Advising and Instructing Reinforcement Learning Agents with LTL and Automata

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Credits

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Papers appearing at

• Canadian AI (Toro Icarte et al., 2018b),
• AAMAS 2018 (Toro Icarte et al., 2018a),
• and ICML 2018 (Toro Icarte et al., 2018c)
Outline

1. Reinforcement Learning (RL):
   - What is RL?
   - Two difficulties in applying RL

2. Instructions for Reinforcement Learning
   - LTL formulas
   - Reward Machines

3. Advice for Reinforcement Learning

4. Summary
How does Reinforcement Learning work?

Based on diagram from Sutton and Barto (1998, Figure 3.1)
Two difficulties in applying RL

- **Reward specification**: It is really hard to define proper reward functions for complex tasks.
- **Sample efficiency**: RL agents might require billions of interactions with the environment to learn good policies.
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Example environment

Luigi can collect raw materials:
- wood
- grass
- iron
- gold
- gems

... and make new objects in:
- factory
- toolshed
- workbench

Make a bridge: get wood, iron, and use the factory
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Linear Temporal Logic (LTL) (Pnueli, 1977)

LTL augments propositional logic with the **temporal** operators
○ (*next*), ◇ (*eventually*), and U (*until*):

\[
\varphi ::= p \mid \neg \varphi \mid \varphi_1 \land \varphi_2 \mid \bigcirc \varphi \mid \Diamond \varphi \mid \varphi_1 \mathbf{U} \varphi_2
\]

where *p* is an atomic symbol.
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\]

where \( p \) is an atomic symbol.

**Examples:**

\[ \Diamond \text{got\_wood} \quad (1) \]
\[ \Diamond (\text{got\_grass} \land \Diamond \text{used\_factory}) \quad (2) \]
\[ \Diamond \text{got\_wood} \lor \Diamond \text{got\_iron} \quad (3) \]
\[ \Diamond \text{got\_grass} \land \Diamond \text{got\_iron} \quad (4) \]
\[ (\text{is\_night} \rightarrow \text{at\_shelter}) \mathbf{U} \text{got\_wood} \quad (5) \]
Instructing RL agents with co-safe LTL

**General idea:**

- Reward the agent when it satisfies the formula.
- Therefore, an optimal policy would satisfy the formula **as soon as possible.**
Instructing RL agents with co-safe LTL

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- Therefore, an optimal policy would satisfy the formula as soon as possible.

Main advantage:

- **Standard RL**: The reward function is a black box.
- **RL with LTL**: The LTL formula exposes the task’s structure to the agent.
Example

Consider telling the agent to learn a policy for the following task:

$$\varphi = \lozenge(got\_iron \land \lozenge used\_factory) \land \lozenge got\_gold$$
Example

Consider telling the agent to learn a policy for the following task:

\[ \varphi = \Diamond(got\_iron \land \Diamond used\_factory) \land \Diamond got\_gold \]

Then, the agent knows that at some point it might have to satisfy some of the following formulas:

\[ \varphi_1 = \Diamond(got\_iron \land \Diamond used\_factory) \]
\[ \varphi_2 = \Diamond used\_factory \land \Diamond got\_gold \]
\[ \varphi_3 = \Diamond used\_factory \]
\[ \varphi_4 = \Diamond got\_gold \]
Example

Consider telling the agent to learn a policy for the following task:

$$\varphi = \Diamond (\text{got} \_ \text{iron} \land \Diamond \text{used} \_ \text{factory}) \land \Diamond \text{got} \_ \text{gold}$$

Then, the agent knows that at some point it might have to satisfy some of the following formulas:

$$\varphi_1 = \Diamond (\text{got} \_ \text{iron} \land \Diamond \text{used} \_ \text{factory})$$
$$\varphi_2 = \Diamond \text{used} \_ \text{factory} \land \Diamond \text{got} \_ \text{gold}$$
$$\varphi_3 = \Diamond \text{used} \_ \text{factory}$$
$$\varphi_4 = \Diamond \text{got} \_ \text{gold}$$

We proposed to combine this knowledge with off-policy (deep) RL to learn optimal policies for the task and each subtask in parallel.
Our approach (red curve) finds better policies faster than standard DRL (blue curve)
Results

Our approach (red curve) finds better policies faster than standard DRL (blue curve) and Hierarchical DRL (yellow and cyan curves).

**Paper:** “Teaching Multiple Tasks to an RL Agent using LTL”  
**Code:** [https://bitbucket.org/RToroIcarte/lpopl](https://bitbucket.org/RToroIcarte/lpopl)
Instructing RL agents with automata

Our ICML paper generalizes the previous idea to work over automata representations of the reward function.
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Figure: A reward machine
Instructing RL agents with automata

Our ICML paper generalizes the previous idea to work over automata representations of the reward function.

In this case, our approach learns one policy for each node.

Figure: A reward machine
More results

Our approach (red curve) finds better policies faster than standard DRL (blue curve) and Hierarchical DRL (yellow and cyan curves).

**Paper**: “Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning”

**Code**: [https://bitbucket.org/RToroIcarte/qrm](https://bitbucket.org/RToroIcarte/qrm)
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LTL as an advice language

Advice suggests how to achieve rewards, but does not define the rewards.

Idea:

• Use a model-based RL algorithm.
• Guide the exploration with a heuristic estimating what actions will make progress towards satisfying the (finite) LTL advice.
  • Good advice can reduce the amount of exploration required to learn a good policy,
  • Bad advice will eventually be recovered from.

Paper: “Advice-Based Exploration in Model-Based Reinforcement Learning”
Summary

Instructions:

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- “Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning” (ICML 2018)
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Advice:

• “Advice-Based Exploration in Model-Based Reinforcement Learning” (Canadian AI 2018)
References


