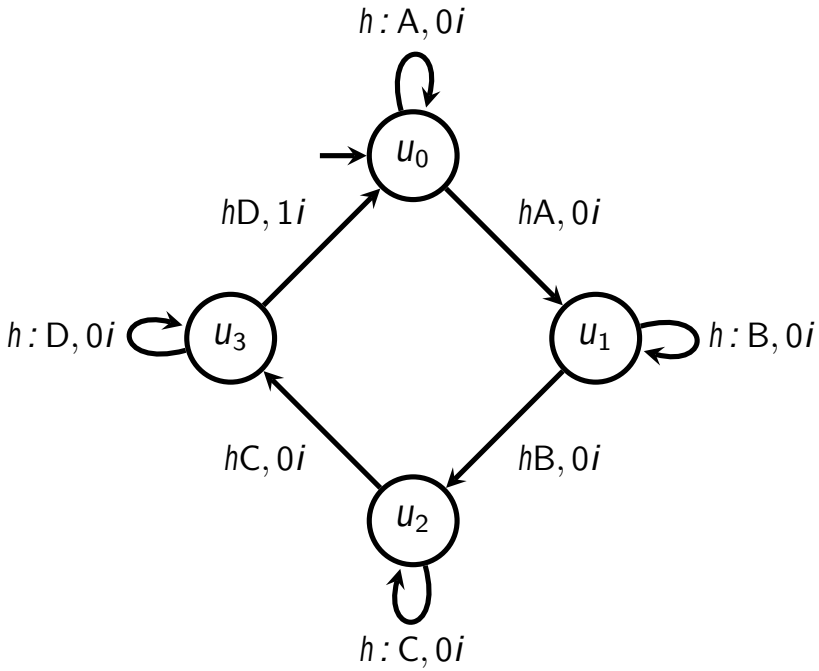




Reason: Policy π_c goes to the closest c.

Q-learning for Reward Machines (QRM)

QRM (our approach)



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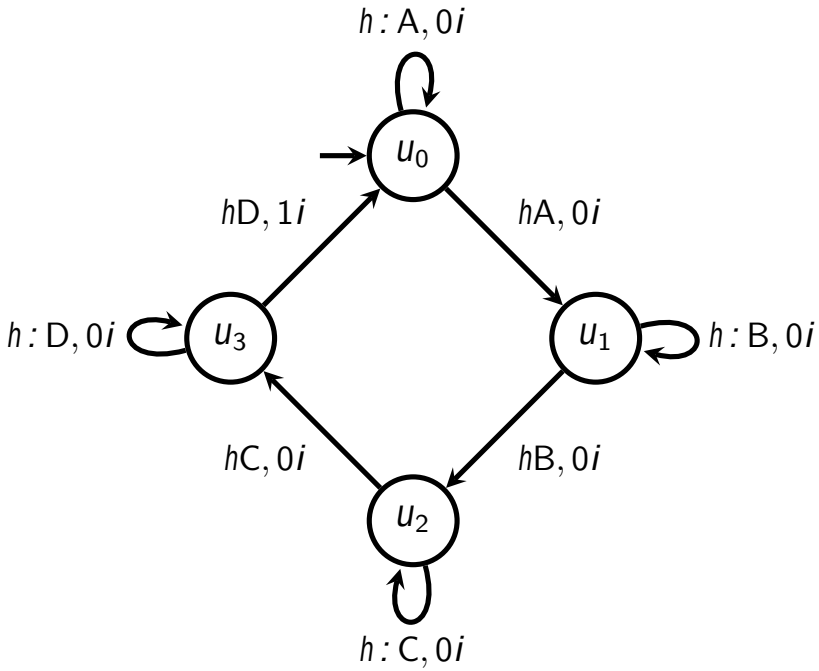
1. Learn one policy (q-function) per state in the reward machine.



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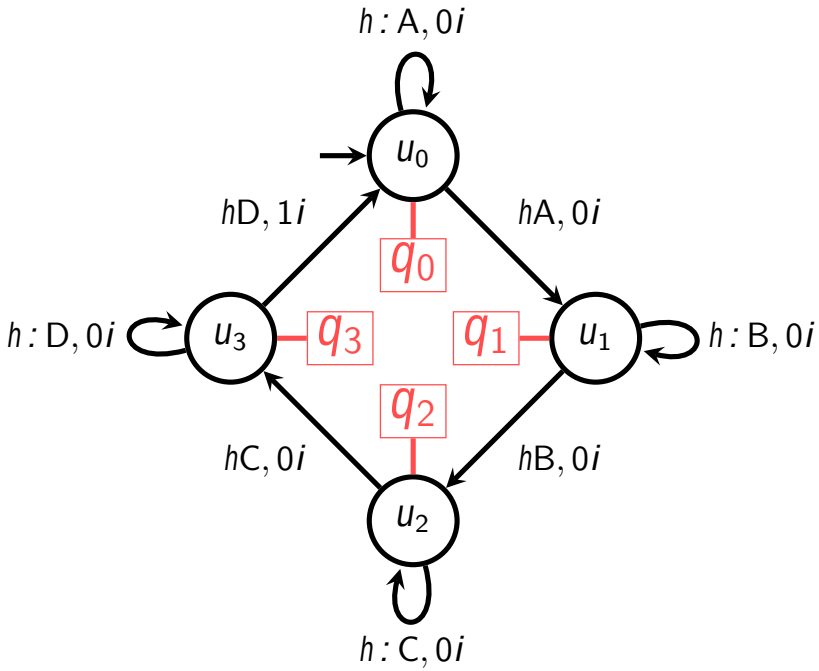

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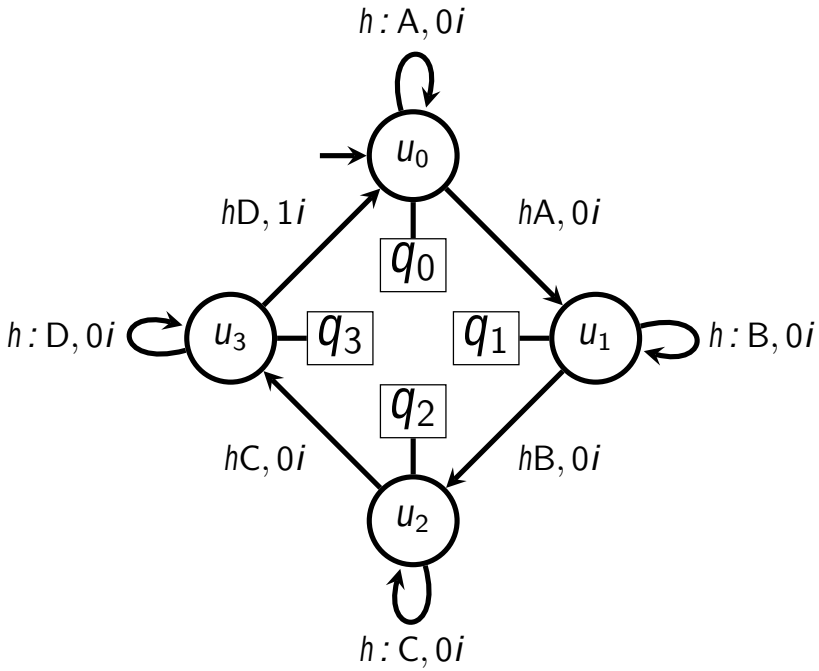

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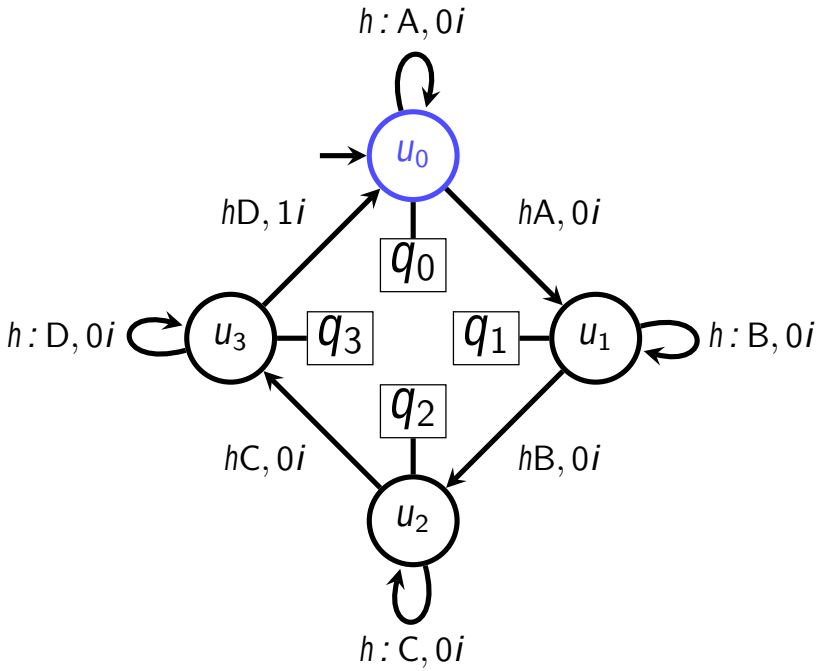

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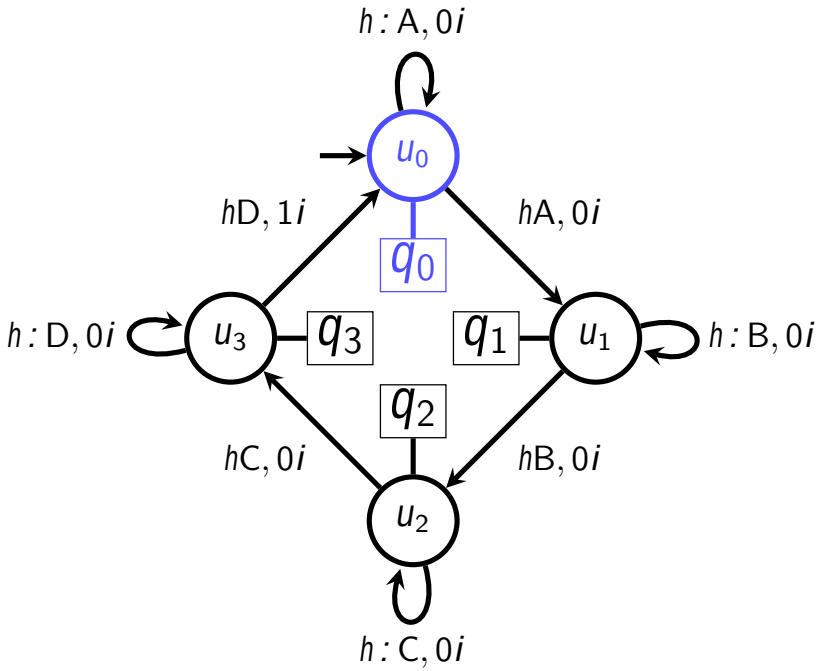

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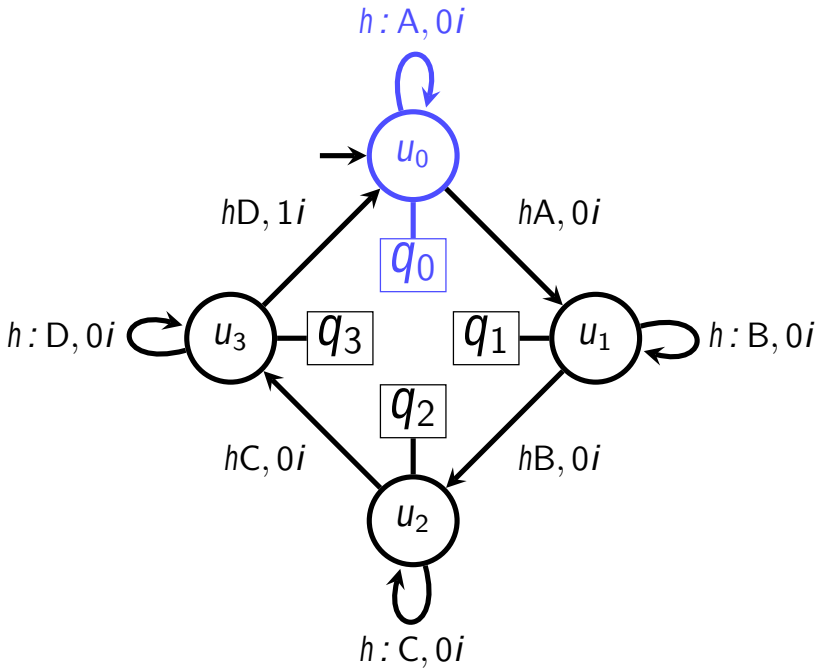

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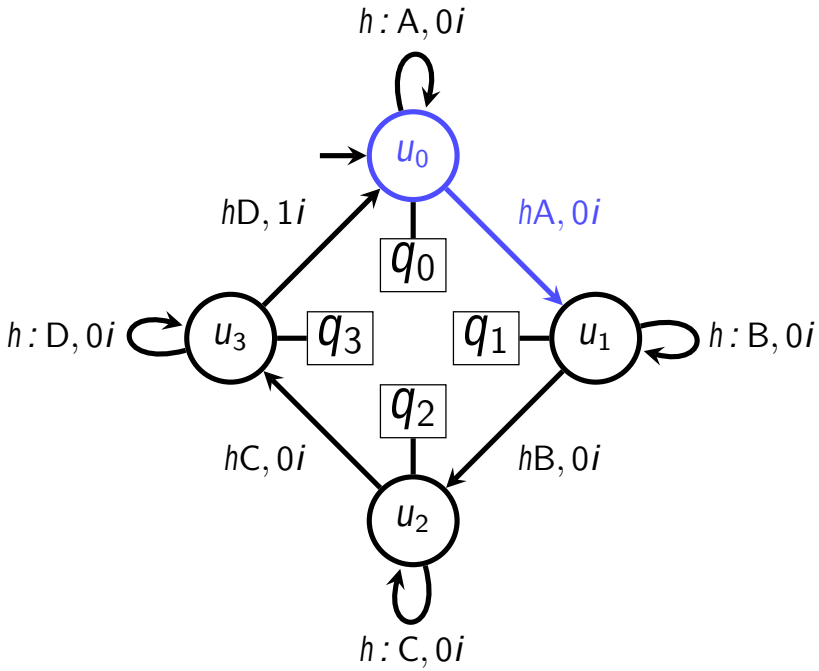

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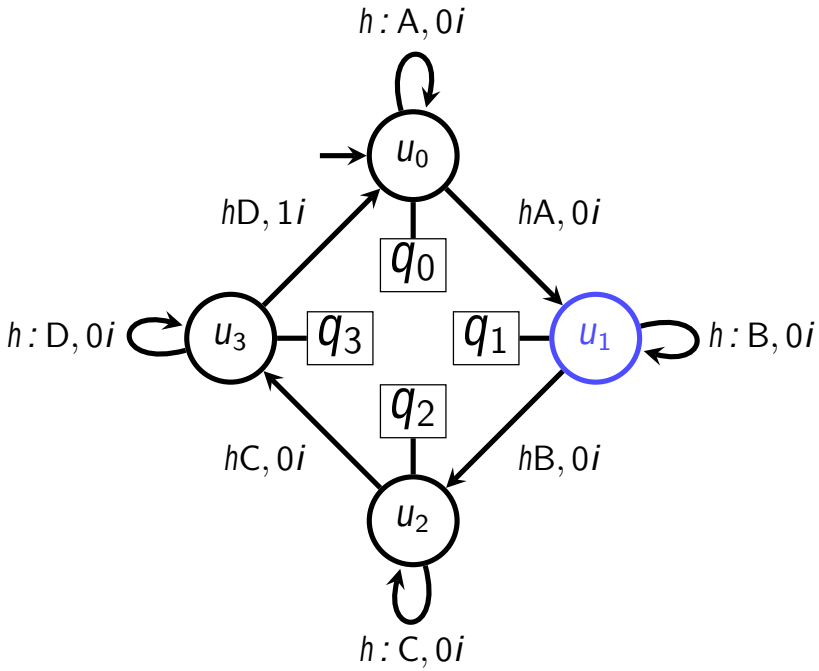

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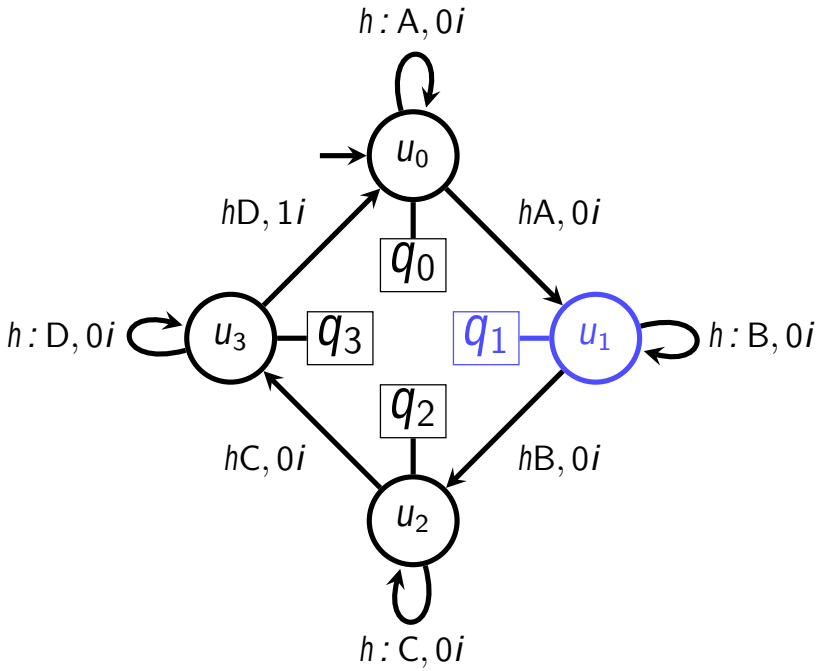

Q-learning for Reward Machines (QRM)

QRM (our approach)

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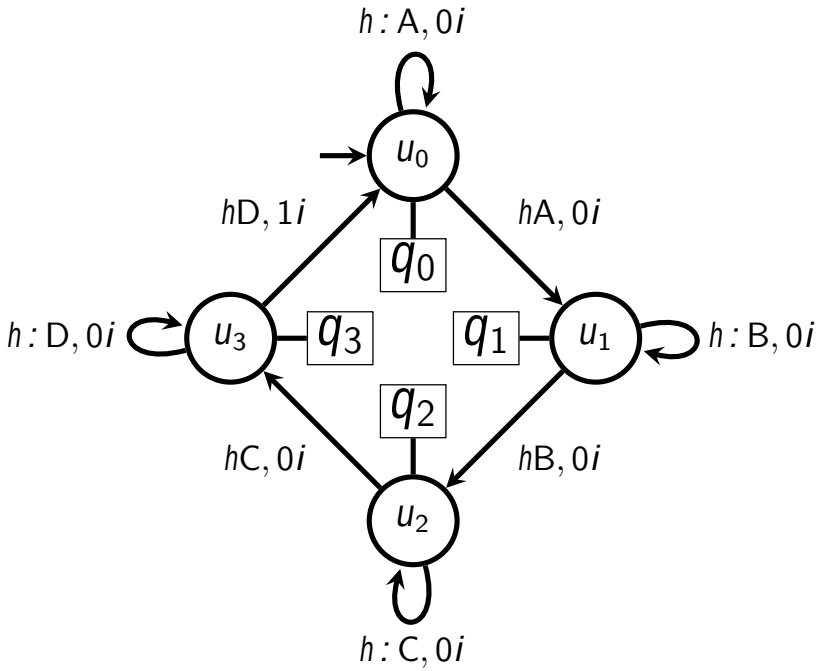
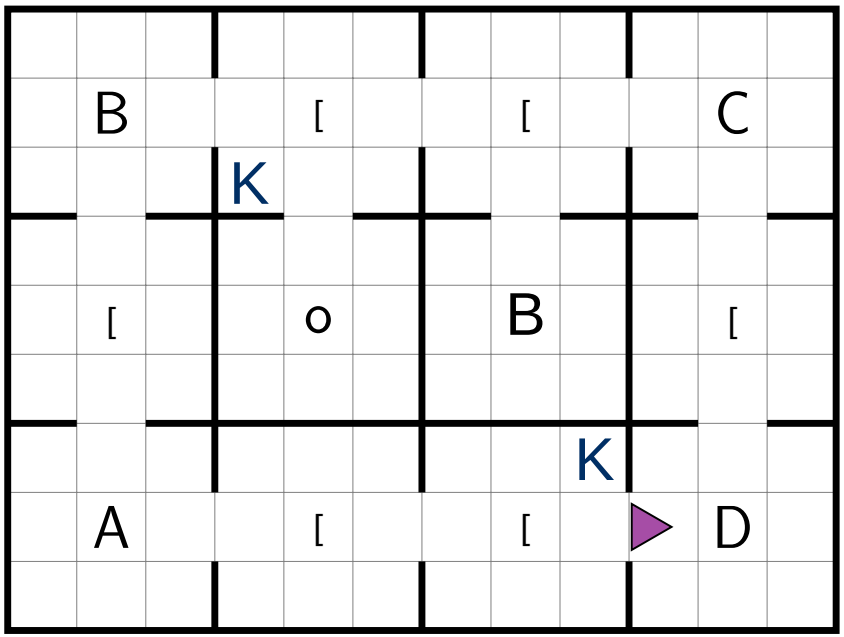
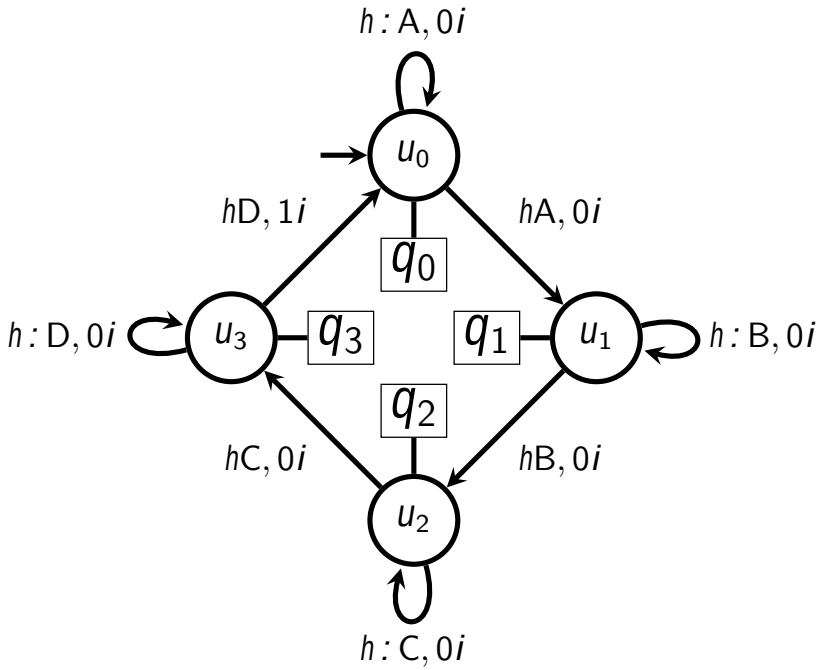
3. Reuse experience to update all the q-values at the same time.

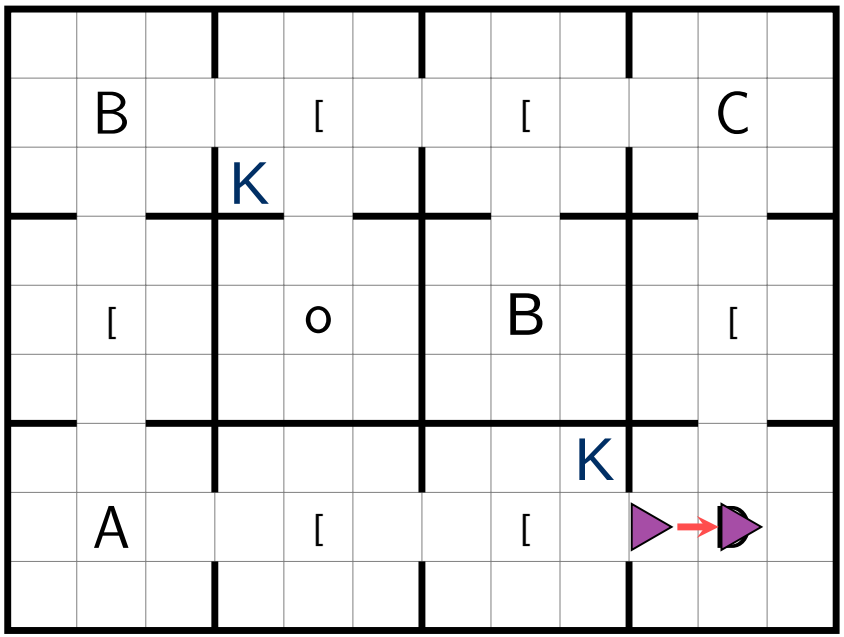


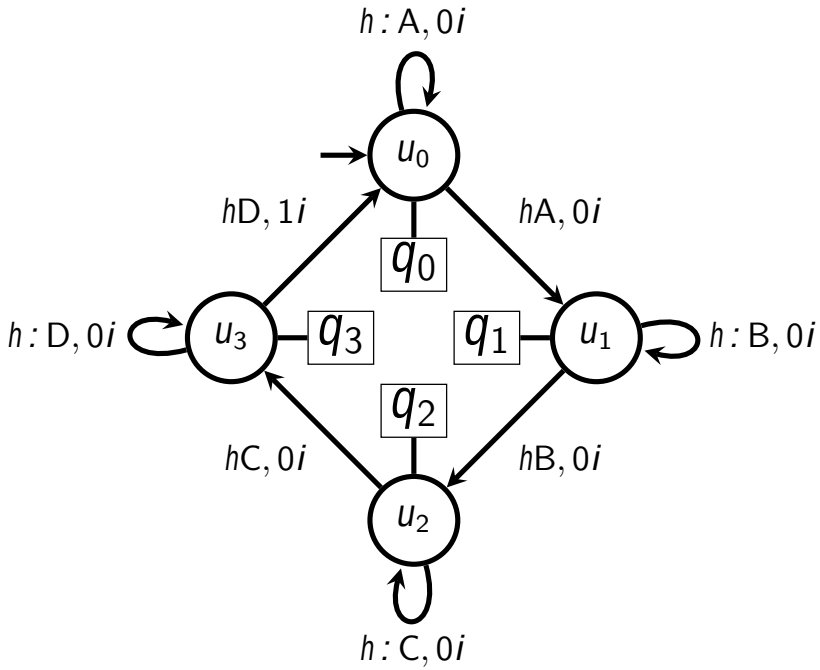
QRM learning step





QRM learning step





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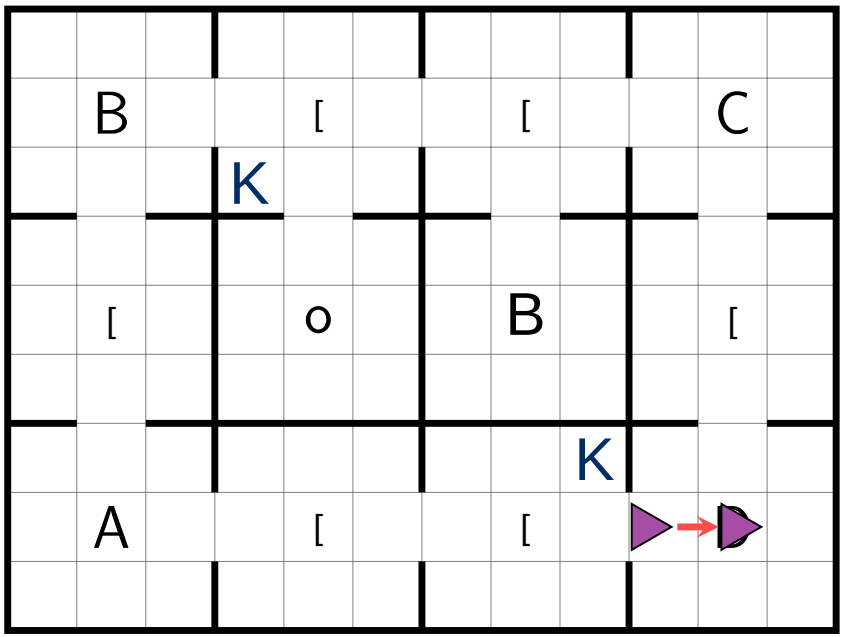

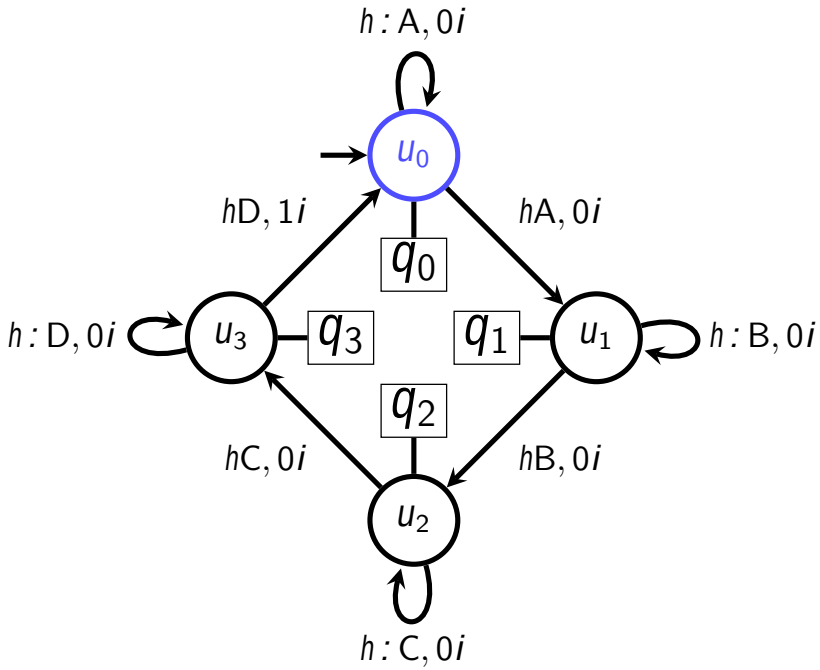

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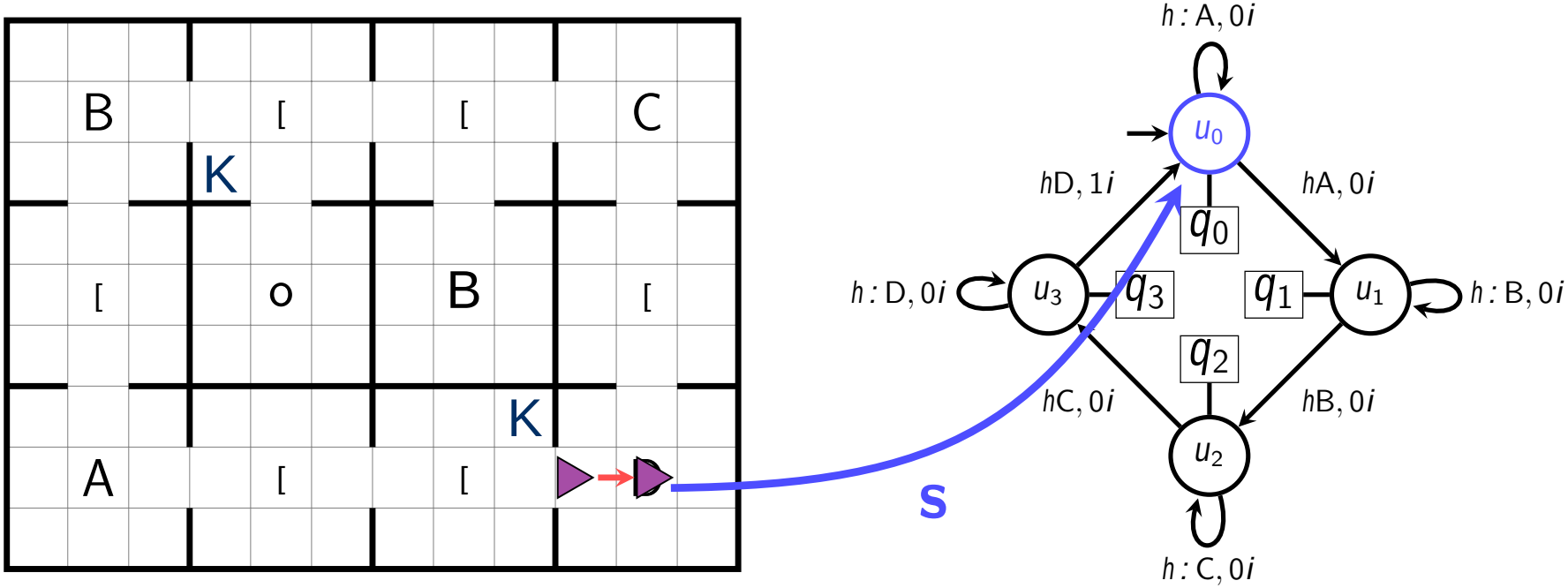

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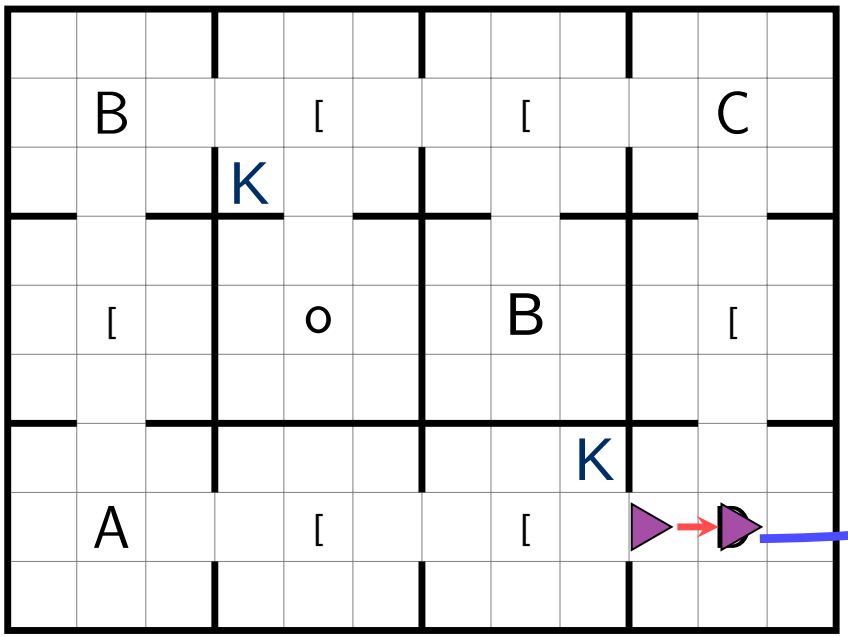

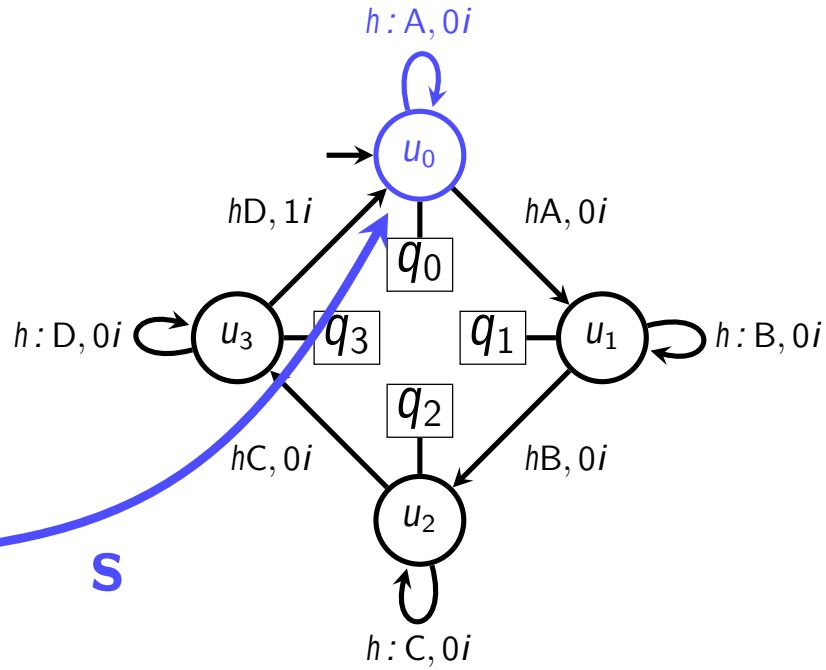

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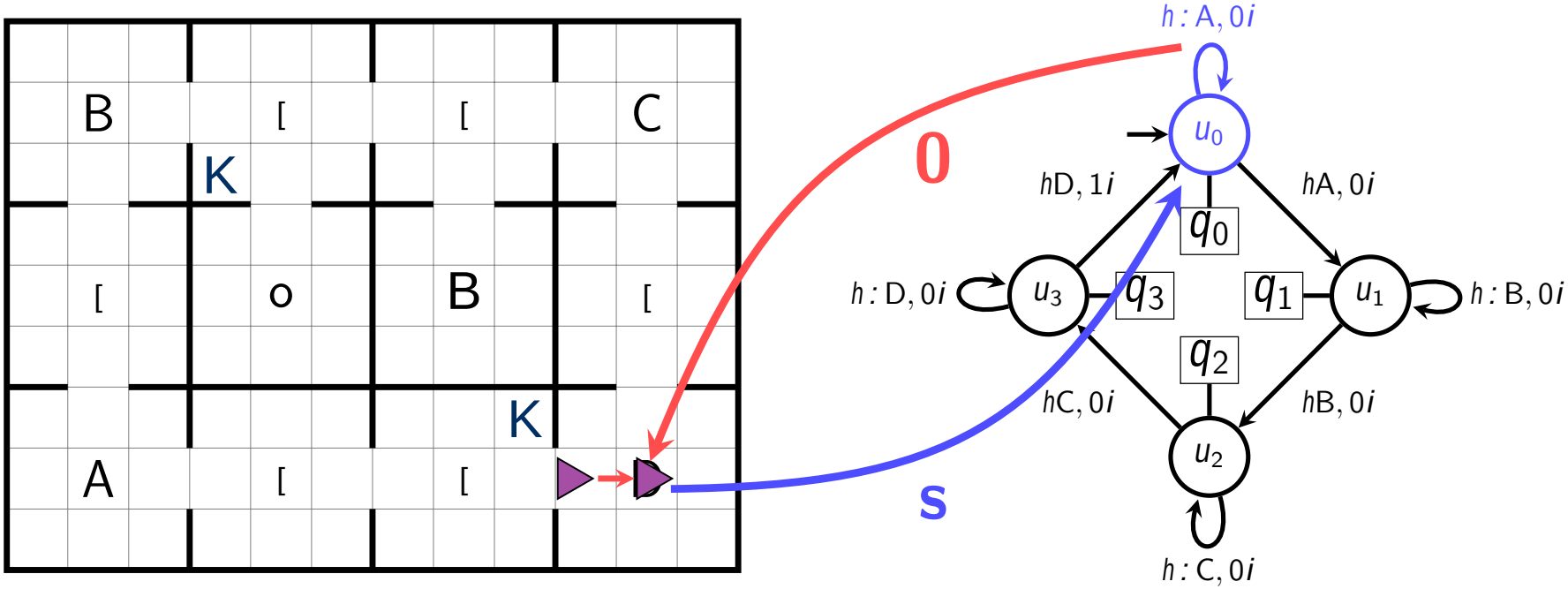

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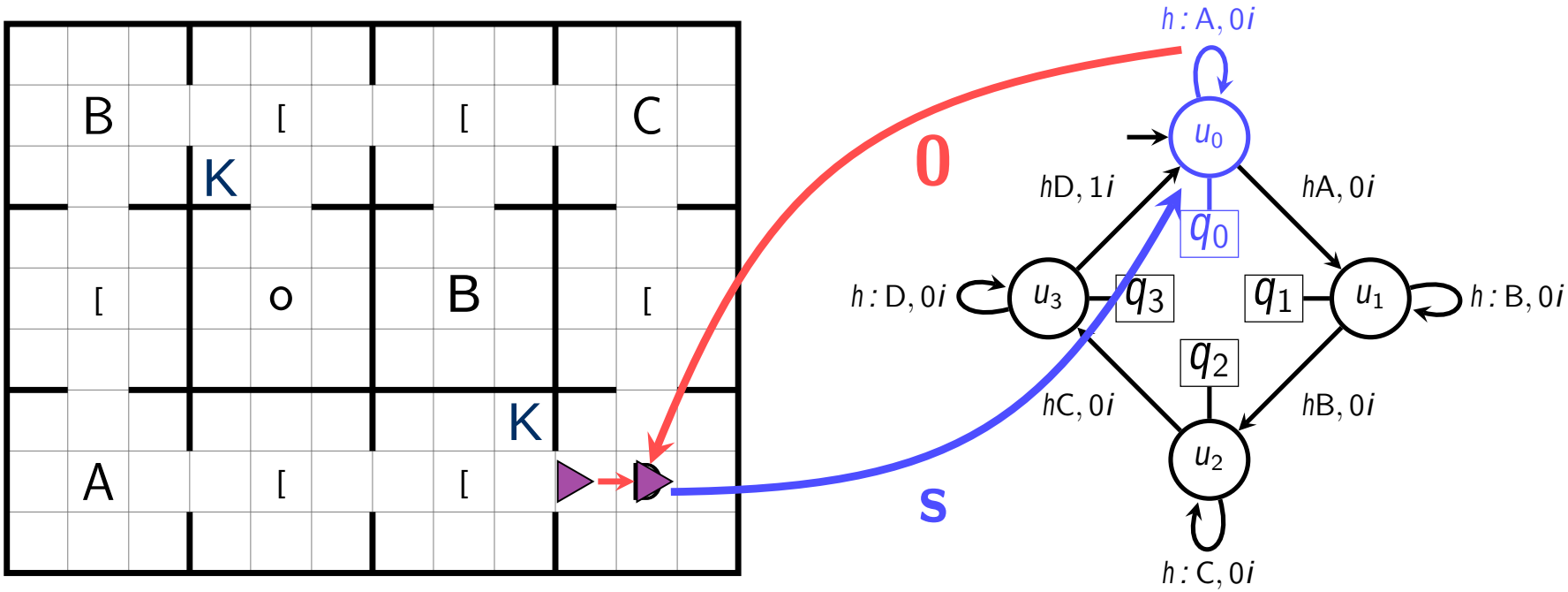
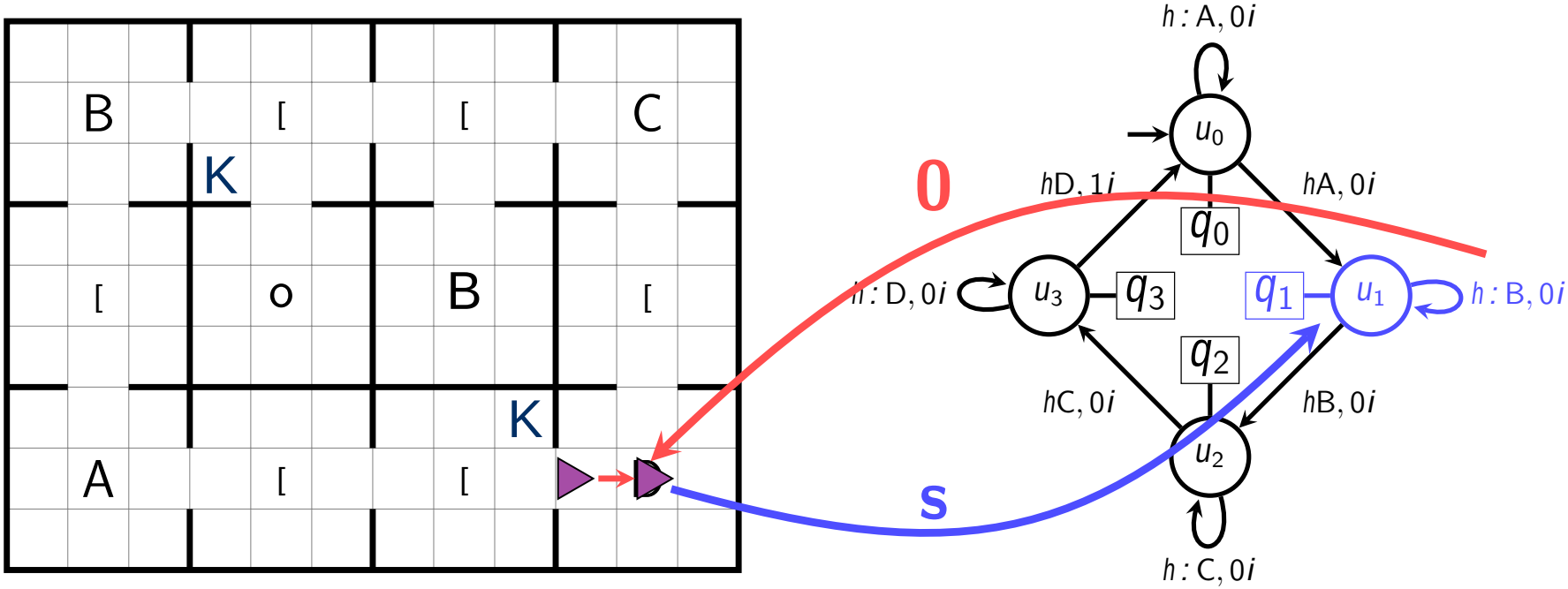


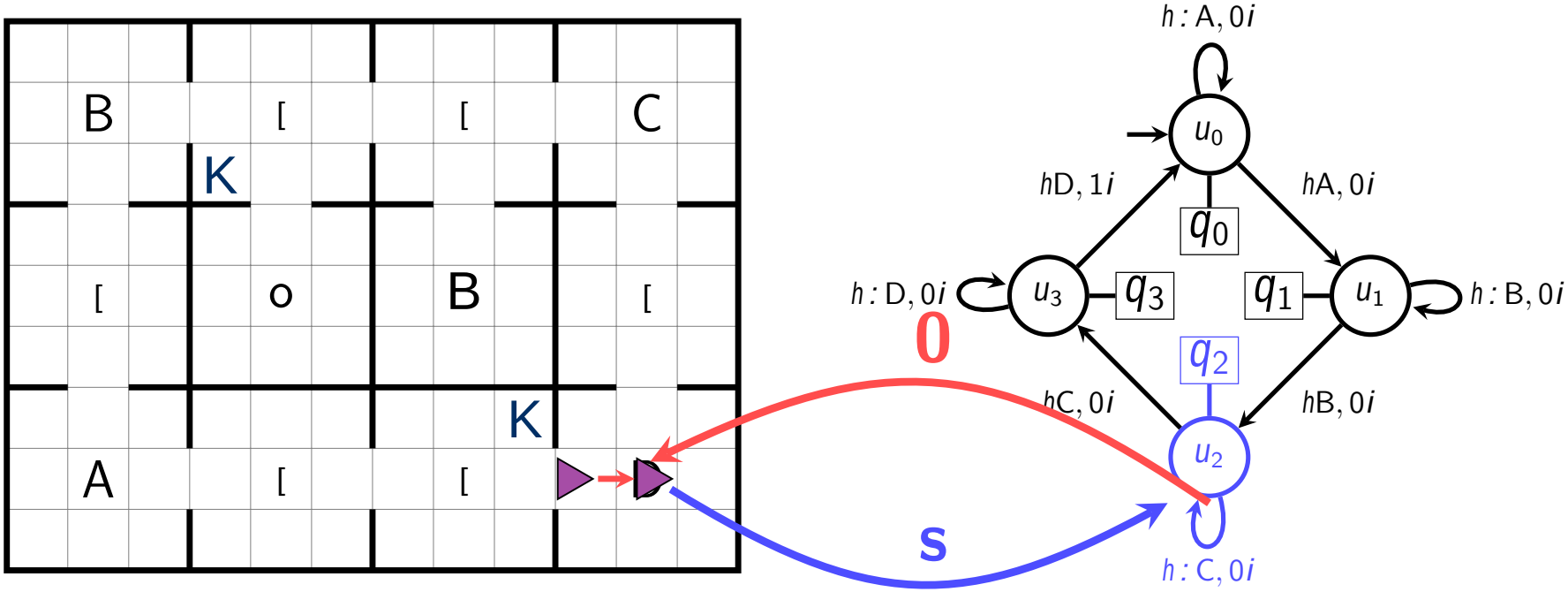
$$\mathbf{q_0}(s,a) \overset{\alpha}{\leftarrow} \mathbf{0} + \gamma \max_{a'} \mathbf{q_0}(s',a')$$

QRM learning step



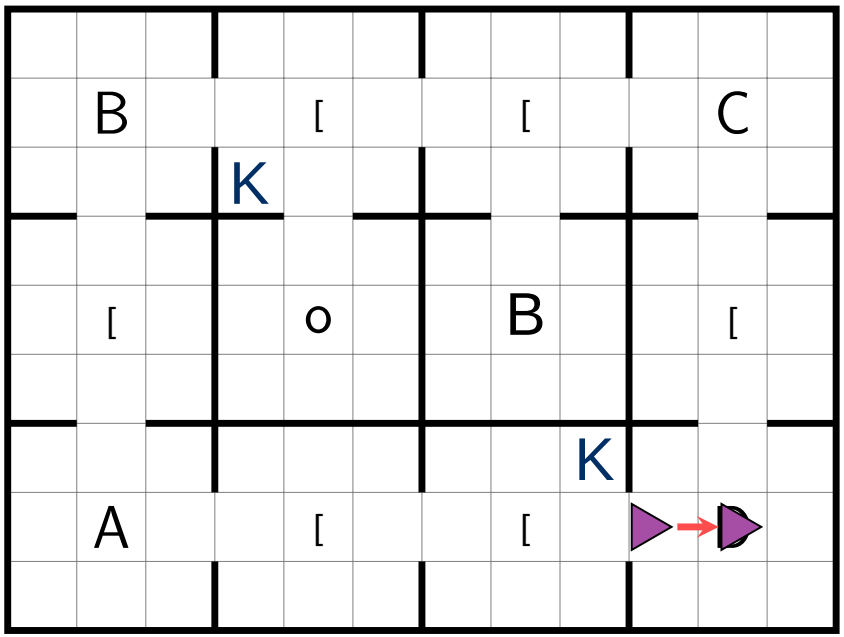
$$\mathbf{q_1}(s,a) \overset{\alpha}{\leftarrow} \mathbf{0} + \gamma \max_{a'} \mathbf{q_1}(s',a')$$

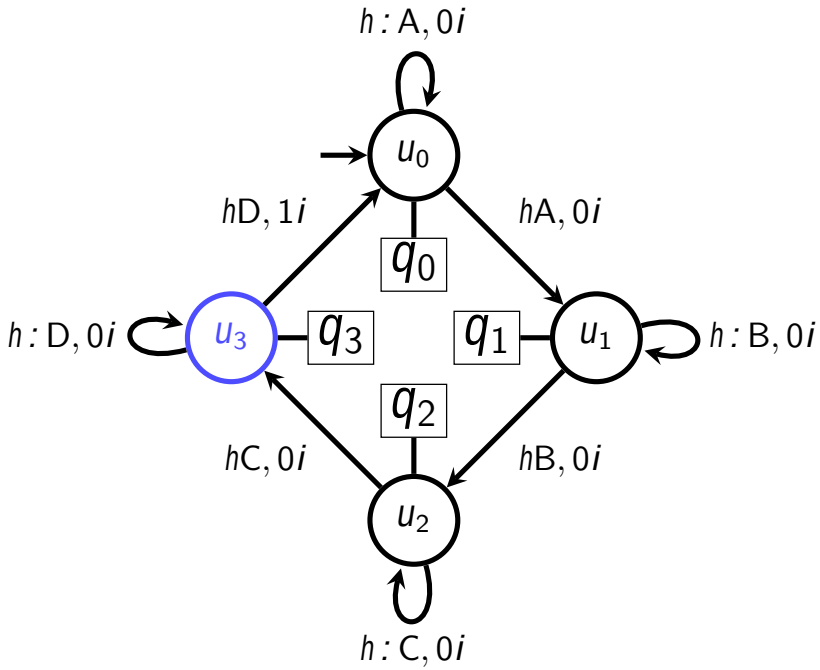
QRM learning step



$$\mathbf{q_2}(s,a) \overset{\alpha}{\leftarrow} \mathbf{0} + \gamma \max_{a'} \mathbf{q_2}(s',a')$$

QRM learning step





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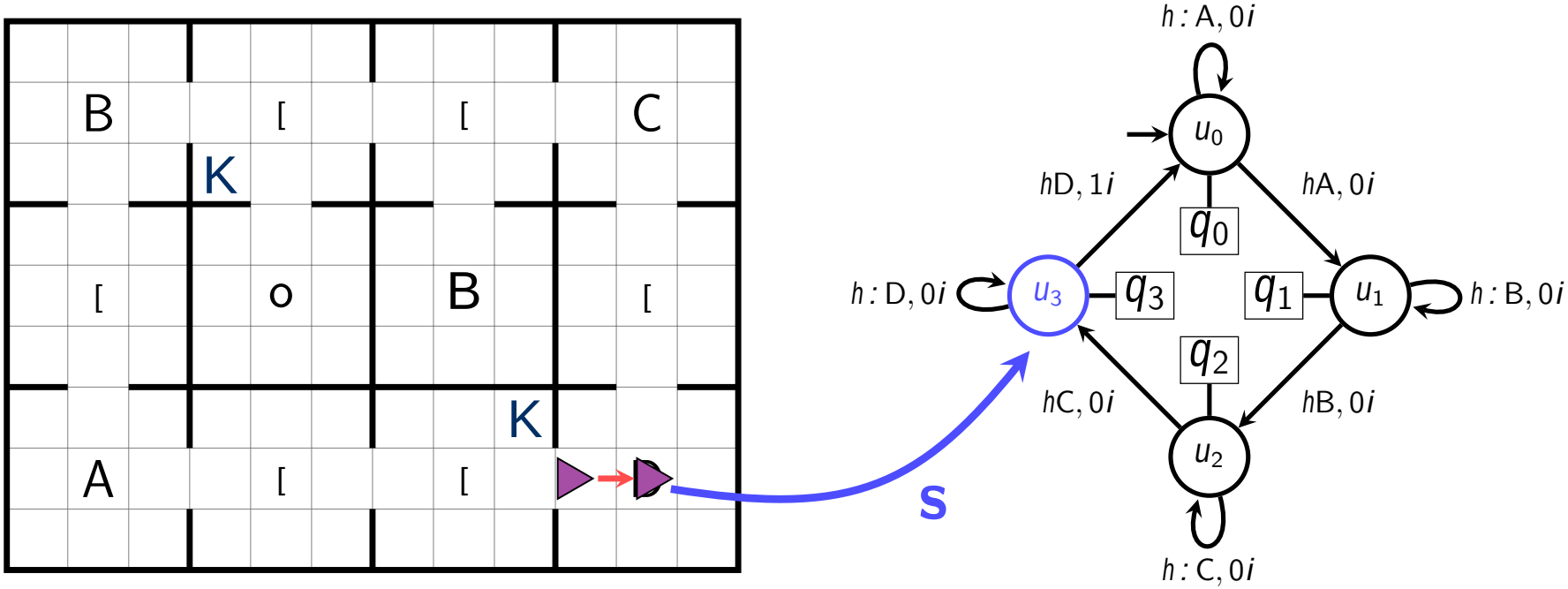

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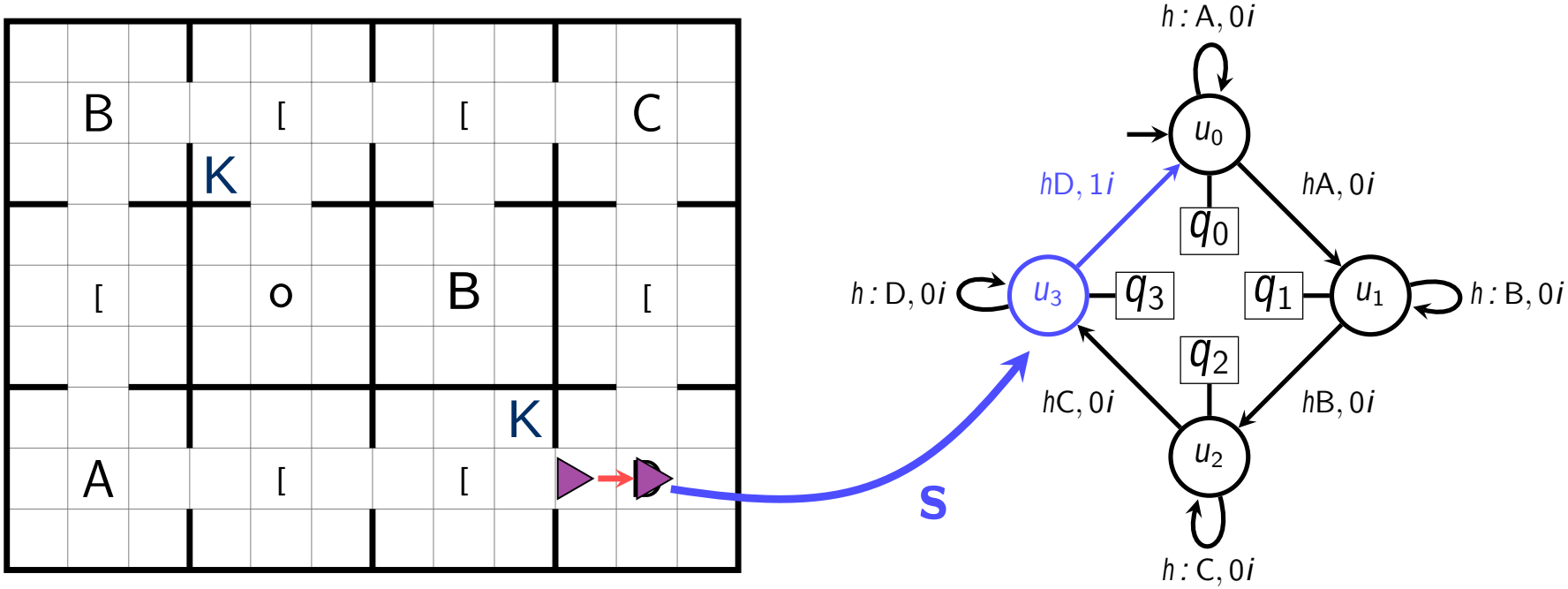
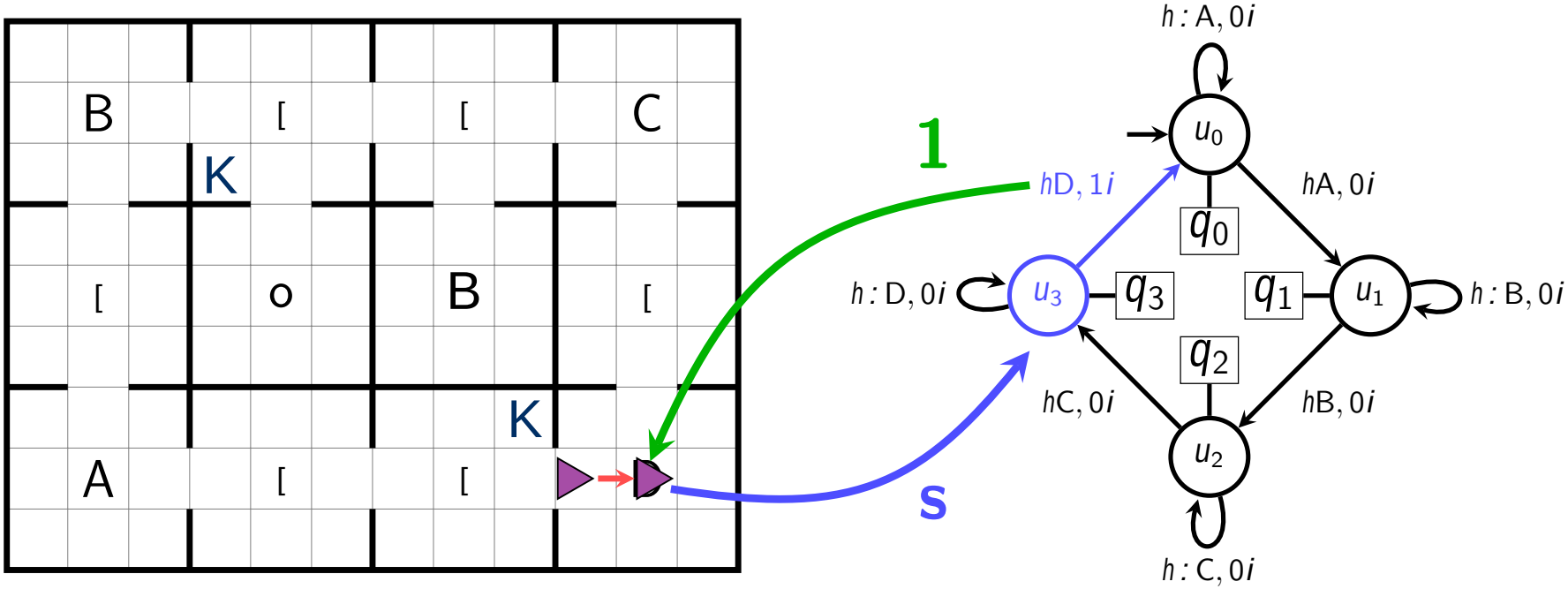


QRM learning step



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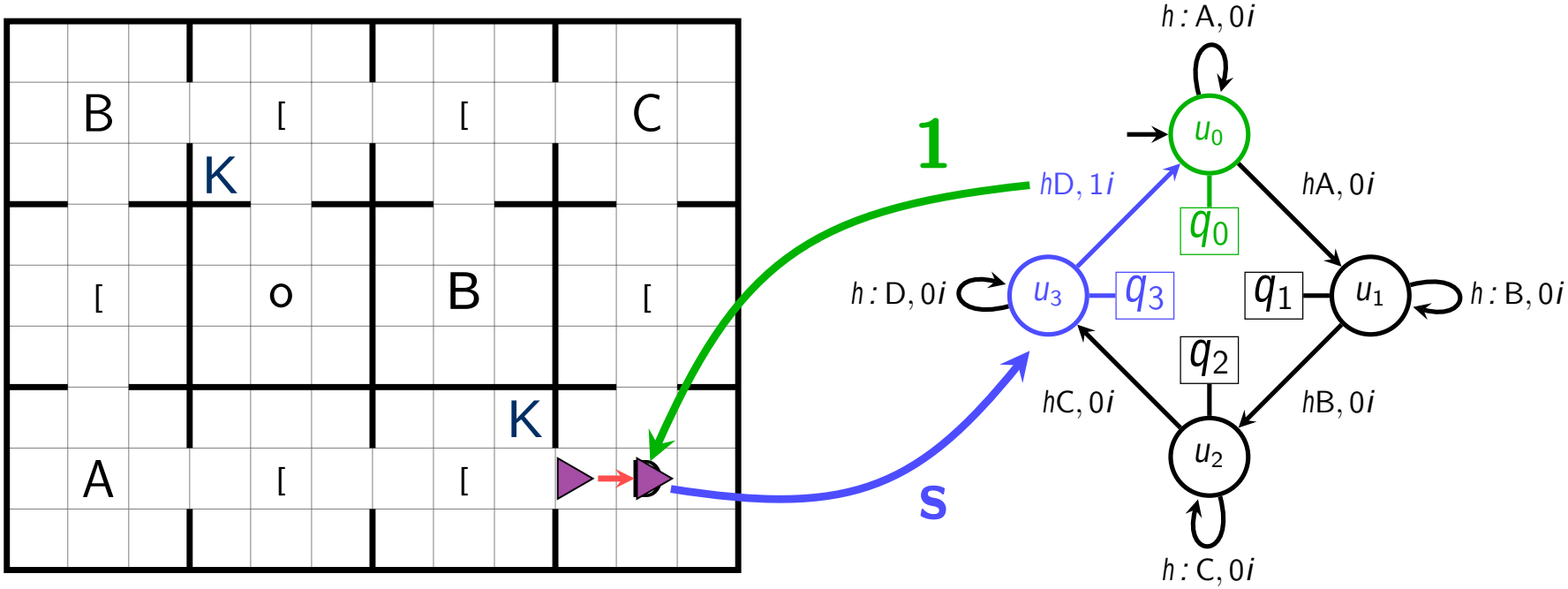
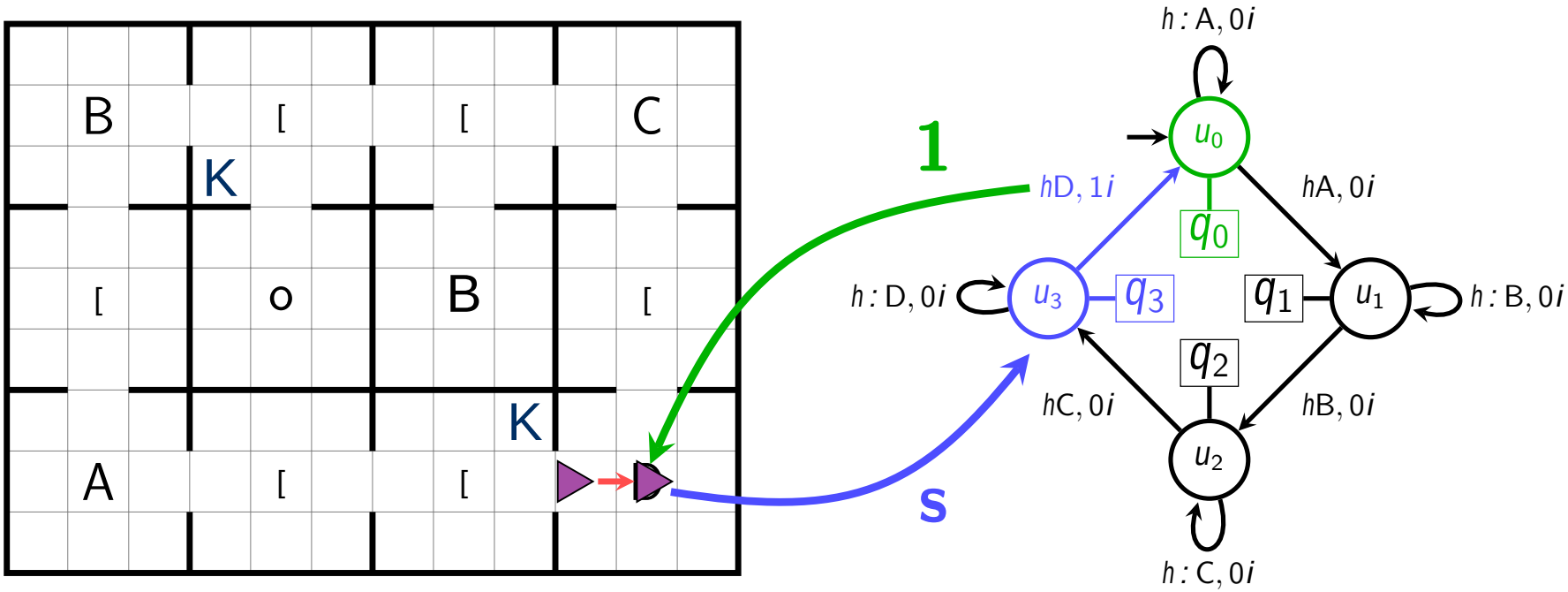


$$\mathbf{q_3}(s,a) \overset{\alpha}{} \mathbf{1} + \gamma \max_{a'} \mathbf{q_0}(s',a')$$

QRM learning step



Theorem

QRM converges to an optimal policy in the limit.

Outline

Outline

Experiments

Two discrete grid domains:

- Office domain (4 tasks).
- Craft domain (10 tasks).

Experiments

Two discrete grid domains:

- Office domain (4 tasks).
- Craft domain (10 tasks).

One continuous state space domain:

- Water domain (10 tasks).

Discrete domains

Algorithms

Q-Learning over a cross-product MDP (**Q-learning**)
Hierarchical RL based on options (**HRL**)
Hierarchical RL with option pruning (**HRL-RM**)
Q-learning for reward machines (**QRM**)

Discrete domains

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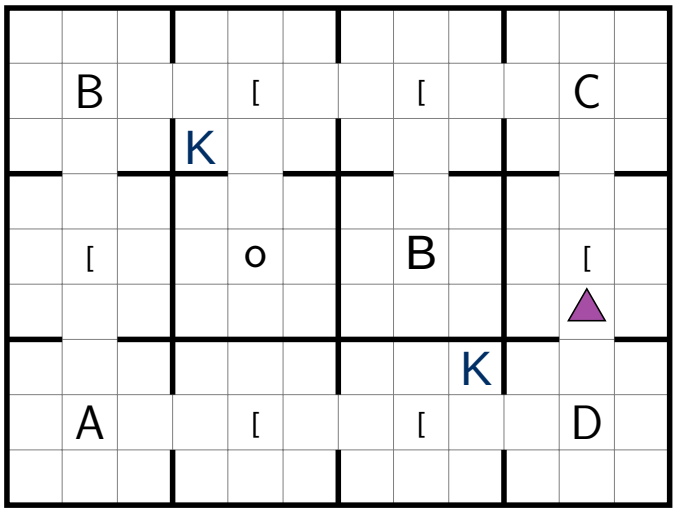
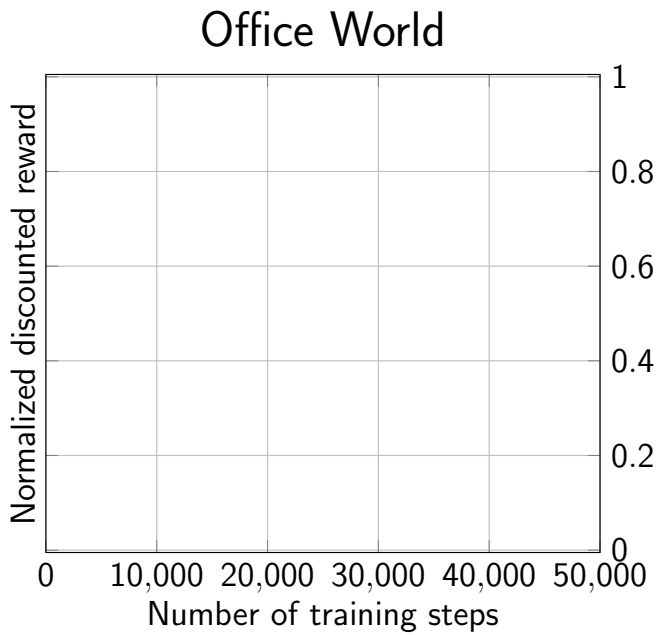
Method	**Optimality?**	**Decomposition?**
Q-learning	3	
HRL		3
HRL-RM		3
QRM	3	3

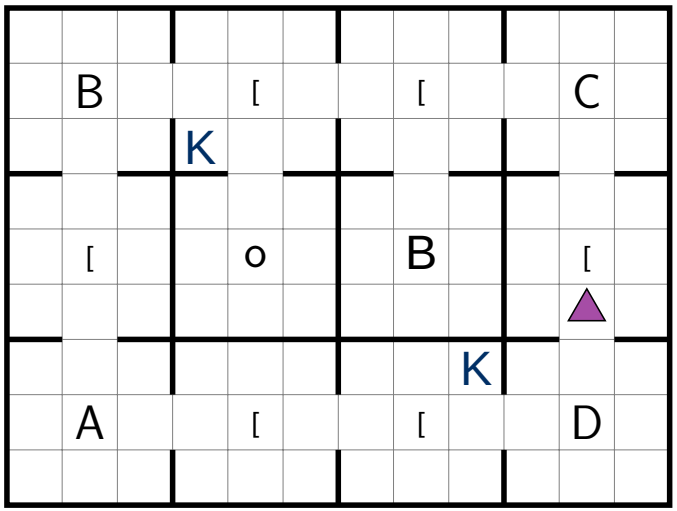
The office domain

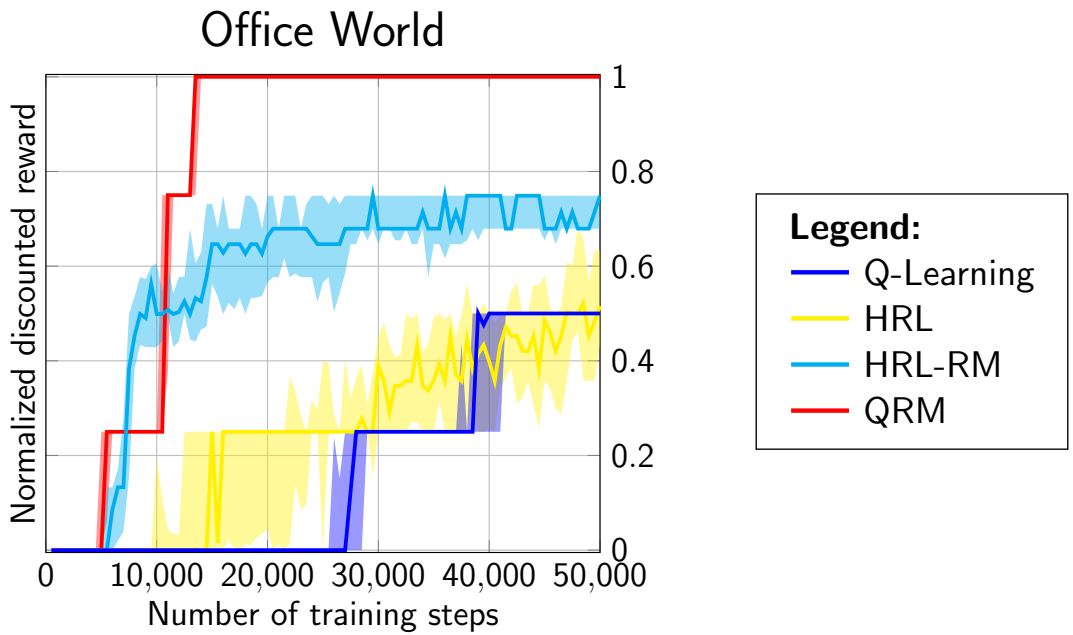




4 tasks (30 independent trials)

The office domain





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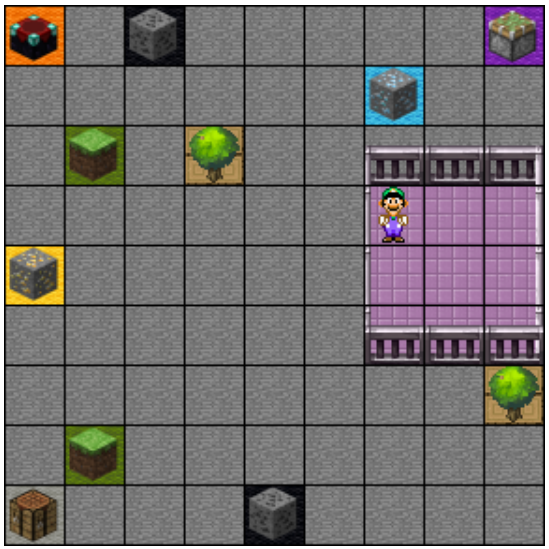
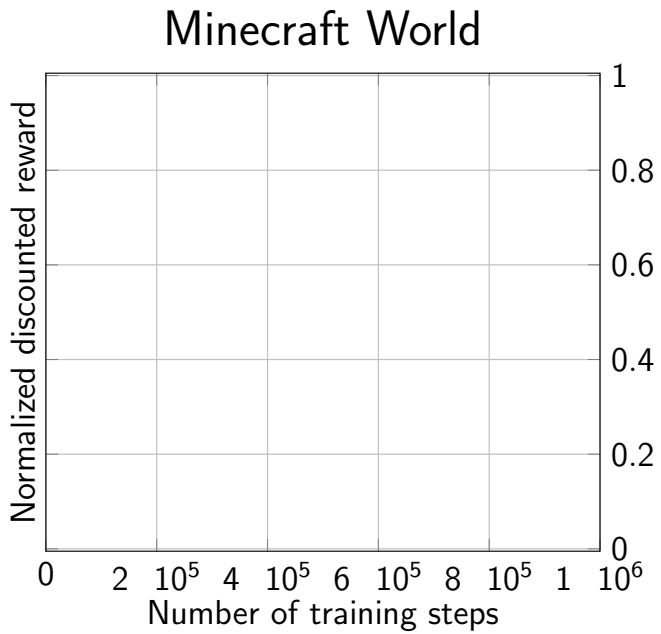
The craft domain

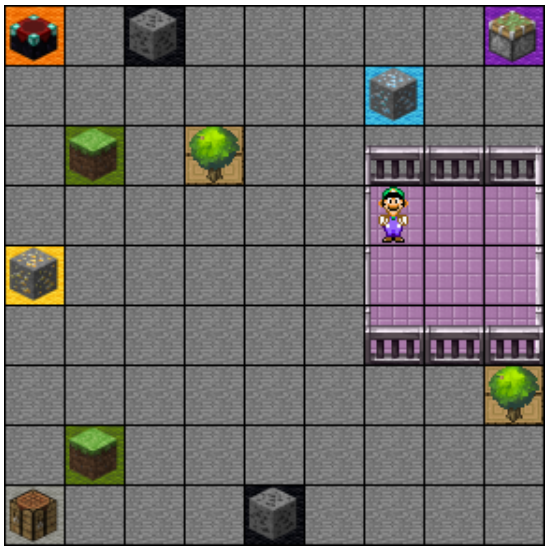


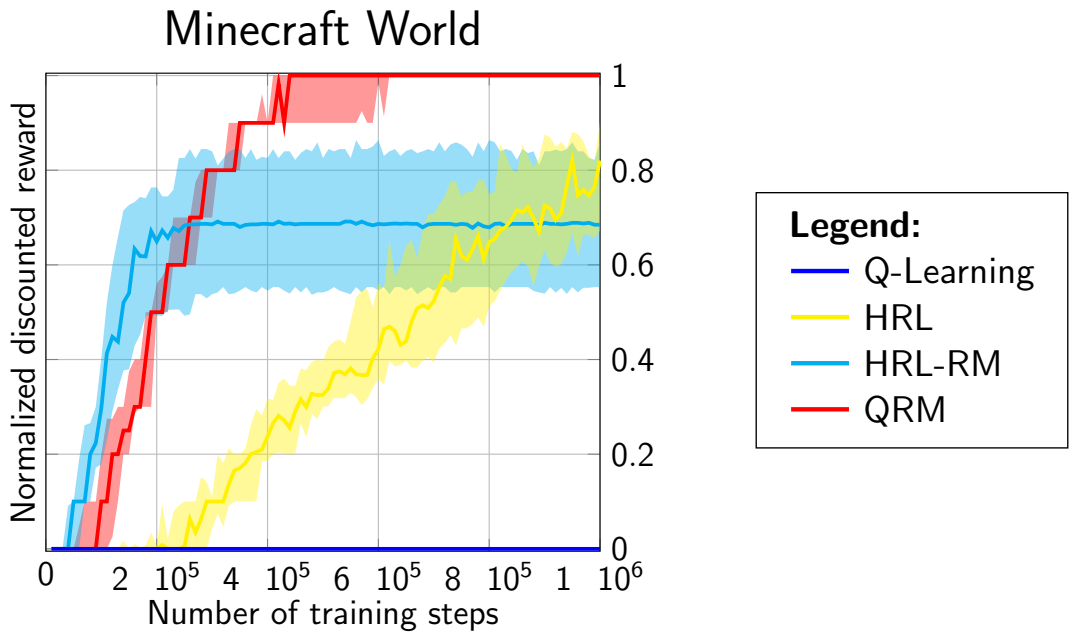


10 tasks defined by Andreas et al.[1] over 10 random maps (3 trials)

[1] Modular Multitask Reinforcement Learning with Policy Sketches by Andreas et al. (ICML-17)

The craft domain





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Continuous domains

From tabular QRM to Deep QRM

We replaced q-learning by Double DQN with prioritized experience replay in our four approaches.

Continuous domains

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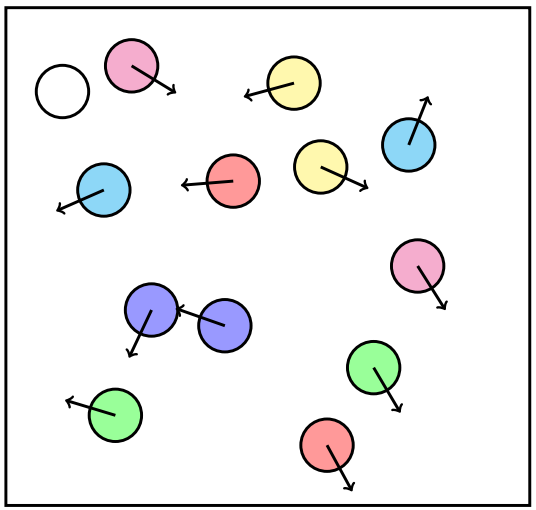
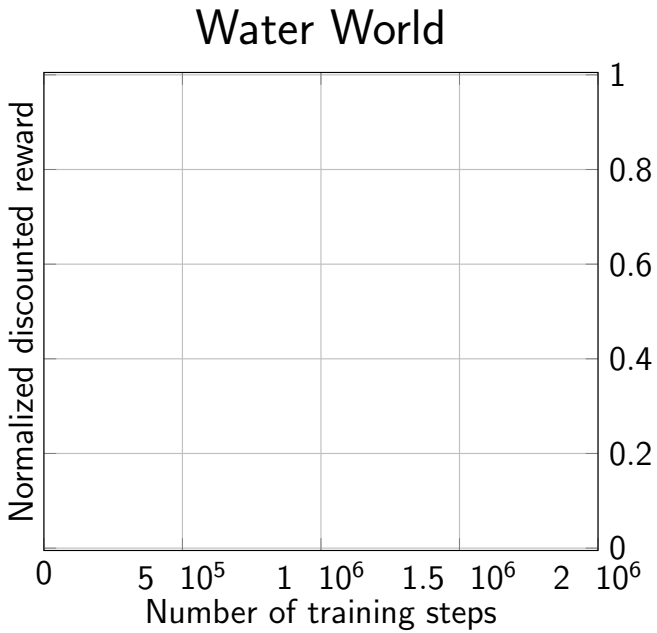
Method	**Optimality?**	**Decomposition?**
DDQN		
DHRL		3
DHRL-RM		3
DQRM		3

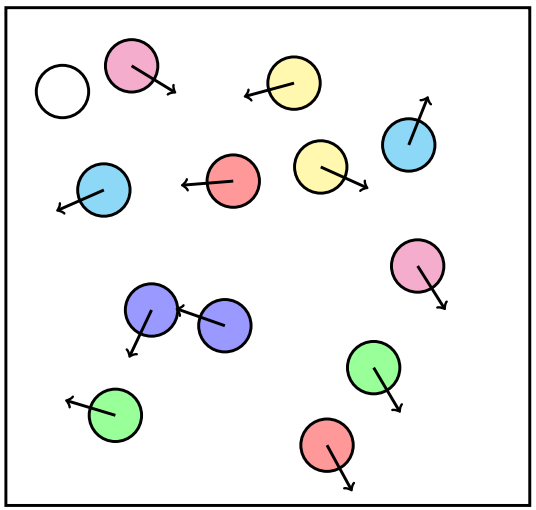
The water domain

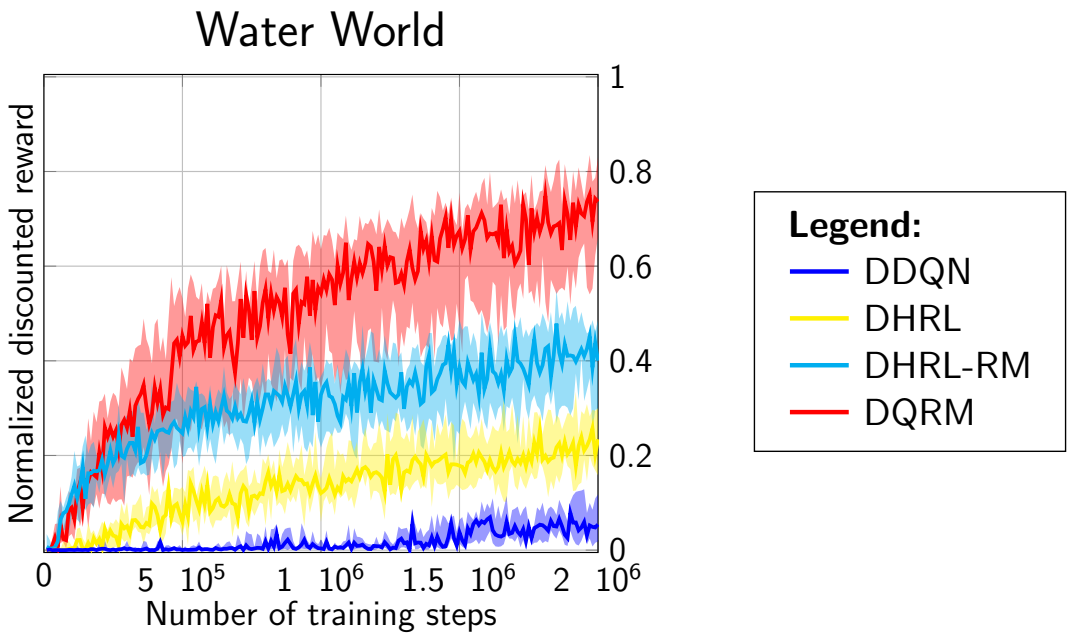




10 tasks over 10 random maps (3 trials per map)

The water domain





10 tasks over 10 random maps (3 trials per map)

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Related work

Hierarchical RL (task decomposition):

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HRL might converge to suboptimal policies.

Lot of relations between QRM and HRL (more in the paper!)

Related work

Linear Temporal Logic (task specification):

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- Li, X., Vasile, C. I., & Belta, C. (2017). Reinforcement learning with temporal logic rewards. In *IROS* (pp. 38343839).
- Littman, M. L., Topcu, U., Fu, J., Isbell, C., Wen, M., & MacGlashan, J. (2017). Environment-independent task speci cations via GLTL. *arXiv preprint arXiv:1704.04341*.
- Toro Icarte, R., Klassen, T., Valenzano, R., & McIlraith, S. (2018). Teaching multiple tasks to an RL agent using LTL. In *AAMAS* (pp. 452-461).
- Hasanbeig, M., Abate, A., & Kroening, D. (2018). Logically-Correct Reinforcement Learning. *arXiv preprint arXiv:1801.08099*.

Related work

Linear Temporal Logic (task specification):

- Li, X., Vasile, C. I., & Belta, C. (2017). Reinforcement learning with temporal logic rewards. In *IROS* (pp. 38343839).
- Littman, M. L., Topcu, U., Fu, J., Isbell, C., Wen, M., & MacGlashan, J. (2017). Environment-independent task speci cations via GLTL. *arXiv preprint arXiv:1704.04341*.
- Toro Icarte, R., Klassen, T., Valenzano, R., & McIlraith, S. (2018). Teaching multiple tasks to an RL agent using LTL. In *AAMAS* (pp. 452-461).
- Hasanbeig, M., Abate, A., & Kroening, D. (2018). Logically-Correct Reinforcement Learning. *arXiv preprint arXiv:1801.08099*.

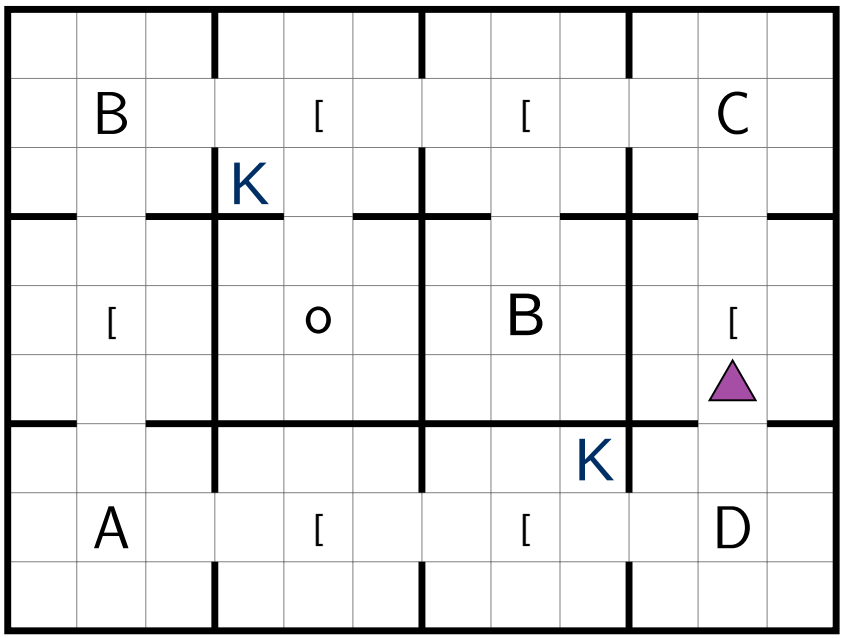
RMs can express reward functions that cannot be expressed in LTL.

Outline

Outline

Concluding remarks

We proposed to show the reward function's code to the agent

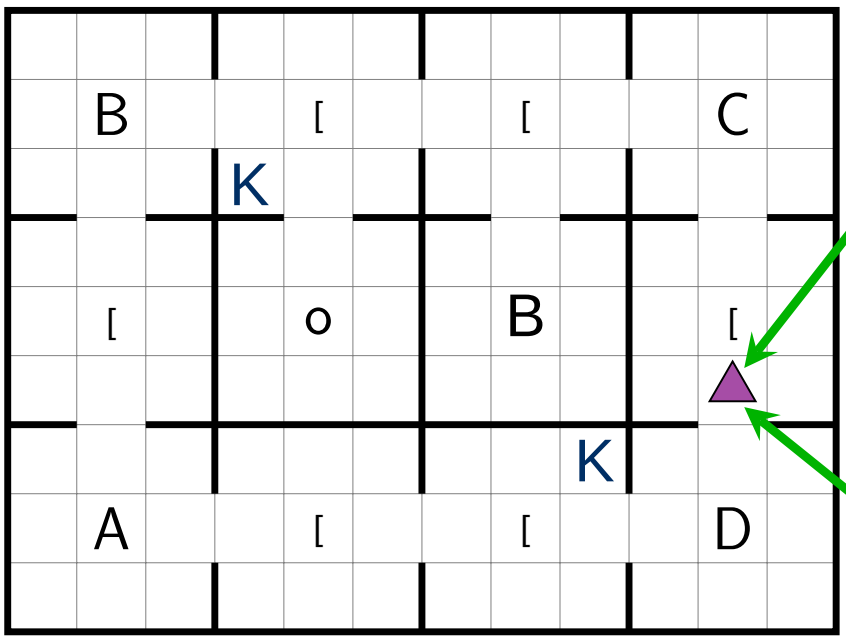



```
m = 0 # global variable
def get_reward(s):
  if m == 0 and s.at("A"):
    m = 1
  if m == 1 and s.at("B"):
    m = 2
  if m == 2 and s.at("C"):
    m = 3
  if m == 3 and s.at("D"):
    m = 0
    return 1
  return 0
```

Reward Function

Concluding remarks

... so it can exploit the reward's structure.

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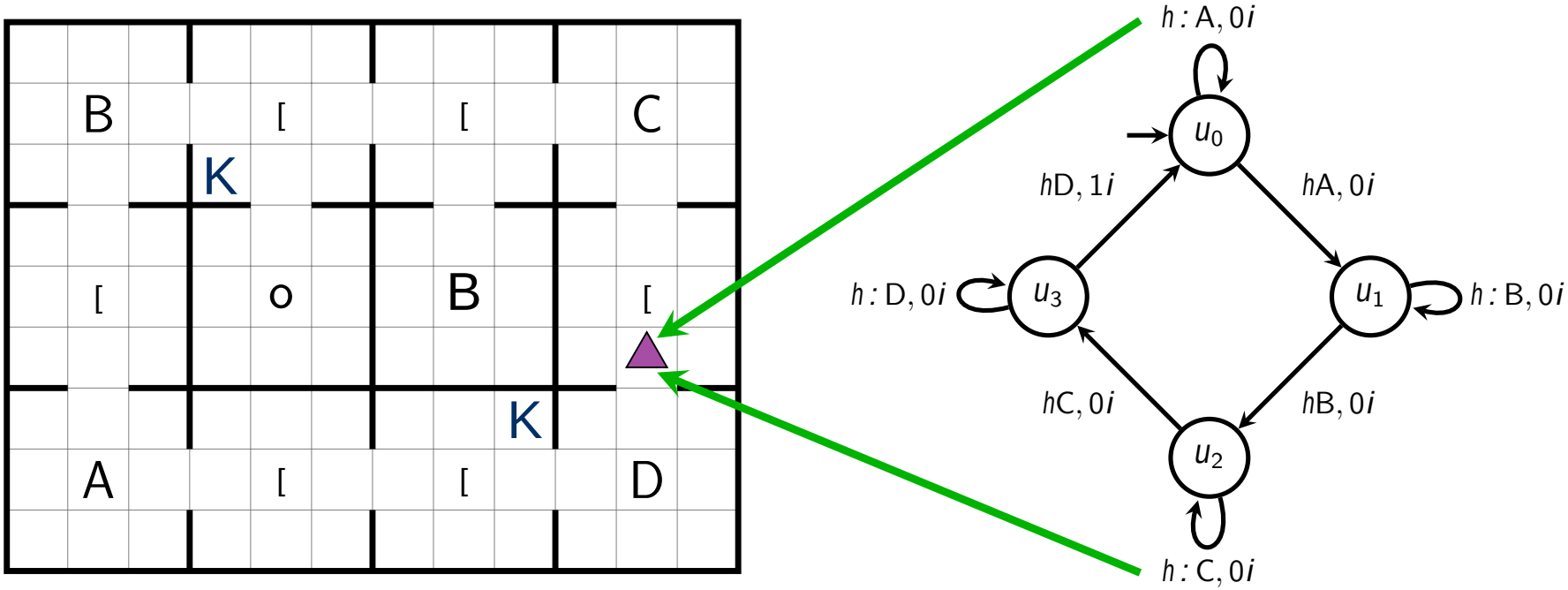
    return 1
  return 0
```

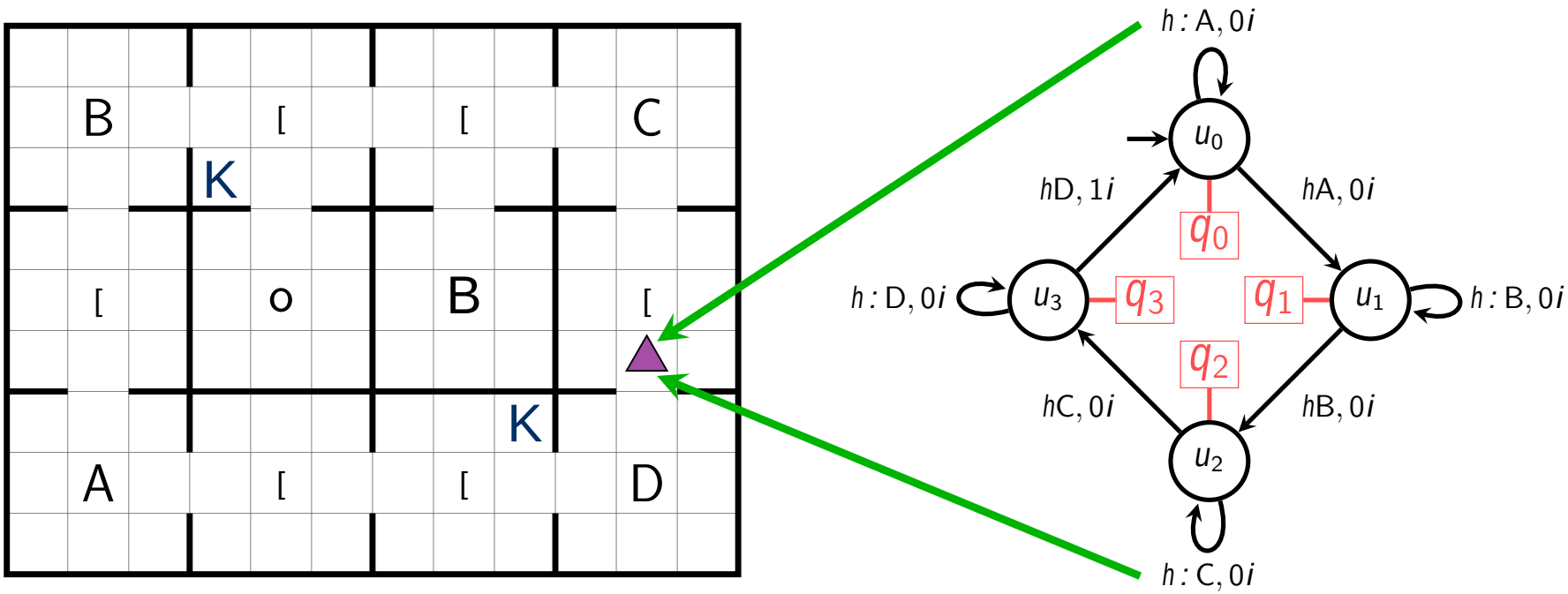
Concluding remarks

To define reward functions, we used reward machines



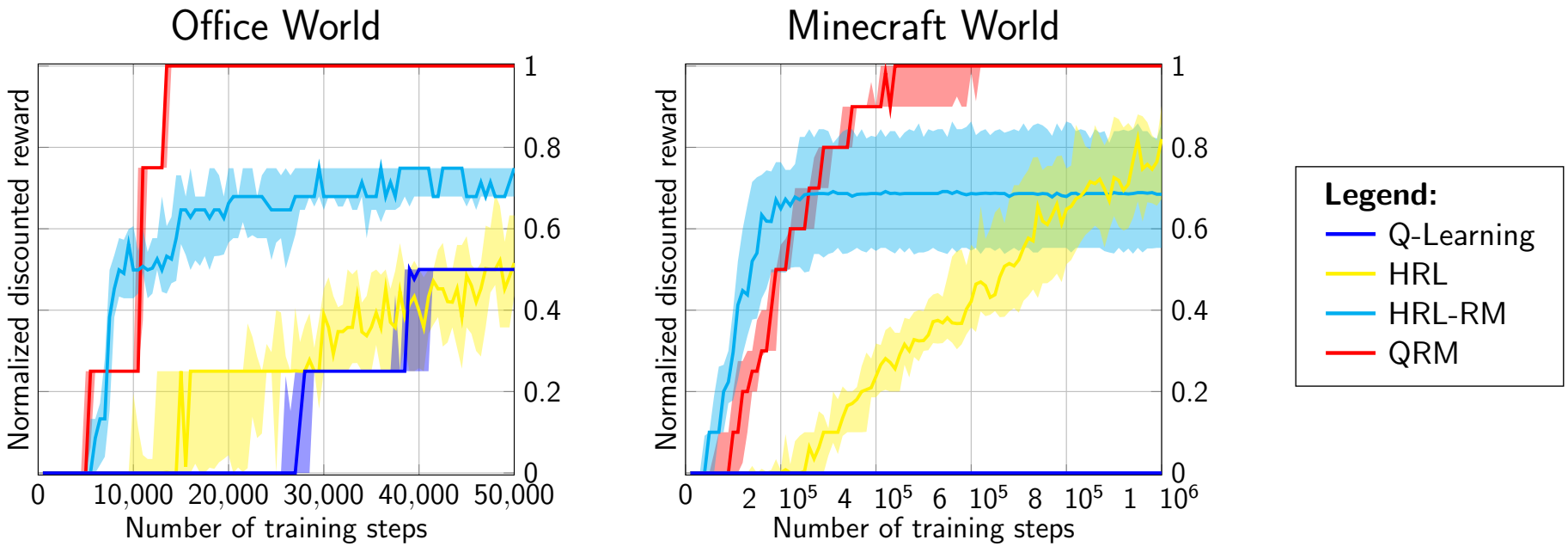
Concluding remarks

... and showed how to decompose the problem using QRM.



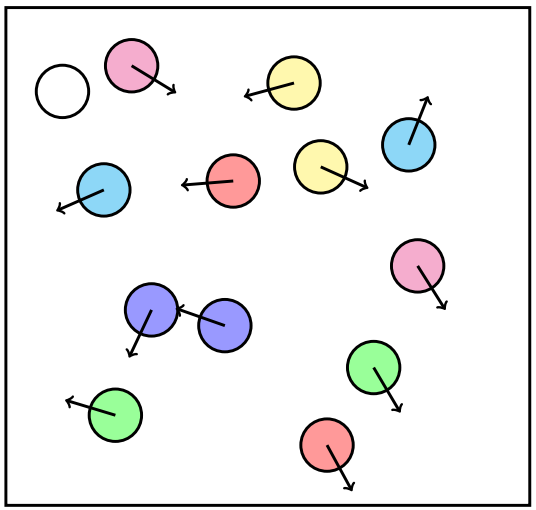
Concluding remarks

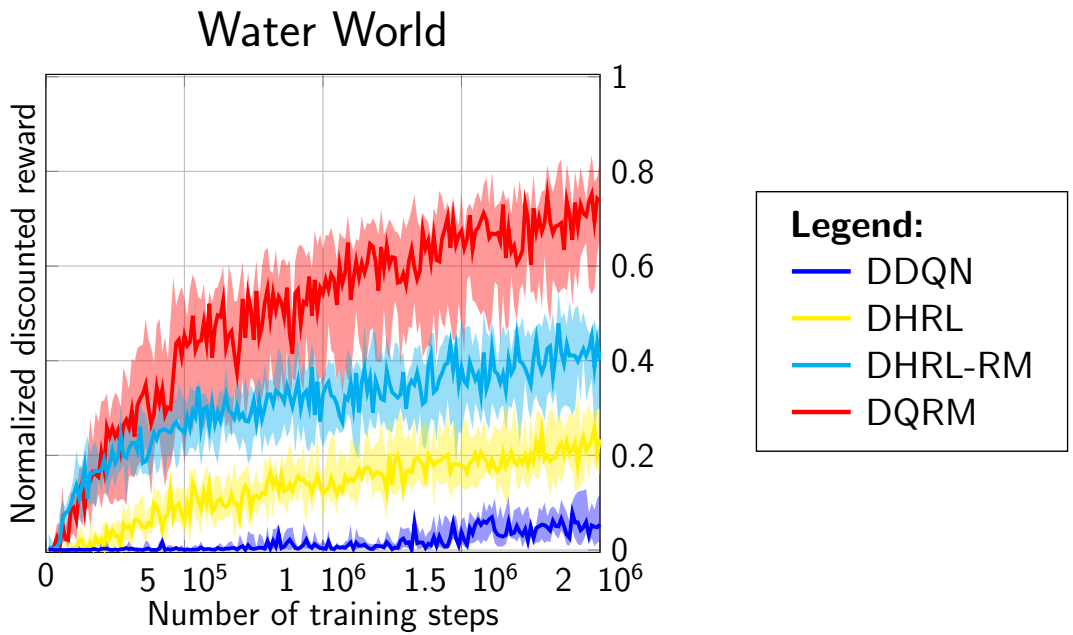
QRM outperformed plain RL and HRL in 2 discrete domains.



Concluding remarks

... and was also effective when combined with deep learning.





Thanks!

Title: Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning

Code: `https://bitbucket.org/RToroIcarte/qrm`

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