# Reinforcement Learning with Reward Machines for Energy Optimisation

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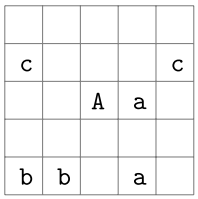
## Motivation

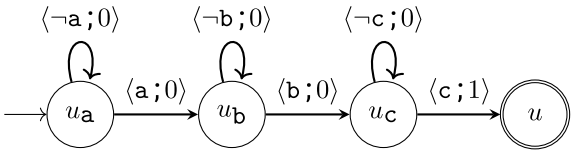
- Reward machines (RMs) can handle **non-Markovian rewards**. This is useful for partially observable or sparse environments.
- Agents with access to the RM structure can simulate experiences, speeding up learning. Thus, learning is **sample-efficient**.
- However, RMs only accept Boolean features. Hence, we aim to extent RMs with **numeric features** so that RMs can excel in inherently numeric tasks like energy optimisation.

## Example Environment: Craft Domain




Picture depicts an example map in the Craft domain, a simple grid world with four-connected cells. Agent A and objects of types a, b, and c are located on the map. Agent A can visit any object of the instructed type.

## Original Boolean RM

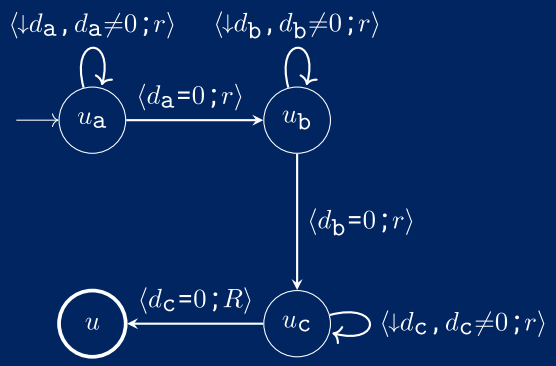



Boolean RM was introduced by Icarte et al. In the example task, the agent should visit a, b, and c in order. **Boolean features** a, b, and c become `True` upon the agent's arrival at the respective cell. The rewards are sparse. **Automatic reward shaping** can be applied.

## RM Structure Exploitation

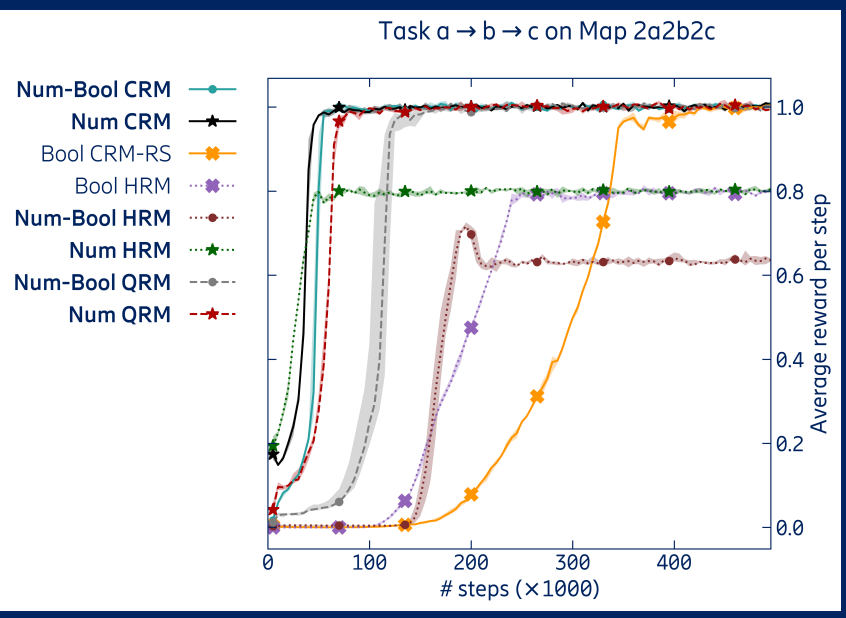
- (BASELINE) **QRM: cross-product *Q*-learning** over the environment and RM states. QRM handles non-Markovian rewards but doesn't offer sample efficiency.
- (RM EXPLOITED) **CRM: *Q*-learning with RM counterfactual experiences**. The agent simulates experiences for each RM state per single interaction with the environment!
- (RM EXPLOITED) **HRM: hierarchical *Q*-learning with RMs**. The agent learns high- and low-level policies to transition between RM states greedily.

## Numeric–Boolean RM




Agent–target Manhattan distance $d$ (numeric feature) is translated to two Boolean features: $\downarrow d$ ($d$ decreases) and $d{=}0$ (target is reached). If $d$ decreases, the agent is rewarded with fixed $r > 0$. If the target is reached, transition to the next RM state occurs. Thus, the agent is positively reinforced to approach the target.

## Results




## Conclusion

**Numeric–Boolean and numeric RMs speed up learning** in comparison with Boolean RMs with automatic reward shaping, while offering **interpretable reward acquisition**.

However, for complete realisation of the potential of numeric features, we need to allow numeric features govern both RM transitions and rewards.

## Future Work

- Let **numeric features guide RM transitions** as well.
- Include change in numeric features into rewards.
- Test tabular domains with obstacles, continuous-space domains, and continuous-control tasks.
- Apply numeric RMs for energy optimisation of radio units in radio base stations.