Reinforcement Learning for LTL$_f$/LDL$_f$ Goals

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Abstract

MDPs extended with LTL$_f$/LDL$_f$ non-Markovian rewards have recently attracted interest as a way to specify rewards declaratively. In this paper, we discuss how a reinforcement learning agent can learn policies fulfilling LTL$_f$/LDL$_f$ goals. In particular we focus on the case where we have two separate representations of the world: one for the agent, using the (predefined, possibly low-level) features available to it, and one for the goal, expressed in terms of high-level (human-understandable) fluents. We formally define the problem and show how it can be solved. Moreover, we provide experimental evidence that keeping the RL agent feature space separated from the goal's can work in practice, showing interesting cases where the agent can indeed learn a policy that fulfills the LTL$_f$/LDL$_f$ goal using only its features (augmented with additional memory).

Introduction

Markov Decision Processes (MDP) are widely used to model uncertainty in action executions and to find solutions in terms of policies optimizing (discounted) cumulative rewards. Recently, interest in Decision Processes with non-Markovian rewards (NMRDPs) (Bacchus, Boutilier, and Grove 1996; Thiébaux et al. 2006; Slaney 2005; Gretton 2007; Gretton 2014) has been revived and motivated by the difficulty in rewarding complex behaviors directly on MDPs (Littman 2015; Littman et al. 2017). In this context, the use of linear-time temporal logics over finite traces has been independently advocated by (Camacho et al. 2017b; Camacho et al. 2017a) and (Brafman, De Giacomo, and Patrizi 2017; Brafman, De Giacomo, and Patrizi 2018). Both research groups propose to use LTL$_f$ or its more general extension LDL$_f$ to model temporal properties of dynamic systems (De Giacomo and Vardi 2013; De Giacomo and Vardi 2015; De Giacomo and Vardi 2016; De Giacomo et al. 2014; Baier et al. 2008; Fritz and McIlraith 2007; Torres and Baier 2015; Camacho et al. 2017c).

The logic LTL$_f$ is the classical linear time logic LTL (Pnueli 1977) interpreted over finite traces, formed by a finite (instead of infinite as in LTL) sequence of propositional interpretations. Instead, LDL$_f$ is a proper extension of LTL$_f$, which allows to express regular expressions over such sequences, hence mixing procedural and declarative specifications as advocated in some work in Reasoning about Actions and Planning (Levesque et al. 1997; Baier et al. 2008).

The crucial point of both LTL$_f$ and LDL$_f$ is that their formulas can be transformed into finite state automata; this, in turn, allows for transforming an NMRDP with non-Markovian LTL$_f$/LDL$_f$ rewards into an equivalent MDP over an extended state space, obtained as the cross product of the states of the NMRDP and the states of the automaton.

Reinforcement Learning (RL) with non-Markovian models requires a much more complex machinery than the standard MDP setting (see, e.g.,(Whitehead and Lin 1995)) as, in the general case, it needs to track the whole system history, instead of the current state only. An approach to resort to learning techniques for the standard setting consists in reducing the non-Markovian model to an equivalent MDP. This is adopted in a recent work which investigates RL with rewards expressed by formulas of a probabilistic variant of classical LTL over infinite sequences (Littman et al. 2017). In that work, it is claimed that learning for standard LTL is not possible, in the general case. In this work we adopt a similar approach, by still reducing the problem to standard MDP, but we focus on full LTL$_f$/LDL$_f$ (interpreted over finite sequences), showing that we can obtain a fully equivalent MDP whose optimal policies are also optimal policies for the original problem.

Thus, we show that RL for LTL$_f$/LDL$_f$ non-Markovian goals can be reduced to standard RL over an equivalent MDP by exploiting the properties of LTL$_f$/LDL$_f$ non-Markovian rewards (Brafman, De Giacomo, and Patrizi 2018). This result has a practical importance, since it does not require the definition of new RL algorithms and thus makes the learning process easy and effective.

Then we turn to a different case. We assume to have a learning agent equipped with sensing procedures to compute a set of features from the world that forms its states and with a set of actions that it can do. We want to use this agent to learn one (or simultaneously many) task whose goal(s) are expressed in LTL$_f$/LDL$_f$. Such goals are expressed over a representation of the world that is *not* the one used by the agent (oversimplifying, we may say that the agent has a low-level representation), but a convenient high level representation suitable to express declaratively temporally extended goals. In other words, we study the possibility of having *two separate representations* of the world:

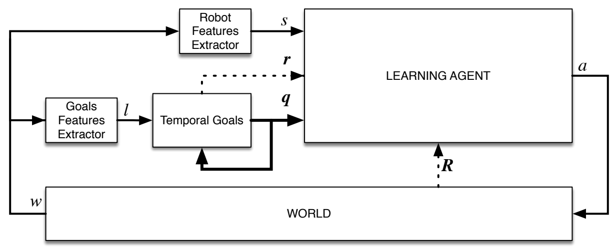

Figure 1: Reinforcement learning agent at work

- one for expressing the dynamics of the RL agent;
- one for expressing the $\text{LTL}_f/\text{LDL}_f$ goals.

These two representations use different classes of features from the real world: the first includes the features that the agent can directly access, while the second includes the features needed to evaluate the $\text{LTL}_f/\text{LDL}_f$ goal (cf. Figure 1).

For example, consider a robotic paddle playing the BREAKOUT game. The paddle has to drive the ball to hit a wall of bricks. The robotic paddle perceives its position and the position and velocity of the balls. Though it does not perceive the position and the status of the bricks, however the environment gives suitable rewards when they are broken.

Now suppose we want to express in LTL_f or LDL_f the goal: break first the columns on the left, then those at the center, and finally those on the right. To express this goal we do need a representation of bricks' position and their status (broken or not) of the $\text{LTL}_f/\text{LDL}_f$ formula. A plain application of RL algorithms in the equivalent MDP requires the extension of the state space for the learning agent with memory for keeping track of the stages of the goals, as well as the representation of the bricks' positions and their status. While adding memory is not problematic, keeping track of bricks' positions and their status may require sophisticates sensors[1]. Moreover, what about if the bricks are too far for the available sensors to detect them?

For this reason we want to keep the representations separated and we study the problem of RL in the case in which the learning agent cannot access the high-level representation used to express the goals. The interest in having separate representations is manifold:

1. The agent feature space can be designed separately from the features needed to express the goal, thus promoting *separation of concerns* which, in turn, facilitates the design; this separation facilitates also the *reuse* of representations already available, possibly developed for the standard setting.
2. A reduced agent's feature space allows for realizing *simpler agents* (think, e.g., of a mobile robot platform, where one can avoid specific sensors and perception routines), while preserving the possibly of tackling complex declarative goals which cannot be represented in the agent's feature space.
3. Reducing the agent's feature space may yield a *reduced state space* to be explored by the RL-agent.

Clearly, the two separate representations (i.e., the two sets of features) need to be somehow correlated in reality. The crucial point, however, is that in order to perform RL effectively, *such a correlation does not need to be formalized*. In this paper, we set this framework and provide proofs and experimental evidence that an RL agent can learn policies to reach $\text{LTL}_f/\text{LDL}_f$ goals without including in the state space representation the features needed to evaluate the corresponding $\text{LTL}_f/\text{LDL}_f$ formula.

[1]Notice it may require equipping the robot with better sensors, e.g., replacing an inexpensive Kinect-like device with full-fledged distance lasers.

Preliminaries

MDP's. A Markov Decision Process (MDP) $\mathcal{M} = \langle S, A, Tr, R \rangle$ contains a set S of states, a set A of actions, a transition function $Tr : S \times A \to Prob(S)$ that returns for every state s and action a a distribution over the next state, and a reward function $R : S \times A \times S \to \mathbb{R}$ that specifies the reward (a real value) received by the agent when transitioning from state s to state s' by applying action a.

A solution to an MDP is a function, called a *policy*, assigning an action to each state, possibly conditioned on past states and actions. The *value* of a policy ρ at state s, denoted $v^\rho(s)$, is the expected sum of (possibly discounted) rewards when starting at state s and selecting actions based on ρ.

RL is the task of learning a possibly optimal policy, from an initial state s_0, on an MDP where only S and A are known, while Tr and R are not. Typically, the MDP is assumed to start in an initial state s_0, so policy optimality is evaluated wrt $v^\rho(s_0)$. Every MDP has an *optimal* policy ρ^*. In discounted cumulative settings , there exists an optimal policy that is *stationary* $\rho : S \to A$, i.e., ρ depends only on the current state, and deterministic (Puterman 2005).

In the standard RL setting, rewards are assigned based only on the current state and chosen action. In this sense they are called Markovian. In this paper, we consider RL for non-Markovian rewards, which we assume specified in LTL_f and LDL_f, two logics recently proposed for expressing such rewards (Camacho et al. 2017b; Brafman, De Giacomo, and Patrizi 2018).

LTL_f/LDL_f. Linear-time Temporal Logic over finite traces, LTL_f, is essentially standard LTL (Pnueli 1977) interpreted over finite, instead of over infinite, traces (De Giacomo and Vardi 2013). Given a set $\mathcal{P}$ of propositional symbols, LTL_f formulas φ are defined as follows:

$$\varphi \quad ::= \quad \phi \mid \neg\varphi \mid \varphi_1 \wedge \varphi_2 \mid \circ\varphi \mid \varphi_1 \mathcal{U} \varphi_2$$

where ϕ is a propositional formula over $\mathcal{P}$, $\circ$ is the *next* operator and $\mathcal{U}$ is the *until* operator. We use the standard abbreviations: $\varphi_1 \vee \varphi_2 \doteq \neg(\neg\varphi_1 \wedge \neg\varphi_2)$; *eventually* as $\Diamond\varphi \doteq true\, \mathcal{U} \varphi$; *always* as $\Box\varphi \doteq \neg\Diamond\neg\varphi$; week next $\bullet\varphi \doteq \neg\circ\neg\varphi$ (note that on finite traces $\neg\circ\varphi \not\equiv \circ\neg\varphi$); and $Last \doteq \bullet false$ denoting the end of the trace. LTL_f is as expressive as first-order logic (FO) over finite traces and star-free regular expressions (RE). LTL_f can be extended to LDL_f, which is expressive as monadic second-order logic (MSO) over finite traces (De Giacomo and Vardi 2013).

Formally, LDL_f formulas φ are built as follows:

$$\begin{array}{lcl}\varphi & ::= & tt \mid \neg\varphi \mid \varphi_1 \wedge \varphi_2 \mid \langle\varrho\rangle\varphi \\ \varrho & ::= & \phi \mid \varphi? \mid \varrho_1 + \varrho_2 \mid \varrho_1;\varrho_2 \mid \varrho^*\end{array}$$

where tt stands for logical true; ϕ is a propositional formula over $\mathcal{P}$; ϱ denotes path expressions, which are RE over propositional formulas ϕ with the addition of the test construct $\varphi?$ typical of PDL. We use abbreviations $[\varrho]\varphi \doteq \neg\langle\varrho\rangle\neg\varphi$ as in PDL. Intuitively, $\langle\varrho\rangle\varphi$ states that, from the current step in the trace, there exists an execution satisfying the RE ϱ such that its last step satisfies φ, while $[\varrho]\varphi$ states that, from the current step, all executions satisfying the RE ϱ are such that their last step satisfies φ. Tests are used to insert into the execution path checks for satisfaction of additional LDL_f formulas.

Given an $\text{LTL}_f/\text{LDL}_f$ formula φ, we can construct a deterministic finite state automaton (DFA) (Rabin and Scott 1959) $\mathcal{A}_\varphi$ that tracks satisfaction of φ, given a finite trace [2], accepting a sequence of propositional interpretations *iff* the sequence satisfies φ. This construction is a key element in the efficient transformation from non-Markovian rewards to Markovian rewards over an extended MDP (Brafman, De Giacomo, and Patrizi 2018).

The idea is to use $\text{LTL}_f/\text{LDL}_f$ formulas to specify when sequences of state-action pairs, rather than one pair only, should be rewarded. Notice that we can easily incorporate the executed action in the current state by using propositions. In this way, we can make $\text{LTL}_f/\text{LDL}_f$ deal with actions, as well. From now on, we assume this is the case.

NMRDP's. A non-Markovian reward decision process (NMRDP) (Bacchus, Boutilier, and Grove 1996) is a tuple $M = \langle S, A, Tr, \bar{R}\rangle$, where S, A and Tr are as in an MDP, but the reward $\bar{R}$ is a real-valued function over finite state-action sequences (referred to as *traces*), i.e., $\bar{R} : (S \times A)^* \to \mathbb{R}$. Given a (possibly infinite) trace $\pi = \langle s_0, a_1, \dots, s_{n-1}, a_n\rangle$, the *value* of π is: $v(\pi) = \sum_{i=1}^{|\pi|} \gamma^{i-1}\bar{R}(\langle\pi(1), \pi(2), \dots, \pi(i)\rangle)$, where $0 < \gamma \leq 1$ is the discount factor and $\pi(i)$ denotes the pair (s_{i-1}, a_i). In such a NMRDP model, policies are also non-Markovian $\bar{\rho} : S^* \to A$. Since every policy induces a distribution over the set of possible infinite traces, we can define the value of a policy $\bar{\rho}$ given an initial state s_0:

$$v^{\bar{\rho}}(s) = E_{\pi\sim M,\bar{\rho},s_0} v(\pi).$$

That is, $v^{\bar{\rho}}(s)$ is the expected value of infinite traces, where the distribution over traces is defined by the initial state s_0, the transition function Tr, and the policy $\bar{\rho}$.

[2] An analogous transformation to automata applies to several other formalisms for representing non-Markovian rewards (Bacchus, Boutilier, and Grove 1996; Thiébaux et al. 2006; Slaney 2005; Gretton 2007; Gretton 2014; Lacerda, Parker, and Hawes 2014; Lacerda, Parker, and Hawes 2015). All results presented here apply to those formalisms as well.

Specifying a non-Markovian reward function explicitly is cumbersome and unintuitive, even if only a finite number of traces are to be rewarded. $\text{LTL}_f/\text{LDL}_f$ provides an intuitive and convenient language for specifying $\bar{R}$ implicitly, using a pair $\{(\varphi, r)\}$, where the atomic propositions of φ correspond to boolean propositions (e.g., relational value comparison) over the components of the state vector. Intuitively, if the current (partial) trace is $\pi = \langle s_0, a_1, \dots, s_{n-1}, a_n\rangle$, the agent receives at s_n a reward r if φ_i is satisfied by π. Formally, $\bar{R}(\pi) = r$ if $\pi \models \varphi$ and $\bar{R}(\pi) = 0$, otherwise. From now on, we assume $\bar{R}$ is thus specified.

RL for NMRDP with $\text{LTL}_f/\text{LDL}_f$ rewards

In (Brafman, De Giacomo, and Patrizi 2018) it is shown that $\text{LTL}_f/\text{LDL}_f$ provides an intuitive and convenient language for specifying $\bar{R}$, using a a set of pairs $\{(\varphi_i, r_i)\}_{i=1}^m$, where φ_i is a $\text{LTL}_f/\text{LDL}_f$ formula selecting the traces to reward and r_i is the reward assigned to those traces. Note that the atomic propositions $\mathcal{P}$ used in φ_i correspond to boolean propositions (e.g., relational value comparison) over the components of the state vector. Intuitively, if the current (partial) trace is $\pi = \langle s_0, a_1, \dots, s_{n-1}, a_n\rangle$, the agent receives at s_n a reward r if φ_i is satisfied by π. Formally, $\bar{R}(\pi) = r_i$ if $\pi \models \varphi$ and $\bar{R}(\pi) = 0$, otherwise.

We are interested in doing reinforcement learning in the setting of (Brafman, De Giacomo, and Patrizi 2018). That is we want to learn a (possibly optimal) policy for an NMRDP $M = \langle S, A, Tr, \{(\varphi_i, r_i)\}_{i=1}^m\rangle$, whose rewards r_i are given on traces specified by $\text{LTL}_f/\text{LDL}_f$ formulas φ_i, where state space S, action set A and $\text{LTL}_f/\text{LDL}_f$ reward formulas φ_i are known, while the transitions Tr and the rewards r_i are not.

Formally, given the NMRDP $M = \langle S, A, Tr, \{(\varphi_i, r_i)\}_{i=1}^m\rangle$, with Tr and r_i unknown to the learning agent, but sampled during learning, and an initial state $s_0 \in S$, the RL problem over M consists in learning an optimal policy $\bar{\rho}$. Note that, since NMRDP rewards are based on traces, instead of on state-action pairs, typical learning algorithms, such as Q-learning or SARSA (Sutton and Barto 1998), which are based on MDPs, are not applicable.

However in (Brafman, De Giacomo, and Patrizi 2018), it has been shown that for any NMRDP $M = \langle S, A, Tr, \{(\varphi_i, r_i)\}_{i=1}^m\rangle$, there exists an MDP $M' = \langle S', A', Tr', R'\rangle$ that is *equivalent* to M in the sense that the states of M can be (injectively) mapped into those of M', in such a way that corresponding (under the mapping) states yield same transition probabilities and corresponding traces have same rewards (Bacchus, Boutilier, and Grove 1996). Denoting with $\mathcal{A}_{\varphi_i} = \langle 2^{\mathcal{P}}, Q_i, q_{i0}, \delta_i, F_i\rangle$ (notice that $S \subseteq 2^{\mathcal{P}}$ and δ_i is total) the DFA associated with φ_i, the equivalent MDP $M' = \langle S', A', Tr', R'\rangle$ is built as follows (Brafman, De Giacomo, and Patrizi 2018):

- $S' = Q_1 \times \cdots \times Q_m \times S$ is the set of states;
- $A' = A$;

- $Tr' : S' \times A' \times S' \to [0,1]$ is defined as follows:

$$Tr'(q_1, \ldots, q_m, s, a, q'_1, \ldots, q'_m, s') = \begin{cases} Tr(s,a,s') & \text{if } \forall i : \delta_i(q_i, s') = q'_i \\ 0 & \text{otherwise;} \end{cases}$$

- $R' : S' \times A \times S' \to \mathbb{R}$ is defined as:

$$R'(q_1, \ldots, q_m, s, a, q'_1, \ldots, q'_m, s') = \sum_{i: q'_i \in F_i} r_i$$

Theorem 1 ((Brafman, De Giacomo, and Patrizi 2018))**.** *The NMRDP $M = \langle S, A, Tr, \{(\varphi_i, r_i)\}_{i=1}^m \rangle$ is equivalent to the MDP $M' = \langle S', A', Tr', R' \rangle$ defined above.*

Let ρ' be a (Markovian) policy for M'. It is easy to define an *equivalent* policy on M, i.e., a policy that guarantees the same rewards. To this end, consider a trace $\pi = \langle s_0, a_1, s_1, \ldots, s_{n-1}, a_n \rangle$ of M, and assume it leads to state s_n. Moreover, let q_i be the state of A_{φ_i} on the input π. We define the (non-Markovian) policy $\bar{\rho}$ equivalent to ρ' as $\bar{\rho}(\pi) = \rho'(q_1, \ldots, q_m, s_n)$. In particular we have:

Theorem 2 ((Bacchus, Boutilier, and Grove 1996))**.** *Given an NMRDP M, let ρ' be an optimal policy for an equivalent MDP M'. Then, the policy $\bar{\rho}$ for M that is equivalent to ρ' is optimal for M.*

Obviously, typical learning techniques, such as Q-learning or SARSA, are applicable on (the state space of) M' and we can learn an optimal policy ρ' for M'. Thus, an optimal policy for M can be learnt on M'. Of course, none of these structures is (completely) known to the learning agent, and the above transformation is never done explicitly. Rather, the agent carries out the learning process by assuming that the underlying model is M' instead of M.

Observe that the state space of M' is the product of the state spaces of M and $\mathcal{A}_{\varphi_i}$, and that the reward R' is Markovian. In other words, the (stateful) structure of the $\text{LTL}_f/\text{LDL}_f$ formulas φ_i used in the (non-Markovian) reward of M is *compiled* into the states of M'.

Theorem 3. *RL for $\text{LTL}_f/\text{LDL}_f$ rewards φ over an NMRDP $M = \langle S, A, Tr, \{(\varphi_i, r_i)\{_{i=1}^m \rangle$, with Tr and r_i unknown to the learning agent can be reduced to RL over the MDP M' defined above.*

RL for $\text{LTL}_f/\text{LDL}_f$ goals

In this section, we focus on a particularly interesting case.

- We consider a learning agent constituted by MDP $M_{ag} = \langle S, A, Tr, R \rangle$ with transition Tr and R unknown and sampled from the environment (e.g., a learning agent for Breakout). We assume that such learning agent has a special action $stop$ which deems the end of an episode, and which sets a special flag $Done$ to true (c.f., (Brafman, De Giacomo, and Patrizi 2018)).
- We consider arbitrary $\text{LTL}_f/\text{LDL}_f$ formulas φ_i ($i = 1, \ldots, m$) over a set of fluents $\mathcal{F}$, which are not among the features that form the states S of the learning agent M_{ag}, except for the special flag $Done$, which is set by the agent's action $stop$. We denote by $\mathcal{L} = 2^{\mathcal{F}}$ the set of possible fluents configurations (analogously to S denoting the set of configurations of the features available to M_{ag}). In other words the formula φ_i is selecting sequences of fluents configurations $\ell_1, \cdots, \ell_n$, with $\ell_k \in \mathcal{L}$, whose relationship with the sequences of states $s_1, \ldots, s_n$, with $s_k \in S$ of M_{ag} is unknown.
- We are interested in devising a policy for the learning agent M_{ag} such that at the end of the episode, i.e., when the agent executes *stop*[3], the $\text{LTL}_f/\text{LDL}_f$ goal formulas φ_i ($i = 1, \ldots, m$) are satisfied. More precisely, given rewards r_i to be assigned to (complete) episodes satisfying formula φ_i ($i = 1, \ldots, m$), we want to learn a (non-Markovian) policy that is optimal wrt the sum of the rewards r_i ($i = 1, \ldots, m$) and R in M_{ag}.

Oversimplifying, we may say that S is the set of configurations of the low-level features for the learning agent M_{ag}, while $\mathcal{L}$ is the set of configuration of the high-level features needed for expressing φ_i.

Note that both are features in the sense that they are a representation of properties of the world but they look at different facets of the world itself.

More precisely, let W be the set of *world states*, i.e., the states of the real world. A *feature* is a function f_j that maps a world state to the values of another domain D_j, such as reals, finite enumerations, Booleans, etc., i.e., $f_j : W \to D_j$. The *feature vector* of a world state w_h is the vector $\mathbf{f}(w_h) = \langle f_1(w_h), \ldots, f_d(w_h) \rangle$ of feature values corresponding to w_h. Given a state of the world w_h the corresponding *configuration s_h of the learning agent M_{ag}* is formed by the components of the feature vector $\mathbf{f}(w_h)$ that produce its state, while the corresponding *configuration of fluents ℓ_h* is formed by the components that assign truth values to the fluents according to the feature vector $\mathbf{f}(w_h)$. In other words, a subset of features are used to describe agent states s_h and another subset (for simplicity, assumed disjoint from the previous one) are used to evaluate the fluents in ℓ_h. Hence, given a sequence $w_1, \ldots, w_n$ of world states we get the correspondent sequence of sequences learning agent states $s_1, \ldots, s_n$ and simultaneously the sequence of fluent configurations $\ell_1, \ldots, \ell_n$. Notice that we do not have a formalization for $w_1, \ldots, w_n$ but we do have that for $s_1, \ldots, s_n$ and for $\ell_1, \ldots, \ell_n$.

Now the agent actions in A induce a transition distribution over the features and fluents configuration, i.e.,

$$Tr_{ag}^g : S \times \mathcal{L} \times A \to Prob(S \times \mathcal{L}).$$

Such a transition distribution together with the initial values of the fluents ℓ_0 and of the agent state s_0 allow us to describe a probabilistic transition system accounting for the dynamics of the fluents and agent states. Moreover, when Tr_{ag}^g is projected on S only, i.e., the $\mathcal{L}$ components are marginalized, we get Tr of M_{ag}. Obviously, both Tr_{ag}^g and Tr are unknown to the learning agent. On the other hand, in response to an agent action a_h performed in the current state w_h (in the state s_h of the agent and the configuration ℓ_h of the fluents), the world changes into w_{h+1} from which s_{h+1} and ℓ_{h+1}. This is all we need to proceed.

[3]Note that the agent is unaware that *stop* ends the episode.

We are interested in devising policies for the learning agent such that at the end of the episode, i.e., when the agent executes *stop*, the LTL$_f$/LDL$_f$ goal formulas φ_i ($i = 1, \ldots, m$) are satisfied. Now we can state our problem formally.

Problem definition: *We define* RL for LTL$_f$/LDL$_f$ goals, *denoted as*

$$M_{ag}^{goal} = \langle S, A, R, \mathcal{L}, Tr_{ag}^{g}, \{(\varphi_i, r_i)\}_{i=1}^{m}\rangle$$

with Tr_{ag}^{g}, R and r_i unknown,the following problem: given a learning agent $M_{ag} = \langle S, A, Tr, R\rangle$, with Tr and R unknown and a set $\{(\varphi_i, r_i)\}_{i=1}^{m}$ of LTL$_f$/LDL$_f$ *formulas with associated rewards, find a (non-Markovian) policy $\bar{\rho} : S^* \to A$ that is optimal wrt the sum of the rewards r_i and R.*

Observe that an optimal policy for our problem, although not depending on $\mathcal{L}$, is guaranteed to satisfy the LTL$_f$/LDL$_f$ goal formulas.

To devise a solution technique, we start by transforming $M_{ag}^{goal} = \langle S, A, Tr_{ag}^{g}, R, \mathcal{L}, \{(\varphi_i, r_i)\}_{i=1}^{m}\rangle$ into an NMRDP $M_{ag}^{nmr} = \langle S \times \mathcal{L}, A, Tr_{ag}^{g}, \{(\varphi'_i, r_i)\}_{i=1}^{m} \cup \{(\varphi_s, R(s, a, s'))\}_{s\in S, a\in A, s'\in S}\rangle$ where:

- States are pairs (s, ℓ) formed by an agent configuration s and a fluents configuration ℓ.
- $\varphi'_i = \varphi_i \wedge \Diamond Done$.
- $\varphi_s = \Diamond(s \wedge a \wedge \circ(Last \wedge s'))$.
- Tr_{ag}^{g}, r_i and $R(s, a, s')$ are unknown and sampled from the environment.

Formulas φ'_i simply require to evaluate the corresponding goal formula φ_i after having done the action *stop*, which sets the fluent $Done$ to true and ends the episode. Hence it gives the reward associated to the goal at the end of the episode. The formulas $\Diamond(s \wedge a \wedge \circ(Last \wedge s'))$, one per (s, a, s'), requires both states s and action a are followed by s' are evaluated at the end of the current (partial) trace (notice the use of $Last$). In this case, the reward $R(s, a, s')$ from M_{ag} associated with (s, a, s') is given.

Notice that policies for M_{ag}^{nmr} have the form $(S \times \mathcal{L})^* \to A$ which needs to be restricted to have the form required by our problem M_{ag}^{goal}.

A policy $\bar{\rho} : (S \times \mathcal{L})^* \to A$ *has the form* $S^* \to A$ when for any sequence of n states $\langle s_1 \cdots s_n\rangle$, we have that for any pair of sequences of fluent configurations $\langle \ell'_1 \cdots \ell'_n\rangle$, $\langle \ell''_1 \cdots \ell''_n\rangle$ the policy returns the same action, $\bar{\rho}(\langle s_1, \ell'_1\rangle \cdots \langle s_n, \ell'_n\rangle) = \bar{\rho}(\langle s_1, \ell''_1\rangle \cdots \langle s_n, \ell''_n\rangle)$. In other words, a policy $\bar{\rho} : (S \times \mathcal{L})^* \to A$ has the form $\bar{\rho} : S^* \to A$ when it does not depend on the fluents $\mathcal{L}$. We can now state the following result.

Theorem 4. *RL for* LTL$_f$/LDL$_f$ *goals* $M_{ag}^{goal} = \langle S, A, Tr_{ag}^{g}, R, \mathcal{L}, \{(\varphi_i, r_i)\}_{i=1}^{m}\rangle$ *can be reduced to RL over the NRMDP* $M_{ag}^{nmr} = \langle S \times \mathcal{L}, A, Tr_{ag}^{g}, \{(\varphi'_i, r_i)\}_{i=1}^{m} \cup \{(\varphi_s, R(s, a, s'))\}_{s\in S, a\in A, s'\in S}\rangle$*, restricting policies to be learned to have the form* $S^* \to A$.

Observe that by restricting M_{ag}^{nmr} policies to S^* in general we may discard policies that have a better reward but depend on $\mathcal{L}$. On the other hand, these policies need to change the learning agent in order to allow it to observe $\mathcal{L}$ as well. As mentioned in the introduction, we are interested in keeping the learning agent as it is, apart for additional memory.

As a second step, we apply the construction of the previous section and obtain a new MDP learning agent. In such construction, however, because of the triviality of their automata, we do not need to keep track of state φ_s, but just give the reward $R(s, a, s')$ associated to (s, a, s'). Instead we do need to keep track of state of the DFAs $\mathcal{A}_{\varphi_i}$ corresponding to the formulas φ'_i. Hence, from M_{ag}^{nmr}, we get an MDP $M'_{ag} = \langle S', A', Tr'_{ag}, R'\rangle$ where:

- $S' = Q_1 \times \cdots \times Q_m \times S \times \mathcal{L}$ is the set of states;
- $Tr'_{ag} : S' \times A' \times S' \to [0, 1]$ is defined as follows:

$$Tr'_{ag}(q_1, \ldots, q_m, s, \ell, a, q'_1, \ldots, q'_m, s', \ell') = \begin{cases} Tr(s, \ell, , a, s', \ell') & \text{if } \forall i : \delta_i(q_i, \ell') = q'_i \\ 0 & \text{otherwise;} \end{cases}$$

- $R' : S' \times A \times S' \to \mathbb{R}$ is defined as:

$$R'(q_1, \ldots, q_m, s, \ell, a, q'_1, \ldots, q'_m, s', \ell') = \sum\nolimits_{i:q'_i\in F_i} r_i + R(s, a, s')$$

Finally we observe that the environment gives now both the rewards $R(s, a, s')$ of the original learning agent, and the rewards r_i associated to the formula so has to guide the agent towards the satisfaction of the goal (progressing correctly the DFAs $\mathcal{A}_{\varphi_i}$).

By applying Theorem 1 we get that NMRDP M_{ag}^{nmr} and the MDP M'_{ag} are equivalent, i.e., any policy of M_{ag}^{nmr} has an equivalent policy (hence guaranteeing the same reward) in M'_{ag} and vice versa. Hence we can learn policy on M'_{ag} instead of M_{ag}^{nmr}.

Hence we can refine Theorem 4 into the following one.

Theorem 5. *RL for* LTL$_f$/LDL$_f$ *goals* $M_{ag}^{goal} = \langle S, A, Tr_{ag}^{g}, R, \mathcal{L}, \{(\varphi_i, r_i)\}_{i=1}^{m}\rangle$ *can be reduced to RL over the MDP* $M'_{ag} = \langle S', A, Tr'_{ag}, R'\rangle$*, restricting policies to be learned to have the form* $Q_1 \times \ldots \times Q_n \times S \to A$.

As before, a policy $Q_1 \times \ldots \times Q_n \times S \times \mathcal{L} \to A$ *has the form* $Q_1 \times \ldots \times Q_n \times S \to A$ when any ℓ and ℓ' the policy returns the same action, $\rho(q_1, \ldots, q_n s, \ell) = \rho(q_1, \ldots, q_n s, \ell')$.

The final step is to solve our original RL task on M_{ag}^{goal} by performing RL on a new MDP $M_{ag}^{new} = \langle Q_1 \times \cdots \times Q_m \times S, A, Tr''_{ag}, R''\rangle$ where:

- Transitions distribution Tr''_{ag} is the marginalization wrt $\mathcal{L}$ of Tr'_{ag} and is unknown;
- Rewards R" is defined as:

$$R''(q_1, \ldots, q_m, s, a, q'_1, \ldots, q'_m, s') = \sum_{i:q'_i\in F_i} r_i + R(s, a, s').$$

- States q_i of DFAs $\mathcal{A}_{\varphi_i}$ are progressed correctly by the environment.

Indeed we can show the following result.

Theorem 6. *RL for* $\text{LTL}_f/\text{LDL}_f$ *goals* $M_{ag}^{goal} = \langle S, A, Tr', R, \mathcal{L}, \{(\varphi_i, r_i)\}_{i=1}^m \rangle$ *can be reduced to RL over the MDP* $M_{ag}^{new} = \langle Q_1 \times \cdots \times Q_m \times S, A, Tr''_{ag}, R'' \rangle$ *and the optimal policy* ρ_{ag}^{new} *learned for* M_{ag}^{new} *can be reduced to a corresponding optimal policy for* M_{ag}^{goal}.

Proof Sketch. From Theorem 5, by the following observations. First, the rewards returned by R'' in Tr''_{ag} coincide with those returned by R' in Tr'_{ag}. Second, to compute an optimal policy for M'_{ag} of the form $Q_1 \times \ldots \times Q_n \times S \to A$, in computing $Tr'_{ag}(q_1, \ldots, q_m, s, \ell, a, q'_1, \ldots, q'_m, s', \ell')$ we can compute $q'_1, \ldots, q'_m$ from $q_1, \ldots, q_m$ and ℓ', hence we do not need ℓ, and we only need $Tr'_{ag}(q_1, \ldots, q_m, s, \ell, a, q'_1, \ldots, q'_m, s', \ell')$ marginalized over ℓ'. As a consequence the value function v^ρ for a policy of the form $\rho : Q_1 \times \ldots \times Q_n \times S \to A$ in M'_{ag} is such that for all ℓ_1 and ℓ_2, $v^\rho(q_1, \ldots, q_m, s, \ell_1) = v^\rho(q_1, \ldots, q_m, s, \ell_2)$. □

We use this result in the implementation and experiments describe in the following section.

Automata-based reward shaping

Reward shaping is a well-known technique to guide the agent during the learning process and so reduce the time needed to learn. The possibility of using reward shaping in the context of RL for $\text{LTL}_f/\text{LDL}_f$ rewards has been exploited in (Camacho et al. 2017a). The idea is to supply additional rewards in a proper manner such that the optimal policy is the same of the original MDP. Formally, the original reward $R(s, a, s')$ is replaced by $R'(s, a, s') = R(s, a, s') + F(s, a, s')$, where $F(s, a, s')$ is the *shaping reward function*. In (Ng, Harada, and Russell 1999) it has been shown that potential-based reward shaping of the form $F(s, a, s') = \gamma\Phi(s') - \Phi(s)$, for some $\Phi : S \to \mathbb{R}$, is a necessary and sufficient condition for policy invariance under this kind of reward transformation, i.e. the optimal and near-optimal MDP solutions are preserved.

It is crucial to observe that one can define two potential-based reward shaping functions and use them simultaneously by summing the potential functions.

We observe that, the use of reward shaping when using $\text{LTL}_f/\text{LDL}_f$ rewards φ can be automatized. Given a $\text{LTL}_f/\text{LDL}_f$ formula φ we build the associated DFA $\mathcal{A}_\varphi$. This operation is made *off-line*, i.e. before the learning process. Then we associate automatically to the states of the DFA a potential function $\Phi(q)$ whose value decreases proportionally with the minimum distance between the automaton state q and any accepting state. The potential functions gives a positive reward when the agent performs an action leading to a q' that is one step closer to an accepting state, and a negative one in the opposite case. Moreover, with $\gamma < 1$, a penalty is given if $\Phi(q) = \Phi(q')$.

Reward shaping can also be used when the DFAs of the $\text{LTL}_f/\text{LDL}_f$ formulas are constructed *on-the-fly* (Brafman, De Giacomo, and Patrizi 2018) so as to avoid to compute the entire automaton off-line. To do so we can rely on *dynamic reward shaping* (Devlin and Kudenko 2012). The idea is to build $\mathcal{A}_\varphi$ progressively while learning. During the learning

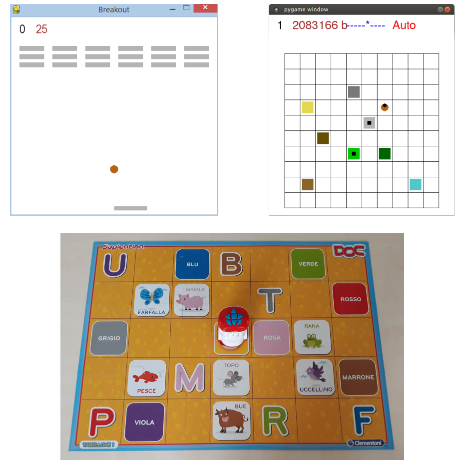

Figure 2: Experimental scenarios: BREAKOUT, SAPIENTINO, MINECRAFT

process, at every step, the value of the fluents $\ell \in \mathcal{L}$ is observed and the successor state q' of the current state q of the DFA on-the-fly is computed. Then, the transition and the new state just observed are added into the "built" automaton at time t, $\mathcal{A}_{\varphi,t}$, yielding $\mathcal{A}_{\varphi,t'}$. The potential function Φ for $\mathcal{A}_{\varphi,t'}$ is recomputed for the new version of the automaton. In this case, the shaping reward function takes the following form:

$$F(q, t, a, q', t') = \gamma\Phi(q', t') - \Phi(q, t)$$

where $\Phi(q, t)$ is the same of the off-line variant (with some additional heuristics) but computed on the automaton $\mathcal{A}_{\varphi,t}$. Optimality and near-optimality guarantees are still preserved as explained in (Devlin and Kudenko 2012).

Theorem 7. *Automata-based reward shaping, both in off-line and on-the-fly variants, preserves optimality and near-optimality of the MDP solutions.*

Proof. For the off-line case, the shaping-reward function Φ is, by construction, potential based, hence fulfilling the premises of theorems in (Ng, Harada, and Russell 1999) and (Grześ 2017). Also for the on-the-fly variant, we observe that our construction is compliant with the requirements shown in (Devlin and Kudenko 2012). □

Experiments

Next we show experimentally the application of RL for $\text{LTL}_f/\text{LDL}_f$ goals in three scenarios (see Figure 2).

The experimental analysis provides evidence that RL algorithms for MDPs can be actually and efficiently used to learn a policy for RL for $\text{LTL}_f/\text{LDL}_f$ goals, once the latter are transformed into MDPs, as explained in the previous sections. In other words, for the problem considered in this paper, it is not necessary to devise new algorithms. The overall practical meaning of the approach described in this paper is that a learning agent M_{ag} that is able to learn tasks with Markovian rewards in a given environment with some algorithm, can as well learn tasks specified by $\text{LTL}_f/\text{LDL}_f$

formulas in this environment without changing the state representation (except for allowing additional memory to store states of DFAs) and without changing the learning algorithm.

As explained in the previous section, each $\text{LTL}_f/\text{LDL}_f$ goal is transformed in the corresponding DFA. A high positive reward is associated to the satisfaction of the $\text{LTL}_f/\text{LDL}_f$ formula and hence to the final state of the DFA. A reward shaping technique (as described in the previous section) is applied to guide the search through the states of the DFA.

During the learning phase, each episode terminates when any of the following conditions is verified: 1) the goal is reached, 2) a failure state is reached (i.e., a state from which it is not possible to reach the goal), 3) a maximum number of actions have been executed (to avoid infinite loops). Each experiment (i.e., a sequence of episodes to learn a policy) terminates after a time limit that is different for each problem and is reported in the next sections. Such time limits have been chosen to guarantee to always find a policy achieving the goal, although it is not possible to guarantee its optimality in general.

All the problems described below have been solved with n-step Sarsa algorithm, configured with $\gamma = 0.999$, $\epsilon = 0.2$, $n = 100$. The trend of the solutions is anyway not sensitive to these parameters[4].

Algorithms have been implemented as single-thread non-optimized Python procedures, in a modular and abstract way to operate on every problem. In particular, the RL algorithm works with a state representation composed by a pair of integer values (the first representing an encoding of the state space S, the second an encoding of $Q_1 \times \ldots \times Q_n$) and with an integer value expressing the action. We have made use of reward shaping to speed up the learning process (we report only off-line variants).

More details about the experimental configurations, source code of the implementation allowing for reproducing the results contained in this paper, and videos of the found policies are available in the web site `https://sites.google.com/site/kr2018paper95`.

Breakout scenario. BREAKOUT has been widely used to demonstrate RL approaches. The goal of the game is to control the paddle in order to drive a ball to hit all the bricks in the screen. In this case we defined an extended version of the game as follows:

1. *Goal*: LR: the bricks must be removed from left to right: all the bricks in column i must be removed before completing any other column $j > i$;
2. *Actions*: MOVE: the robot moves sideways to bounce the ball; FIRE: the robot can both move and fire straight up to remove bricks.

State representation. The following features are used in this game: f_x: x position of the paddle; $f_{bx}, f_{by}, f_{dx}, f_{dy}$: position and direction of movement of the ball, $f_{r_(i,j)}$: status of each brick $r_{i,j}$ (present or removed). The state space S for the agent is formed by tuples in $f_x \times f_{bx} \times f_{by} \times f_{dx} \times f_{dy}$, while the fluent configurations $\mathcal{L}$ are tuples with $f_{r_{i,j}}$, for any i, j. Notice that all positions are discretized with respect to the actual pixel positions in the simulator used for the game.

[4]Results obtained varying these parameters are not reported for lack of space.

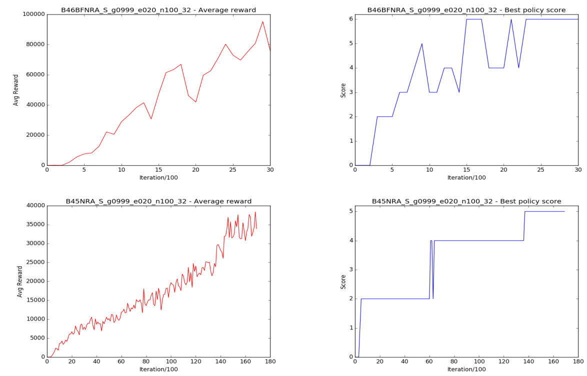

Figure 3: Results in Breakout. Top: MOVE + FIRE 4x6 bricks (5 minutes). Bottom MOVE only 4x5 bricks (1 hour).

Results. Figure 3 shows the results of two experiments in the Breakout scenario with different configurations (5 minutes for Breakout 4x6 MOVE + FIRE, 1 hour long for Breakout 4x5 MOVE only). Left plots shows the average reward over the number of iterations, increasing as expected, while right plots show the score (i.e., the number of columns correctly broken) of the best policy computed so far (i.e., the results obtained in runs without exploration). The figures show how the agent is able to progressively learn how to progress over the states of the DFA corresponding to the $\text{LTL}_f/\text{LDL}_f$ goal. Similar results are obtained in different configurations.

Sapientino scenario. SAPIENTINO Doc is an educational game for 5-8 y.o. children in which a small mobile robot has to be programmed in order to visit specific cells in a 5x7 grid. Cells contain concepts that must be matched by the children (e.g., a colored animal, a color, and the initial letter of the name of the animal). The robot executes sequences of actions given in input by children with a keyboard on the robot's top side. During execution, the robot moves on the grid and executes an action (actually a *bip*) to announce that the current cell has been reached (this is called a *visit* of a cell). A pair of consecutive visits are correct when they refer to cells containing matching concepts. In this paper, we generalize this game as follows. As in the real game, we consider a 5x7 grid with 7 triplets of colored cells, each triplet representing three matching concepts. In addition to the real game, we consider three groups of possible variants:

1. *Goals*: S2: the robot has to visit at least two cells of the same color for each color, in a given order among the colors (the order of the colors is predefined: first, cells of color C_1, second cells of color C_2, and so on.); S3: the robot has to visit all the triplets of each color, in a given order among the colors.
2. *Actions*: OMNI: omni-directional movements (actions: up, down, left, right), DIFFERENTIAL: differential drive (actions: forward, backward, turn left, turn right).

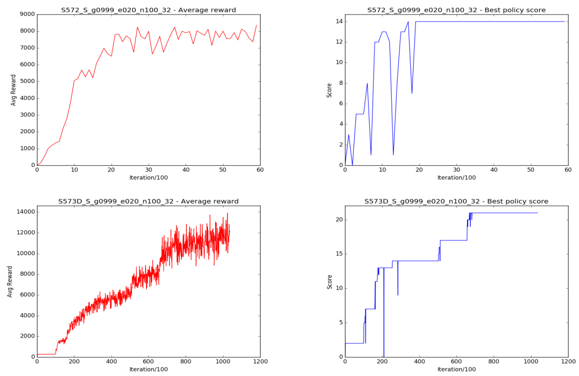

Figure 4: Results in Sapientino. Top: S2 OMNI (3 minutes). Bottom: S3 DIFFERENTIAL (1 hour).

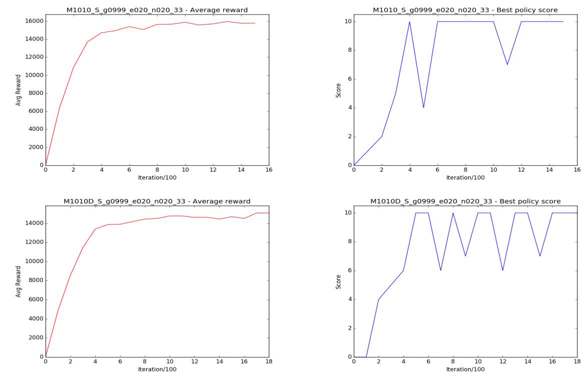

Figure 5: Results in Minecraft. Top: OMNI (5 minutes). Bottom: DIFFERENTIAL (15 minutes).

The goals for these games can be expressed with LTL_f formulas. A fragment of LTL_f formula for the first game relative to the first color C_1 is

$$\neg bip\,\mathcal{U}(\bigvee_{j=1,2,3} cell_{C_1,j} \wedge bip) \wedge$$
$$\bigwedge_{j=1,2,3} \Box(cell_{C_1,j} \wedge bip \rightarrow \circ\Box(bip \rightarrow \neg cell_{C_1,j})) \wedge$$
$$\bigvee_{j=1,2,3} \Box(cell_{C_1,j} \wedge bip \rightarrow \circ(\neg bip\,\mathcal{U} \bigvee_{k\neq j} cell_{C_1,k} \wedge bip)$$

For other colors C_{i+1}, we use a similar formula, but requiring that $\bigvee_{j=1,2,3} cell_{C_i,j} \wedge bip$ has already been satisfied.

State representation. For this game, we define the following features: f_x, f_y, f_θ reporting the x, y, θ pose of the agent in the grid; f_b reporting that a *bip* action has just been executed, and f_c reporting the color of the current cell. The agent space state S is defined by tuples in $f_x \times f_y$ for the OMNI agent and in $f_x \times f_y \times f_\theta$ for the POSEONLY agent, while the fluent configurations $\mathcal{L}$ are described by $f_b \times f_c$.

Results. As in the previous example, in Figure 4, left plots shows the average reward over the number of iterations and right plots show the score (i.e., the number of cells correctly visited) of the best policy. The figures show again how the agent is able to progressively learn how to progress over the states of the DFA corresponding to the $\text{LTL}_f/\text{LDL}_f$ goal (score = 14 for S2 goal, score = 21 for the S3 goal). Similar results are obtained in different configurations.

Minecraft scenario. As an example of modularity of the approach, we used the very same agent used in SAPIENTINO scenario in a MINECRAFT scenario. Here the agent has to accomplish 10 tasks (each one specified with an $\text{LTL}_f/\text{LDL}_f$ goal, thus involving non-Markovian rewards). Given that both the games are performed on a grid and that only the position of the grid is relevant for the tasks, the representation of the states S in the two agents is exactly the same (notice that the contribution of the DFAs is encoded in an integer value and thus although the two tasks have different goals, the agent only needs to know an encoding of the current state of the DFAs). The set of actions A, the fluent configurations $\mathcal{L}$ and the component progressing the DFAs are instead different.

Figure 5 shows experiments in this domain where the OMNI and DIFFERENTIAL agents learned 10 tasks. The meaning of the plots is the same as for the ones commented before, with the score defined as the number of tasks successfully accomplished. These experiments show that a learning agent can learn different tasks (specified with $\text{LTL}_f/\text{LDL}_f$ goals) in different scenarios without changing its internal representation S and learning algorithm, when a suitable component provides to the agent an encoding of the current status of the DFAs evaluating the $\text{LTL}_f/\text{LDL}_f$ goals.

Summarizing, the experimental results presented in this section confirm the effectiveness of the proposed approach for learning tasks specified by $\text{LTL}_f/\text{LDL}_f$ goals by reducing the NMRDP in an equivalent MDP without changing state representation (except for additional memory) and learning algorithm.

Conclusions

In this paper we have shown how to perform RL for $\text{LTL}_f/\text{LDL}_f$ goals by resorting to typical RL techniques based on MDPs. Notably, we have also shown that we can keep the features needed to evaluate $\text{LTL}_f/\text{LDL}_f$ formulas separated from those directly accessible to the learning agent. This yields a separation of concerns that facilitates feature space design and reuse in practical cases.

We are considering several directions for future work. One interesting direction is to learn the $\text{LTL}_f/\text{LDL}_f$ goals. This is related to what in Business Process Management is called (declarative) *process mining* (van der Aalst 2011; Pesic, Schonenberg, and van der Aalst 2007), but also to so-called *model learning* (Angluin 1987; Angluin, Eisenstat, and Fisman 2015; Vaandrager 2017). LTL_f has also been used to model advice to guide the exploration of the RL algorithm (Icarte et al. 2017). This is an interesting aspect that could be considered in our case as well. Finally, an interesting direction for future work is to consider goals specified in logics that have a quantitative interpretation of temporal formulas (Almagor, Boker, and Kupferman 2016; Kupferman 2016). These kind of logics have been used with success in the context of Model Predictive Control (Raman et al. 2014). More generally, as future work, we plan to study the theoretical properties for this separation to be effective, as well as to use this insight to facilitate the design of actual robots embedded in real environments.

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