# Induction and Exploitation of Subgoal Automata for Reinforcement Learning

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## Motivation

- Exploit an abstract subgoal structure of a task.
- Temporal abstractions have been represented using *automata* across several areas, like *reinforcement learning (RL)* and *automated planning*.

### Problem

Current RL methods use *handcrafted automata*.

## Proposed Approach

### ISA (Induction of Subgoal Automata)

A method for learning and exploiting a minimal automaton from observation traces perceived by an RL agent.

- Learn an automaton whose transitions are labeled by propositional formulas representing *subgoals*.
- The *automata learning* is formulated as an *inductive logic programming* task, and *sped up* using a *symmetry breaking* mechanism.
- The automata can be exploited by RL algorithms.

## Tasks

The tasks are *episodic POMDPs* $\mathcal{M}^{\Sigma} = \langle S, S_T, S_G, \Sigma, A, p, r, \gamma, \nu \rangle$ where:

- $S$ is a set of *latent* states,
- $S_T \subseteq S$ is a set of *terminal* latent states,
- $S_G \subseteq S_T$ is a set of *goal* latent states,
- $\Sigma$ is a set of *visible* states,
- $\nu : S \to \Delta(\Sigma)$ is a mapping from latent states to probability distributions over visible states,
- $A$, $p$, $r$ and $\gamma$ are defined as for MDPs.

> - Tasks are enhanced with a set of propositions $\mathcal{O}$ called *observables*.
> - A *labeling function* $L : \Sigma \to 2^{\mathcal{O}}$ maps a state into subsets of observables called *observations*.

**Interaction** At step $t$, the agent observes a tuple $\boldsymbol{\sigma}_t = \langle \sigma_t^{\Sigma}, \sigma_t^{T}, \sigma_t^{G} \rangle$, where:

- $\sigma_t^{\Sigma} \in \Sigma$ is a visible state,
- $\sigma_t^{T} = \mathbb{I}[s_t \in S_T]$ indicates if the latent state is terminal, and
- $\sigma_t^{G} = \mathbb{I}[s_t \in S_G]$ indicates if the latent state is a goal state.

**Example** In the OfficeWorld (Toro Icarte et al., 2018), where $\mathcal{O} = \{☕, \boxtimes, o, A, B, C, D, *\}$, 'deliver coffee to the office while avoiding the $*$'.

- Latent state: $(x, y, has\_☕?)$
- Goal state: $(4, 4, \top)$
- Visible state: $(x, y)$
- Terminal states: $(4, 7, \top), (4, 7, \bot), \ldots$

**Assumptions**

1. The Markov property can be obtained through the combination of visible states and histories of observations.
2. A history of observations is sufficient to determine whether a terminal state is reached and, if so, whether it is a goal state.

## Learning Subgoal Automata from Traces

### Input

- A set of states $U \supseteq \{u_0, u_A, u_R\}$.
- A set of observables $\mathcal{O}$.
- A set of traces $\Lambda^G_{L,\mathcal{O}} \cup \Lambda^D_{L,\mathcal{O}} \cup \Lambda^I_{L,\mathcal{O}}$.
- A max. number of edges $\kappa$ between states.

### Output

The automaton's transition function such that the automaton:

- accepts all *goal traces* $\Lambda^G_{L,\mathcal{O}}$,
- rejects all *dead-end traces* $\Lambda^D_{L,\mathcal{O}}$,
- neither accepts nor rejects *incomplete traces* $\Lambda^I_{L,\mathcal{O}}$.

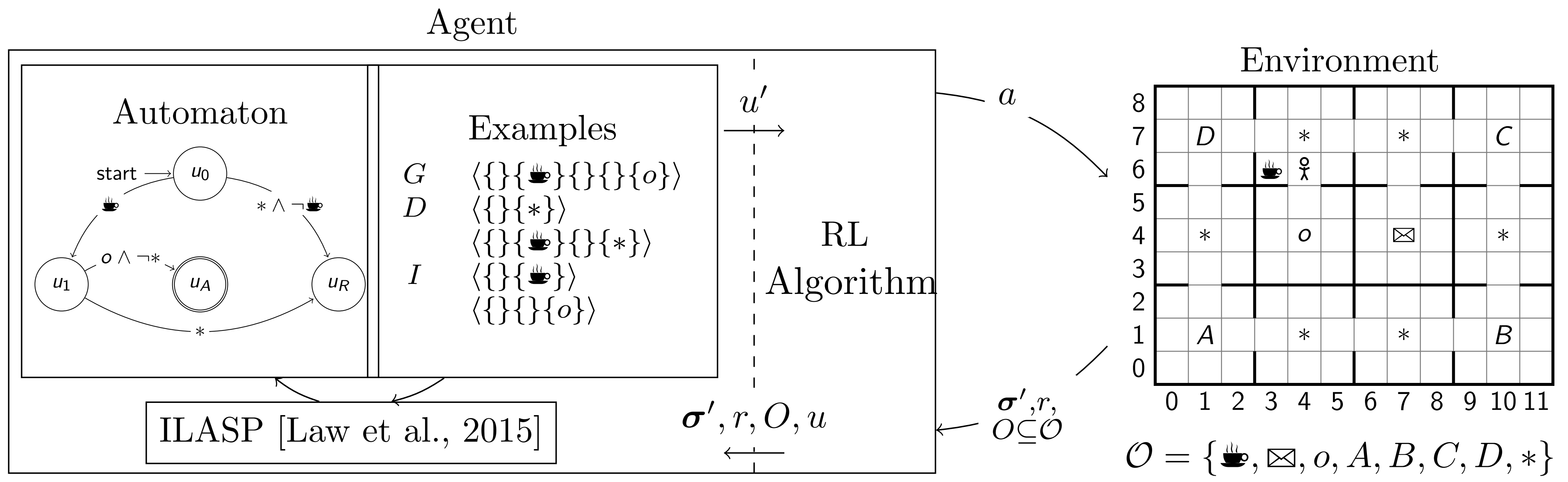
### Example (simplified)

**Transition Function:** $\texttt{ed}(\texttt{u}_0, \texttt{u}_1, 1).\ \texttt{ed}(\texttt{u}_1, \texttt{u}_\texttt{A}, 1).$

$\delta(\texttt{u}_0, \texttt{u}_1, 1, \texttt{T}) \text{ :- } \texttt{obs}(☕, \texttt{T}), \texttt{step}(\texttt{T}).$

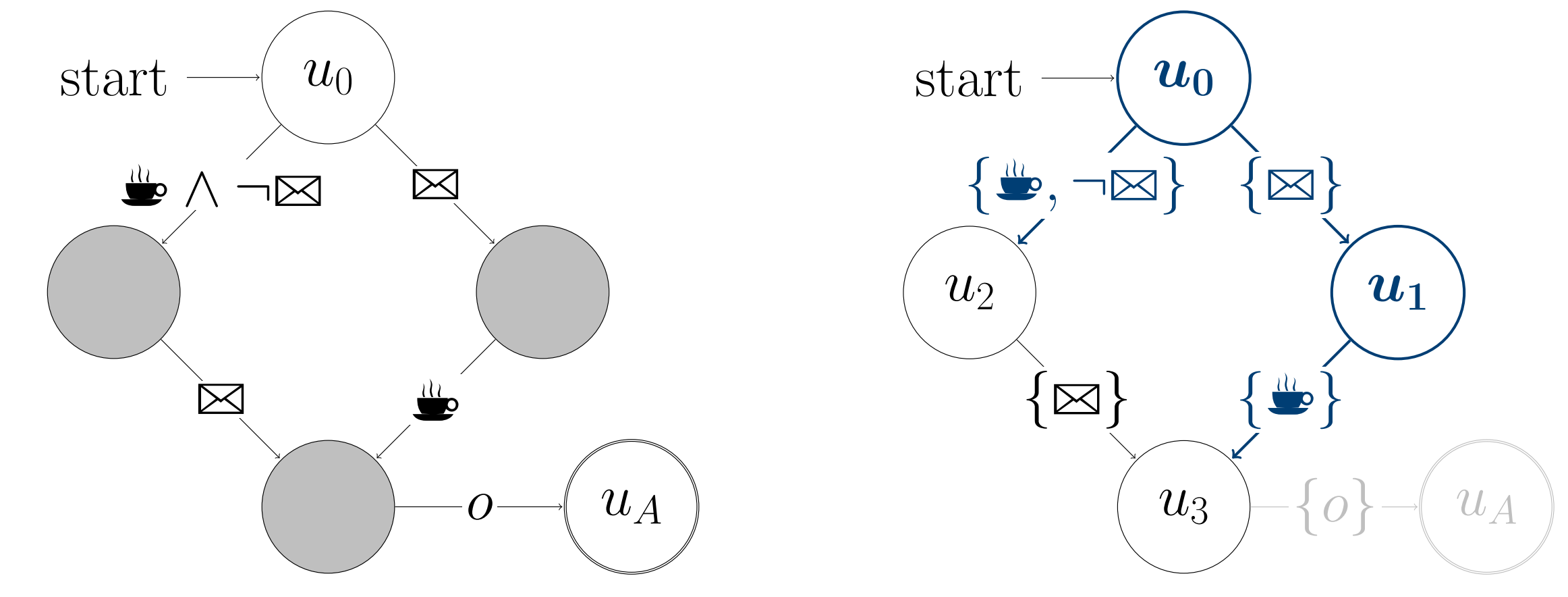
$\delta(\texttt{u}_1, \texttt{u}_\texttt{A}, 1, \texttt{T}) \text{ :- } \texttt{obs}(o, \texttt{T}), \texttt{not obs}(*, \texttt{T}), \texttt{step}(\texttt{T}).$

**Trace:** $\texttt{obs}(☕, 1).\ \texttt{obs}(o, 4).$


Agent
Automaton
start
$u_0$
☕
$* \wedge \neg$☕
$u_1$
$o \wedge \neg *$
$u_A$
$u_R$
$*$
Examples
$G$ $\langle\{\}\{☕\}\{\}\{\}\{o\}\rangle$
$D$ $\langle\{\}\{*\}\rangle$
$\langle\{\}\{☕\}\{\}\{*\}\rangle$
$I$ $\langle\{\}\{☕\}\rangle$
$\langle\{\}\{\}\{o\}\rangle$
ILASP [Law et al., 2015]
$u'$
RL Algorithm
$\boldsymbol{\sigma}', r, O, u$
$a$
$\boldsymbol{\sigma}', r, O \subseteq \mathcal{O}$
Environment
D * * C
☕
* o ✉ *
A * * B
0 1 2 3 4 5 6 7 8 9 10 11
0 1 2 3 4 5 6 7 8
$\mathcal{O} = \{☕, \boxtimes, o, A, B, C, D, *\}$

## Symmetry Breaking

Encode rules that impose a unique *BFS traversal*.



## RL Algorithms

**Hierarchical RL with Options (Sutton et al., 1999)**

- Two decision *levels*:
  1. From a given automaton state, choose a subgoal.
  2. Given a subgoal, choose primitive actions.
- The policy can be *suboptimal*.

**QRM (Toro Icarte et al., 2018)**

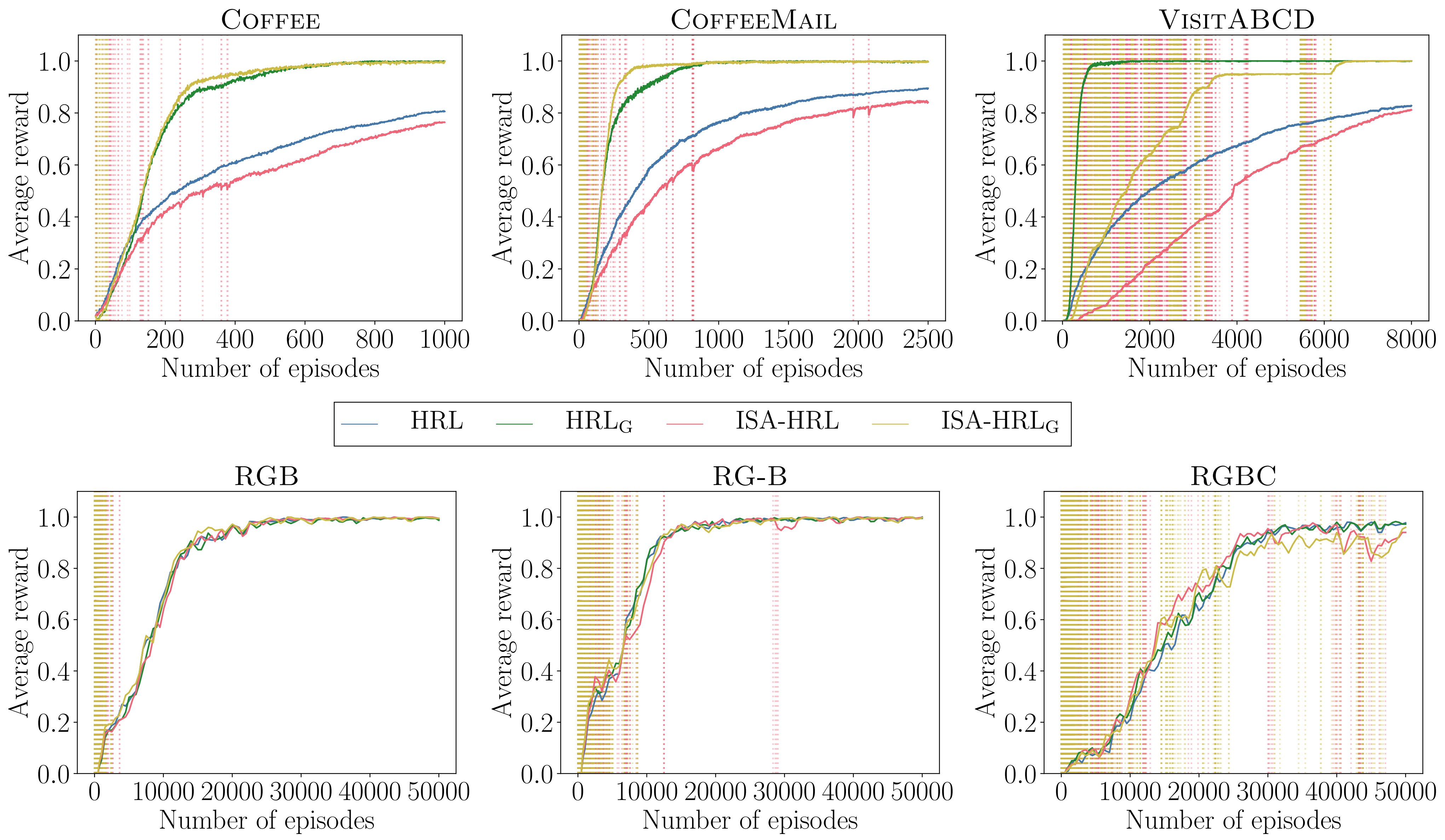
- Transform automaton into a *reward machine*.
- Learns a policy over $\Sigma \times U$.
- Guarantees *optimality* in the tabular case.

## Interleaved Learning Algorithm

RL and automata learning are *interleaved*.

- The *initial automaton* does not accept nor reject anything.
- ILASP runs when a *counterexample* is found.
- The number of states increases when the automaton learning task is UNSAT (iterative deepening).

→ A *minimal* automaton is found for a specific $\kappa$.



## Experiments

- Domains: OfficeWorld (Toro Icarte et al., 2018), CraftWorld (Andreas et al., 2017; Toro Icarte et al., 2018) and WaterWorld (Toro Icarte et al., 2018).
- Given a set of task instances, simultaneously:
  - learn a policy for each of these, and
  - an automaton that generalizes to all of them.
- Default automaton learning: symmetry breaking, acyclicity, $\kappa = 1$, trace compression.
- 20 runs for each experiment.

| | Time (s.) | # Examples | | | | Example Length |
|---|---|---|---|---|---|---|
| | | All | $G$ | $D$ | $I$ | |
| Coffee | 0.4 (0.0) | 8.7 (0.4) | 2.4 (0.1) | 3.0 (0.1) | 3.2 (0.3) | 2.8 (2.1) |
| CoffeeMail | 18.9 (3.3) | 29.0 (1.5) | 3.9 (0.3) | 9.3 (0.6) | 15.8 (1.0) | 4.0 (2.6) |
| VisitABCD | 163.2 (44.3) | 54.9 (3.8) | 1.6 (0.1) | 15.2 (0.9) | 38.1 (3.1) | 5.5 (3.1) |

Automaton learning statistics for OfficeWorld tasks (HRL$_G$)

| | Acyclic | | Cyclic | |
|---|---|---|---|---|
| | No SB | SB | No SB | SB |
| Coffee | 0.5 (0.0) | 0.4 (0.0) | 0.5 (0.0) | 0.5 (0.0) |
| CoffeeMail | 277.4 (70.2) | 18.9 (3.3) | 4204.3 (1334.4)* | 774.7 (434.4) |
| VisitABCD | 1070.0 (725.6) | 163.2 (44.3) | 3293.5 (1199.2)* | 1961.7 (1123.8) |

Total automaton learning time when symmetry breaking is disabled (No SB) and enabled (SB) using HRL$_G$. $*$ = timed out 1-10 runs.

Andreas, J., Klein, D., and Levine, S. (2017). Modular multitask reinforcement learning with policy sketches.

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Sutton, R. S., Precup, D., and Singh, S. P. (1999). Between MDPs and Semi-MDPs: A Framework for Temporal Abstraction in Reinforcement Learning.

Toro Icarte, R., Klassen, T. Q., Valenzano, R. A., and McIlraith, S. A. (2018). Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning.