From STL Rulebooks to Rewards

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Abstract

The automatic synthesis of neural-network controllers for autonomous agents through reinforcement learning has to simultaneously optimize many, possibly conflicting, objectives of various importance. This multi-objective optimization task is reflected in the shape of the reward function, which is most often the result of an ad-hoc and crafty-like activity.

In this paper we propose a principled approach to shaping rewards for reinforcement learning from multiple objectives that are given as a partially-ordered set of signal-temporal-logic (STL) rules. To this end, we first equip STL with a novel quantitative semantics allowing to automatically evaluate individual requirements. We then develop a method for systematically combining evaluations of multiple requirements into a single reward that takes into account the priorities defined by the partial order. We finally evaluate our approach on several case studies, demonstrating its practical applicability.

Introduction

In recent years Reinforcement learning (RL) has become a very popular and successful method for training autonomous agents that are able to solve complex tasks in sophisticated environments (Mnih et al. 2015; Lillicrap et al. 2015; Silver et al. 2017). Autonomous agents are becoming increasingly complex and are expected to satisfy numerous, potentially conflicting, requirements.

The key ingredient in RL is the reward function, a user-provided reinforcement signal that rewards or penalizes an immediate action of the autonomous agent. The reward function must capture all the desired aspects of the agent’s behavior. It follows that reward shaping is essential to obtain optimal policies and significant research effort has been invested in that field (Ng, Harada, and Russell 1999; Laud and DeJong 2003). Autonomous agents are becoming increasingly complex and are expected to satisfy numerous, potentially conflicting, requirements.

There are two major challenges in shaping meaningful rewards, which we illustrate with an autonomous-driving application. The first challenge arises from mapping numerous requirements into a scalar reward signal. In autonomous driving there are more than 200 rules that need to be considered when assessing the actions (Censi et al. 2019). Furthermore, determining the relative importance of different requirements is a highly non-trivial task. In this realm there is a plethora of constraint classes; ranging from safety and traffic rules, to performance, comfort, legal, and ethical requirements.

In this paper we propose a systematic temporal-logic-based approach for shaping rewards in the presence of multiple objectives with varying importance. Our approach is built on top of four major components:

- A formal specification language, for defining the desired objectives.
- Its associated quantitative semantics, allowing to evaluate actions with respect to the individual requirements.
- An additional specification layer, allowing to group sets of specifications and define priorities among them.
- A procedure for automatically generating a reward function from the grouped and prioritized specifications.

The advantage of our approach is the seamless passage from requirements engineering to learning optimal control policies that satisfy these requirements, while relieving the engineer from the burden of manually shaping rewards by tuning the individual contribution of each requirement.

We use Signal Temporal Logic (STL) (Maler and Nickovic 2004) as our specification language. STL allows expressing temporal properties of real-valued behaviours. We define a rich STL fragment for capturing requirements and desired objectives, identifying safety, target, progress and comfort classes of requirements. While we keep their original STL syntax, we propose for each class a special quantitative semantics intended to facilitate the task of training an agent to satisfy that requirement.

We organize STL requirements into a partially-ordered set, called a rulebook (Censi et al. 2019). The order relation reflects the priority among the different requirements. Given a rulebook, we devise a procedure that automatically generates the reward function. The proposed approach is general and can be applied to any environment.

We finally implement the above approach, and demonstrate it on three standard benchmarks from the literature: the cart-pole, the bipedal-walker (classic and hardcore) and the lunar lander. We enrich the benchmark environments with additional obstacles to render the learning task harder. The experimental evaluation shows promising results and demonstrates the practical usability of our approach.
Motivating Cart-Pole Example

We motivate our work with a custom cart-pole example: A pole is attached to a cart that moves between a left and a right limit, within a flat and frictionless environment. Additionally, the environment has a target area within the limits, and a static obstacle standing above the track.

We define five requirements for the cart-pole, as shown in Table 1. Req₁, Req₂, and Req₃ are safety, Req₄ target, and Req₅ comfort requirements, respectively.

| Req ID | Description                      |
|--------|----------------------------------|
| Req₁   | The pole shall never fall from the cart |
| Req₂   | The pole shall never leave the left/right limits |
| Req₃   | The cart shall reach the target in bounded time |
| Req₄   | The cart shall never collide with the obstacle |
| Req₅   | The pole shall never leave the cart |

Table 1: Cart-pole example – informal requirements

We aim to teach the cart-pole to satisfy all above requirements. The system is controlled by applying a continuous force to the cart, allowing the left and right movements of the cart-pole with different velocities. In order to reach the goal and satisfy the target requirement Req₄, the cart-pole must do an uncomfortable and potentially unsafe manoeuvre: since moving a perfectly balanced pole would result in a collision with the obstacle, thus violating the safety requirement Req₂, the cart-pole must lose balancing and pass below it. Furthermore, if the obstacle is too large or the cart do not apply force once passed the obstacle, it may not be able to reach the target without falling down, thus violating the safety requirement Req₁. A sequence of pictures showing a cart-pole successfully overcoming the obstacle in the environment is depicted in Figure 1.

We observe that not all requirements have the same importance for this control task. The safety requirements, naturally define objectives with the highest priority. The target requirement is the next most important objective, while the comfort requirement shall have the lowest priority.

There is a natural research question that we pose in this paper: Is it possible to have a principled way to shape a reward that takes into account all requirements with the order of importance mentioned above? In the remainder of this paper, we will use this motivating example to illustrate the steps that lead to the positive answer to this question.

Related Work

Specifying reward functions for decision-making algorithms is a long-studied problem in the RL community. The reward directly affects the learning process and the resulting policy. A poorly shaped reward might not capture the actual objective and results in problematic behaviors (Amodei et al. 2016). Therefore, shaping the reward helps to effectively steer the RL agent towards favorable behaviors (Ng, Harada, and Russell 1999). Laud and DeJong (2003).

Multi-Objective RL. MORL studies the optimization of multiple and often conflicting objectives. There is a distinction between single- and multi-policy approaches (Rojiers et al. 2013, Liu, Xu, and D. Hu 2015). We focus on the former approach and propose a structured way to combine multiple requirements. There exist several techniques to combine multiple reward signals into a single scalar value (i.e., scalarization), such as linear or non-linear projections (Natarajan and Tadepalli 2003, Barrett and Narayanan 2008, Van Moerbeke, Dragan, and Nowak 2013). Other approaches formulate structured rewards by imposing or assuming a preference ranking on the objectives and finding an equilibrium among them (Gábor, Kalmár, and Szepesvári 1998, Shelton 2001, Zhao, Chen, and W. Hu 2010, Abels et al. 2019). However, many standard RL benchmarks (Brockman et al. 2016) already provide handcrafted rewards, while its derivation lacks a systematic procedure. As a result, defining suitable reward functions for new environments is a non-trivial task.

Reinforcement Learning with Temporal Logic. Temporal Logic (TL) is a well-suited formalism for specifying complex temporal behaviors in an unambiguous way. For this reason, several works adopt TL to specify reward functions. Some works deal with multi-task specifications (Toro Icarte et al. 2018), other works exploit the quantitative semantics of STL and its variants systematically derive a reward (Li, Vasile, and C. Belta 2017, Li, Ma, and C. Belta 2018, Jones et al. 2015, Balakrishnan and Desmukh 2019).

However, classical STL quantitative semantics is non-cumulative and non-markovian by nature, since its evaluation depends on the future trajectory. Some approaches directly address these non-markovian aspects (Camacho et al. 2017, Jothimurugan, Alur, and Bastani 2019, Jiang et al. 2021) by augmenting the original problem with reward machines or proposing alternative formulations. Conversely, we introduce a novel quantitative semantics to provide an immediate reward, more in line with the standard cumulative RL formulation. This formulation allows us to apply our approach to any environment by adopting standard implementation of state-of-the-art RL algorithms (Raffin et al. 2019).

Hierarchically Structured Requirements. Complementary approaches propose to learn dependencies between STL requirements from existing demonstrations (Puranic, Deshmukh, and Nikolaidis 2021a, Puranic, Deshmukh, and Nikolaidis 2021b). Although they use a similar partial ordering of requirements, their reward evaluation procedure significantly differs. While they fix a static weight to each requirement and learn dependencies, we already know the dependencies and introduce a dynamic procedure to weight requirements proportionally to the satisfaction of the partial ordering.

 Preliminaries

Reinforcement Learning (RL). RL aims at inferring a controller of an intelligent agent that takes actions in an environment in a way that maximizes some notion of a cumulative expected reward. The environment is typically modeled as a Markov Decision Process (MDP).
Definition 1 A Markov Decision Process (MDP) is a tuple $M = (S, A, p, R)$, where $S \subseteq \mathbb{R}^n$ is a continuous set of states; $A \subseteq \mathbb{R}^m$ is a continuous set of possible actions; $p : S \times A \times S \to [0, 1]$ is a transition probability function (where $p(s'\mid a, s)$ describes the probability of arriving in state $s'$ if action $a$ was taken at state $s$); $R : S \times A \to \mathbb{R}$ is a reward function, assigning a scalar value to a state-action pair.

In RL, we aim to find a policy $\pi : S \times A \to [0, 1]$ which maps states to action probabilities, such that it maximizes the expected sum of rewards collected over trajectories $\tau$:

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\tau \sim \rho(\cdot\mid \pi)} \left[ \sum_{t=0}^{\infty} R(s_t, a_t) \right].$$

The probability distribution $p(\tau \mid \pi)$ represents the distribution over trajectories observed when sampling actions from some policy $\pi$.

In this work, we test our reward formulation with the Soft Actor-Critic (SAC) algorithm (Haarnoja et al. 2018). SAC is an entropy regularized off-policy RL algorithm that often serves as a benchmark in various continuous-control tasks. In general, SAC is considered to be more robust against premature convergence to some bad local optimum compared to other model-free off-policy methods. Its formulation includes the entropy of the current policy into the optimization objective, encouraging exploratory behavior and penalizing early exploitation of value approximation errors.

Signal Temporal Logic (STL). STL is a specification formalism that allows to express real-time properties of continuous-time real-valued behaviors. An example is a simple bounded stabilization property formulated as follows:

$$\neg \exists t < k < j \in T : \rho(\varphi, w, k)$$

Let $X = \{x_1, \ldots, x_n\}$ be a set of real-valued signal variables. We define a time domain $T$ to be of the form $[0, T] \subseteq \mathbb{R}$. A signal is a function $w : T \to \mathbb{R}^n$. We denote by $w_x : T \to \mathbb{R}$ the projection of $w$ to the variable $x \in X$. Let $\Theta$ be a set of terms of the form $f(Y)$ where $Y \subseteq X$ and $f : \mathbb{R}^{|Y|} \to \mathbb{R}$ is an interpreted function.

The syntax of an STL formula $\varphi$ defined over $X$ is given by the following grammar:

$$\varphi ::= f(Y) > 0 \mid \neg \varphi \mid \varphi_1 \lor \varphi_2 \mid \varphi_1 U \varphi_2 \mid G \varphi \mid F \varphi$$

where $f(Y)$ is a term in $\Theta$ and $I \subseteq [0, \infty)$ is a non-empty interval. We use $U$, $G$ and $F$ as syntactic sugar for the untimed variants of the until $U_{[0,\infty)}$, always $G_{[0,\infty)}$, and eventually $F_{(0,\infty)}$ operators. From the basic Boolean operators of STL, we can derive the other standard operators (implies, conjunction, etc.) as expected.

STL can be equipped with a quantitative semantics based on the infinity norm (Donzé and Maler 2010). The quantitative semantics of an STL formula $\varphi$ with respect to a signal $w$ is described via the robustness function $\rho(\varphi, w, i)$, indicating the degree with which the signal $w$ satisfies or violates $\varphi$ at time $i \in T$:

$$\rho(x > 0, w, i) = w(x, i)$$
$$\rho(\neg \varphi, w, i) = -\rho(\varphi, w, i)$$
$$\rho(\varphi_1 \lor \varphi_2, w, i) = \max(\rho(\varphi_1, w, i), \rho(\varphi_2, w, i))$$
$$\rho(\varphi_1 U \varphi_2, w, i) = \sup_{j \in (i+1) \cap T}(\min(\rho(\varphi_2, w, j), \inf_{i<k<j} \rho(\varphi_1, w, k)))$$
$$\rho(G \varphi, w, i) = \inf_{j \in (i+1) \cap T} \rho(\varphi, w, j)$$
$$\rho(F \varphi, w, i) = \sup_{j \in (i+1) \cap T} \rho(\varphi, w, j)$$

We also define positively saturated $\rho_+(\varphi, w, i) = \max(0, \rho(\varphi, w, i))$ and negatively saturated $\rho_-(\varphi, w, i) = \min(0, \rho(\varphi, w, i))$ robustness. The robustness $\rho(\varphi, w)$ of $\varphi$ with respect to the entire signal $w$ equals to its robustness $\rho(\varphi, w, 0)$ at time 0. We observe that the Boolean satisfaction function $\sigma(\varphi, w)$ is a straight-forward adaptation of the quantitative formulation where max is interpreted as Boolean $\lor$, min as $\land$, sup as $\exists$ and inf as $\forall$. The bounded stabilization requirement given informally above is specified in STL as follows:

$$G(\text{In} > n \to F_{[0,T]}G_{[0,\infty)}(\text{Out} < n)$$

Rulebooks. A rulebook (Censi et al. 2019) is a formalism used to organize the requirements of self-driving cars and other autonomous agents. It is defined as a set of rules, where each rule maps an observed behavior (signal) into a real number indicating the degree of satisfaction/violation of the rule by the behavior. The rules are in addition hierarchically ordered to capture their relative priority.

Definition 2 (Rule) Given a set of signals $W$, a rule $\psi : W \to \mathbb{R}$ is a function mapping a signal $w \in W$ to a real value $\psi(w)$ that usually indicates how well $w$ satisfies or how badly $w$ violates the rule.

Definition 3 (Rulebook) A rulebook $R = (\Psi, \preceq)$ is a tuple consisting of a finite set $\Psi$ of rules and a pre-order $\preceq$ on $\Psi$. Explicitly, we say $\psi \preceq \psi'$ if rule $r$ has lower priority than rule $r'$. 
Shaping Rewards from STL Rulebooks

In this section, we present the main contribution of this paper: A method for systematically shaping rewards from a set of requirements. The proposed approach consists of the following steps:

• Step 1: Formulate the requirements and classify each of them as either a safety, target, or comfort objective,

• Step 2: Formalize each requirement as an STL formula,

• Step 3: Organize STL requirements into a rulebook by defining relative priorities between them; and

• Step 4: Automatically generate the reward function from the rulebook constructed as discussed above.

Classification of Requirements

We propose the classification of requirements according to their role, inspired by the hierarchy of linear temporal logic (LTL) formulas (Manna and Pnueli [1992]. There are four basic classes: (1) safety, of the form \( Gp \), that requires \( p \) to continuously hold, (2) guarantee, of the form \( Fp \), that requires \( p \) to eventually hold, (3) recurrence, of the form \( GFp \), that requires \( p \) to hold infinitely often, and (4) persistence, of the form \( FGp \), that requires \( p \) to continuously hold, starting from a certain point on. We observe that satisfaction of \( Gp \) implies satisfaction of both \( GFp \) and \( FGp \). Conversely, satisfaction of either \( GFp \) or \( FGp \) implies satisfaction of \( Fp \). We also note that from these four classes, one can also derive two compound classes of LTL formulas, namely obligation properties (\( \bigwedge_i (Gp_i \lor Fq_i) \)) and reactivity properties (\( \bigwedge_i (GFp_i \lor FGq_i) \)).

We restrict STL to the fragment that covers safety, guarantee, recurrence, and persistence classes:

\[
\alpha = f(Y) > 0 \\
\varphi := G \alpha | F \alpha | GF \alpha | GF \alpha
\]

where \( Y \subseteq X \). We assume that every \( f(Y) \) and \( \hat{f}(Y) \) is normalized to \([-1, 1]\).

We identify four requirement roles – safety, target, progress and comfort. Safety requirements are naturally associated to the safety class. We associate target requirements to the persistence class – the agent shall reach a target and stay at the target. Finally, we model both progress and comfort requirements as recurrence – progressing and maintaining comfort of the agent shall happen as often as possible. While we adopt this syntactic fragment of STL, we do not keep its infinity-norm quantitative semantics. STL temporal operators are future – an evaluation of a formula at time \( t \) may depend on inputs at times \( t' > t \). It follows that this semantics is inappropriate for continuous rewards.

To alleviate the problem of the infinity-norm semantics with continuous rewards, we define an alternative notion of robustness \( \hat{\rho} \) for the above STL fragment. The new semantics is tailored for shaping immediate rewards and guiding the learning of the RL algorithm:

| Req Id | STL Id | STL Formula | Class |
|-------|--------|-------------|-------|
| Req1  | \( \varphi_1 \) | \( G[\theta] \leq \theta_{\text{max}} \) | Safety |
| Req2  | \( \varphi_2 \) | \( G|x| \leq x_{\text{lim}} \) | Safety |
| Req3  | \( \varphi_3 \) | \( G d(x, O) > 0 \) | Safety |
| Req4  | \( \varphi_4 \) | \( GF d(x, G) = 0 \) | Target |
| Req5  | \( \varphi_5 \) | \( GF \theta \leq \theta_{\text{conf}} \) | Comfort |

Table 2: Cart-pole example – formalized STL requirements

\[
\hat{\rho}(f(Y) > 0, w, i) = \rho(f(Y) > 0, w, i) \\
\hat{\rho}(G \alpha, w, i) = \begin{cases} 0, & \text{if } \rho(\alpha, w, i) \geq 0 \\ -1, & \text{otherwise} \end{cases} \\
\hat{\rho}(F \alpha, w, i) = \begin{cases} 1, & \text{if } \rho(\alpha, w, i) \geq 0 \\ 0, & \text{otherwise} \end{cases} \\
\hat{\rho}(FG \alpha, w, i) = 1 + \rho_-(\alpha, w, i) - \rho_+(-\alpha, w, i) - \rho_+(-\alpha, w, i) \\
\hat{\rho}(GF \alpha, w, i) = \rho_+(\alpha, w, i)
\]

We provide intuition for the definition of \( \hat{\rho} \). A safety property has 0 reward as long as it is satisfied and \(-1\) when violated. A guarantee property is symmetric. A persistence property, modeling a target requirement, gives a maximum reward whenever the agent is already at the target, but also rewards the agent for approaching it (multiplication of the distance from the target and the velocity of coming closer to it). Finally, a recurrence property, which models progress and comfort requirement rewards the level of satisfying the requirement.

Example 1 We consider the cart-pole motivating example and formalize its informal requirements using STL. The state-space of the cart-pole and its environment is the tuple \((x, \dot{x}, \theta, \dot{\theta})\), where \( x \) is the position of the cart, \( \dot{x} \) is its velocity, \( \theta \) is the angle of the pole and \( \dot{\theta} \) is its angular velocity. We first define the following thresholds: (1) \( \theta_{\text{max}} \) – the angle of the pole at which we consider the pole to fall from the cart, (2) \( \delta_{\text{min}} \) – the minimum distance between two non-colliding objects, (3) \( \theta_{\text{conf}} \) – the maximum angle of the pole that we consider to be "comfortable", (4) \( x_{\text{lim}} \) – the position denoting the world limit, (5) \( g \) – the position of the goal, and (6) \( O \) – the set of points defining the static obstacle. Table 2 depicts the formalized requirements for the cart-pole example.

Defining Priorities and Shaping Rewards

In the next step, we define priorities among a set of STL properties \( \Phi = \{ \varphi_1, \ldots, \varphi_n \} \) formalized from the requirements \( \text{Reqs} = \{ \text{Req}_1, \ldots, \text{Req}_n \} \). We perform this step by creating a rulebook \( R = (\Phi, \preceq) \) from \( \Phi \). We note that in many applications, the relative priority between requirements follows naturally from their role. For example, safety has the absolute priority in safety-critical applications, while target and progress requirements typically play a more important role than comfort or performance.

Example 2 Figure 2 depicts the rulebook \( R = (\Phi, \preceq) \), where \( \Phi = \{ \varphi_1, \ldots, \varphi_5 \} \) are cart-pole STL requirements from Table 2 and \( \preceq \) is the partial order that prioritizes safety over target, and target over comfort requirements.
Having motivated the need to have rewards based on hierarchical STL specifications, we introduce the following immediate reward function, which constitutes one of our main contributions. By immediate reward, we mean that the immediate reward function returns a non-trivial reward signal at every time step, as opposed to a sparse (often delayed) reward mechanism.

**Definition 4 (STL-Hierarchical Immediate Reward)**

Let \( R = (\Phi, \preceq) \) be an STL rulebook, \( \varphi \in \Phi \) and, STL specification of the form \( \varphi_0 \), where \( \varphi \in \{ G, F, GF, FG \} \). Then the immediate reward \( R \) is defined as:

\[
R(R, w, i) = \sum_{\varphi \in \Phi} \left( \prod_{\varphi' : \varphi \preceq \varphi'} \rho(\alpha, w, i) \right) \cdot \hat{\rho}(\varphi, w, i). \tag{1}
\]

We can see from Equation (1) that the immediate reward combines the robustness values \( \hat{\rho} \) of all individual requirements in \( \Phi \) using a weighted sum. Each requirement contributes in a way proportional to the degree of satisfaction of all the higher-priority rules.

**Experimental Results**

In order to evaluate our reward shaping approach, we setup and ran three case studies: the cart-pole with obstacle, the bipedal-walker (in classic and hardcore), and the lunar-lander with obstacle. In each case study, we identified a set of requirements \( \{ \text{Req}_1, \ldots, \text{Req}_n \} \), formalized them in STL \( \Phi = \{ \varphi_1, \ldots, \varphi_n \} \), and defined priorities between them using a partially-ordered rulebook \( R = (\Phi, \preceq) \). We assume that \( \Phi \) is partitioned into (at most) four disjoint sets: (1) \( \Phi_S \approx \) safety, (2) \( \Phi_T \approx \) target, (3) \( \Phi_P \approx \) progress, and (4) \( \Phi_C \approx \) comfort requirements.

**Case studies.**

- **Lunar lander:** the agent’s objective is to land at the pad with coordinates \((0, 0)\). In this case, we assume infinite fuel. Landing outside of the pad is also possible. We allow continuous actions to control the lander and add an obstacle to the environment in the vicinity of the landing pad, which makes the landing task harder. We formulate 2 safety, 1 target and 2 comfort STL specifications for the lunar lander.
- **Bipedal walker:** the main objective for the robot is to move forward without falling. We consider two variants of this case study  – the **classical** one with the flat terrain and the **hardcore** one with holes and obstacles. We formulate 1 safety, 1 progress and 3 comfort STL specifications for the bipedal walker. The details of the case studies and relative requirements are found in the Appendix.

**Experimental setup.** For each environment, we train a policy with SAC by adopting a stable state-of-the-art implementation (Raffin et al. 2019). We randomize the starting conditions, such as the agent position, or eventually the obstacle position. Differently from the original task definitions, we set the maximum episode length to 400 steps for the cart-pole with obstacle, 600 for the lunar lander with obstacle, and reduce the length to 500 for the bipedal-walker. While adding the obstacle in the cart-pole and lunar lander makes the setup not precisely comparable with the original environment, the reduction of episode length in the bipedal-walker allows us to perform experiments in a small number of steps and still maintain comparable qualitative results on the learning process. We train SAC for 3 million steps in the bipedal-walker hardcore, while for all the other tasks we use 2 million steps.

**Reward baselines.** We call STL-Hierarchical our formulation of immediate reward from Definition 4. We compare it with the original reward formulation in each environment indicated as Default, and three additional baseline formulations: STL-Sparse, STL-Pessimistic and STL-WeightedSum. 

STL-Sparse is the most straightforward reward shaping approach that uses STL requirements. It interprets the set of requirements \( \Phi \) as the conjunction \( \varphi = \varphi_1 \land \ldots \land \varphi_n \). In this approach, the entire episode \( w \) is recorded, the STL formula \( \varphi \) is evaluated against \( w \) using the infinity-norm STL semantics, and the resulting robustness is assigned as a sparse delayed reward at the end of the episode.

STL-Pessimistic uses the \( \hat{\rho} \) semantics of the combined specifications which have the same priority in the rulebook. Given a set of STL specifications \( \Phi = \Phi_S \cup \Phi_T \cup \Phi_P \cup \Phi_C \), let \( \varphi_S = \bigwedge_{\varphi \in \Phi_S} \varphi, \varphi_T = \bigwedge_{\varphi \in \Phi_T} \varphi, \varphi_P = \bigwedge_{\varphi \in \Phi_P} \varphi \), and \( \varphi_C = \bigwedge_{\varphi \in \Phi_C} \varphi \). We then apply our hierarchical approach to the rulebook formed from \( \Phi^H = \{ \varphi_S, \varphi_T, \varphi_P, \varphi_C \} \) with \( \varphi_S \preceq \varphi_T, \varphi_S \preceq \varphi_P, \varphi_P \preceq \varphi_C \), and \( \varphi_T \preceq \varphi_C \). We call this method pessimistic in the sense that

\[
\hat{\rho}(\varphi_{Role}, w, i) = \min_{\varphi \in \Phi_{Role}} \hat{\rho}(\varphi, w, i)
\]

with \( \text{Role} \in \{ S, T, P, C \} \).

STL-WeightedSum also uses the \( \hat{\rho} \) semantics for each requirement \( \varphi \in \Phi \) and combines them using a weighted sum. However, aiming to replicate the handcrafted weight assignment, we manually encode the weights reflecting the natural ordering of classes with 1 for safety, \( \frac{1}{2} \) for target (or progress) and \( \frac{1}{4} \) for comfort rules. The resulting weighted formulation is

\[
R(\Phi, w, i) = \sum_{\varphi \in \Phi_S} \hat{\rho}(\varphi, w, i) + \frac{1}{2} \sum_{\varphi \in \Phi_T \cup \Phi_P} \hat{\rho}(\varphi, w, i) + \frac{1}{4} \sum_{\varphi \in \Phi_C} \hat{\rho}(\varphi, w, i)
\]

**Experimental Evaluation**

We perform three types of experiments: (1) we compare STL-Hierarchical to other baseline rewards, (2) we refine...
the analysis of behaviors by separating their evaluation per requirement, and (3) we study the impact of ablating requirements from a rulebook on the learned policy. Videos supporting the proposed experiments are provided in the supplementary material.

**Comparison to baseline rewards.** We compare STL-Hierarchical to several baseline formulations and empirically show its superior performance in properly capturing the desired requirements.

Since each reward formulation presents its own scale, the comparison of the learning curves needs an external, unbiased metric. The reward itself does not capture the logical satisfaction of various requirements. To this end, we introduce a custom evaluation-metric $E$, which we use to monitor the learning process. Let $\Phi = \Phi_S \uplus \Phi_T \uplus \Phi_P \uplus \Phi_C$, $\varphi = \bigwedge_{\varphi \in \Phi_S} \varphi, \varphi_T = \bigwedge_{\varphi \in \Phi_T \cup \Phi_P} \varphi$, and $\varphi_C = \bigwedge_{\varphi \in \Phi_C} \varphi$

then:

$$E(\Phi, w) = \sigma(\varphi_S, w) + \frac{1}{2} \sigma(\varphi_T, w) + \frac{1}{2} \sigma_{\text{avg}}(\varphi_C, w)$$

where $\sigma \in \{0, 1\}$ is the satisfaction function. We define also a time-averaged version:

$$\sigma_{\text{avg}}(\varphi, w) = \frac{\sum_{i=1}^{w} \sigma(\varphi, w, i)}{w}.$$  

This non-smooth metric $E$ facilitates categorizing each episode $w$ as (1) satisfying safety properties, if $E(\Phi, w) \geq 1$, satisfying safety, target and progress, if $E(\Phi, w) \geq 1.5$, and additionally maximizing comfort, if $E(\Phi, w)$ is close to 1.75. We emphasize that $E$ is not used for training, and to highlight the convergent behaviour of each learning curve, we also report the average episodic return used during the policy optimization. To address the different scales of each reward formulation, we normalize the returns with respect to the min and max reward observed over the training.

The performance with respect to Evaluation Metric and Normalized Return are reported in Figure 2.

**Offline evaluation of the learned behaviors.** Despite the definition of a custom metric, capturing complex behaviors with a single scalar remains challenging. For this reason, we perform an extensive offline evaluation on cart-pole and lunar lander by comparing the agents trained with STL-Hierarchical against the ones resulting by training with the other baseline formulations. For each of the trained agents, we collect 50 random episodes and evaluate them with respect to each class of requirements. Table 3 reports the Success Rate in satisfying the incremental sets of Safety (S), Safety and Targets (S+T), Safety, Target and Comfort (S+T+C).

We see that STL-Hierarchical is the only reward that consistently completes the task in most of the evaluations. Conversely, the other baselines struggle in capturing the correct objective and result in peculiar behaviours. For example in cart-pole, STL-Sparse eagerly tries to maximize the progress to the origin, by approaching the target area as soon as possible. However, the safety requirement is masked out by the STL infinity-norm semantics, resulting in a policy that is not able to balance the pole once the origin is reached and hence violates the safety requirements. This observation highlight the weakness of using infinity-norm semantics in multi-objective optimization, because the dominant component could mask out the others, even if properly normalized with respect to the signal domain.

**STL-Pessimistic** and **STL-WeightedSum** result in conservative behaviours which prefer to accumulate rewards in the safe area without ever trying to overcome the obstacle. Finally, **Default** also results able to capture the desired behaviour, confirming the good reward shaping proposed in the original environments. However, considering the current training budget, **STL-Hierarchical** results able to produce a more effective learning signal, resulting in better performing policy.

**Ablation study on comfort rules.** We evaluate the impact of individual requirements in the hierarchical structure of the overall reward. We focus on the comfort requirements that have the weakest priority and the smallest influence on the value of the final reward. More specifically, we study how much the comfort requirements contribute to the improvement of the observed comfort. We setup an ablation experiment on the comfort requirements, and compare the performance of resulting policies. We perform this experiment on the bipedal-walker (classical and hardcore) because it is the application with a rich variety of comfort requirements.

Table 4 reports the evaluation of the comfort requirements for policies trained on the rulebook with (+Comfort), and without (-Comfort) comfort requirements. For each seed, we collect again 50 random episodes, and compute the ratio of satisfaction of comfort requirements over each episode.

In both environments, the introduction of comfort rules shows a positive impact on the evaluation, especially in the hardcore version, where the rough terrain makes it challenging to learn a smooth policy. Despite the requirement on the

| Reward          | S Sat.Rate (%) | S+T Sat.Rate (%) | S+T+C Sat.Rate (%) |
|-----------------|---------------|------------------|--------------------|
| Default         | 0.444         | 0.444            | 0.444              |
| STL-Sparse      | 0.000         | 0.000            | 0.000              |
| STL-Pessimistic | 0.532         | 0.000            | 0.000              |
| STL-WeightedSum | 0.932         | 0.000            | 0.000              |
| STL-Hierarchical| 0.788         | 0.588            | 0.574              |

Table 3: Evaluation of cart-pole agents over classes of STL requirements: Safety (S), Target (T), Comfort (C). The results are aggregated over 50 episodes for each of the 5 seeds.

| Reward          | S Sat.Rate (%) | S+T Sat.Rate (%) | S+T+C Sat.Rate (%) |
|-----------------|---------------|------------------|--------------------|
| Default         | 0.984         | 0.500            | 0.494              |
| STL-Sparse      | 0.980         | 0.004            | 0.004              |
| STL-Pessimistic | 0.984         | 0.606            | 0.605              |
| STL-WeightedSum | 0.908         | 0.064            | 0.064              |
| STL-Hierarchical| 0.988         | 0.976            | 0.971              |

Table 4: Evaluation of lunar lander agents over classes of STL requirements: Safety (S), Target (T), Comfort (C). The results are aggregated over 50 episodes for each of the 5 seeds.
We demonstrated the applicability of the proposed method from a set of well-defined rules with well-known priorities. We presented a principled approach for shaping (immediate) rewards from a set of partially-ordered formalized requirements. We believe that our approach can bring many benefits when learning optimal policies for autonomous agents from a set of well-defined rules with well-known priorities. We demonstrated the applicability of the proposed method on three benchmarks and showed the quality of the learned solution with respect to other baseline approaches.

The idea of automatically shaping rewards from a set of partially-ordered specifications, equipped with an evaluation procedure, is general and can be applied to any environment. We made specific design choices that we motivated in the paper to make our framework more concrete. There is nevertheless sufficient room to consider variants of the general approach. The choice of the specification language and its semantics are flexible and are not bound to (a fragment of) STL. Indeed, any representation of requirements equipped with an evaluation function for observed behaviors can be used for hierarchical reward shaping. In this paper, we focused on unbounded temporal operators $F$, $G$, $GF$ and $FG$. The extension to timed specifications, such as the time-bounded target $F_{[0,T]}G\alpha$, would be straightforward, but we believe that it would not affect the learning process – the agent naturally tries to reach the target as soon as possible even without the constraint. On the other hand, the timed operators could be used to evaluate whether a trained agent is able to reach its objectives within specified time.

The original formulation of rulebooks assumes a lexicographic order of requirements evaluation – even a slightly higher robustness of a behaviour with respect to a high-priority requirement masks the robustness of low-priority requirements. We found this definition restrictive and opted for the hierarchical-weighted approach of Equation (1). We plan to compare the two approaches in the future.

In subsequent work, we also plan to apply this approach to autonomous-driving applications, which typically have over 200 requirements. We will study the formalization of requirements beyond safety, progress, and comfort, considering additional classes of requirements, including ethical, legal, and performance objectives.

| Classic version          | +Comfort | -Comfort |
|--------------------------|----------|----------|
| Hull angle               | 0.999 ± 0.005 | 0.922 ± 0.153 |
| Hull angular velocity    | 1.000 ± 0.000 | 1.000 ± 0.000 |
| Vertical oscillation     | 0.972 ± 0.016 | 0.946 ± 0.024 |

| Hardcore version         | +Comfort | -Comfort |
|--------------------------|----------|----------|
| Hull angle               | 0.987 ± 0.061 | 0.882 ± 0.121 |
| Hull angular velocity    | 1.000 ± 0.000 | 0.999 ± 0.001 |
| Vertical oscillation     | 0.909 ± 0.068 | 0.865 ± 0.084 |

Table 5: Evaluation of bipedal-walker (Normal and Hardcore) trained with (+Comfort) and without Comfort rules (-Comfort). The results are averaged over 50 episodes for each of the 5 seeds.
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Appendix

In this appendix we provide our implementation details for the experiments and the training/evaluation. This includes the requirements and STL specifications for the lunar lander and bipedal walker studies. We also include the details of the environment modifications we did to all environments (mainly cart-pole and the lunar lander).

Training and Evaluation Details
Table 6 includes the details of the training parameters used. For training, we evaluate the progress of the policy every 10,000 steps, and use 10 episodes for the evaluation. As mentioned in the main text, we use the SAC implementation from (Raffin et al. 2019). Almost all of the values are default, with the sole exception of the buffer size (5e4 instead of 1e6) which we reduce to be in proportion to the number of steps we train on. We include the rest of the parameters here for completeness.

| Training and Evaluation Parameters | Value |
|-----------------------------------|-------|
| num_steps* | 2e6 |
| evaluate_every | 1e4 |
| num_eval_episodes | 10 |

| SAC Implementation Parameters | Value |
|-------------------------------|-------|
| gamma | 0.99 |
| learning_rate | 0.0003 |
| buffer_size** | 5e4 |
| learning_starts | 100 |
| train_freq | 1 |
| batch_size | 64 |
| tau | 0.005 |
| ent_coef | auto |
| target_update_interval | 1 |
| gradient_steps | 1 |
| target_entropy | auto |
| action_noise | None |

Table 6: Parameters used for training all four environments.* Only the hardcore version of the bipedal walker uses 3e6 steps. ** Only non-default value.

Environment Descriptions

Cart-pole with Obstacle
This was the running example from the main paper. The cart begins on the right side of the obstacle and the goal is to swoop under the obstacle and reach the origin. In our implementation the cart agent takes continuous actions $a \in [-1, 1]$ rather than discrete actions. Every episode the position of the obstacle and the minimum clearance height is randomized. The list of parameters used is found in Table 7 (end of document). In order to make sure that solving the problem would be feasible, we additionally increase the maximum force applicable by the cart; force_mag = 30.0 (originally set to 10.0). The agent’s state is additionally enhanced with the coordinates of obstacle (left, right, bottom, top) and a flag on whether the pole has collided or not. The color changes are purely aesthetic.

Lunar-Lander with Obstacle:
In this case study a lunar lander’s objective is to land at the pad with coordinates (0, 0). In this example, we assume infinite fuel. Landing outside of the pad is also possible (as long as the impact velocity does not exceed a threshold). We allow continuous actions that allow firing the engine to the left or right, firing the main engine, and doing nothing. We add an obstacle to the environment, that makes the landing harder. The original state space of the lunar lander is the tuple $(x, y, \dot{x}, \dot{y}, \theta, \dot{\theta})$, where $(x, y)$ is the position of the lander, $(\dot{x}, \dot{y})$ is its velocity, $\theta$ is the angle of the lander with respect to the direction of gravity ($y$-axis), and $\dot{\theta}$ is its angular velocity. The lander also has contact sensors for both of its legs, and we further enhance the state space with the obstacle coordinates (left, right, top, bottom) and a flag variable on whether the pole has collided or not.

The original environment does not explicitly have a maximum number of allowed steps, which we introduced in order to shorten the computation resources needed before having a convergent policy. Additionally, we do not randomize the obstacle size or position in this use case. The used parameters are found in Table 10 (end of document). Figure 4 shows some frames of the lander surrounding the obstacle (red square above the landing pad) in order to safely reach its target.

In order to define the informal and formal requirements, we also define the following constants: (1) $G$ – the coordinates of the landing area, (2) $O$ – the area that is occupied by the static obstacle, (3) $x_{\text{lim}}$ – the limit of the world, (4) $\theta_{\text{comf}}$ – the maximum comfortable angle and (5) $\dot{\theta}_{\text{comf}}$ – the maximum comfortable angular velocity. Table 7 lists the informal requirements, collected for the lunar-lander example, and their formalization in STL.

| Req Id | STL Id | STL Formula | Class |
|--------|--------|-------------|-------|
| Req1   | $\forall_1$ | $G d(r, O) \geq 0$ | Safety |
| Req2   | $\forall_2$ | $G |x| \leq x_{\text{lim}}$ | Safety |
| Req3   | $\forall_3$ | $FG d(r, O) = 0$ | Target |
| Req4   | $\forall_4$ | $GF |\theta| \leq \theta_{\text{comf}}$ | Comfort |
| Req5   | $\forall_5$ | $GF |\dot{\theta}| \leq \dot{\theta}_{\text{comf}}$ | Comfort |

Table 7: Lunar lander example – informal and formalized STL requirements.
Bipedal-Walker:
In this case study, the main objective for the robot is to move forward without falling. We consider two variants of this case study – the classical one with the flat terrain and the hardcore one with holes and obstacles. A state in this case study is the tuple \((\dot{x}, \dot{y}, \theta, \dot{\theta}, \mathbf{l})\), where \(\dot{x}\) is the horizontal velocity, \(\dot{y}\) is the vertical velocity, \(\theta\) is the hull angle, \(\dot{\theta}\) is the angular velocity and \(\mathbf{l}\) is a vector of 10 LiDAR range-finder measurements. We note that there are additional state variables the agent observes, such as position of joints and joints angular speed, and legs contact with ground. We do not explicitly define them because we do not use them in the requirements. There are also no coordinates in the state vector. We did not alter the agent’s observation space for this environment. The only modification we made to the environment was to terminate it after a fixed number of steps. Since we wanted to showcase the progress class, we wanted to ensure that the walker did not reach the end of the world, and this was the most straightforward way to implement a never-ending world. Table 11 (end of document) lists the used parameters. Figure 5 shows two frames of the normal environment, and two frames of the hardcore environment.

We define the following constants: (1) \(O\) – the set of coordinates occupied by the static obstacle, (2) \(\theta_{\text{conf}}\) – the maximum comfortable angle, (3) \(\dot{\theta}_{\text{conf}}\) – the maximum comfortable angular velocity, and (4) \(\dot{y}_{\text{conf}}\) – the maximum comfortable vertical velocity. Table 8 lists the informal requirements collected for the bipedal walker example, and their formalization in STL.

| Req ID | Description |
|--------|-------------|
| Req\(_1\) | The walker shall never collide with the floor or with any obstacle |
| Req\(_2\) | The walker shall almost always keep walking in the right direction |
| Req\(_3\) | The walker must as often as possible keep the hull balanced within a comfortable angle |
| Req\(_4\) | The walker must as often as possible keep the hull’s angular velocity within a comfortable limit |
| Req\(_5\) | The walker must as often as possible keep a comfortable vertical velocity |

| Req Id | STL Id | STL Formula | Class |
|--------|--------|-------------|-------|
| Req\(_1\) | \(\varphi_1\) | \(G_{\min_{l \in \mathbf{l}} d(l, O) > 0}\) | Safety |
| Req\(_2\) | \(\varphi_2\) | \(GF \dot{x} > 0\) | Progress |
| Req\(_3\) | \(\varphi_3\) | \(GF |\theta| \leq \theta_{\text{conf}}\) | Comfort |
| Req\(_4\) | \(\varphi_4\) | \(GF |\dot{\theta}| \leq \dot{\theta}_{\text{conf}}\) | Comfort |
| Req\(_5\) | \(\varphi_5\) | \(GF |\dot{y}| \leq \dot{y}_{\text{conf}}\) | Comfort |

Table 8: Bipedal-walker example – informal and formalized STL requirements.
Tables of Environment Parameters:

**Cart-pole with obstacle**

| Episode Conditions | | |
|--------------------|---|---|
| max_steps          | 400 | Steps before episode termination. |
| terminate_on_collision | True | Episode ends if pole touches obstacle. |
| x_limit            | 2.5 | Episode ends if $|x| \geq x_{\text{limit}}$. |
| theta_limit        | 90  | Episode ends if $|\theta| \geq \theta_{\text{limit}}$. |

**Reward Parameters**

| x_target          | 0.0 | The cart’s ideal goal. |
|-------------------|-----|------------------------|
| x_target_tol      | 0.25| Goal area. $G = \{x : |x - x_{\text{target}}| \leq x_{\text{target(tol)}} \}$ |
| theta_target      | 0.0 | The pole’s most comfortable angle. |
| theta_conf        | 24  | Comfort limit. $|\theta - \theta_{\text{target}}| \leq \theta_{\text{conf}}$ |

**Initial Conditions**

| x_min_offset      | 1.2 | Cart’s starting position. |
|-------------------|-----|--------------------------|
| x_max_offset      | 2.0 | $x_0 \in [x_{\text{min offset}}, x_{\text{max offset}}]$ |
| obstacle_width    | 0.2 | Obstacle width is fixed. |
| obstacle_min_height | 0.97 | The height of the bottom of the obstacle: $\alpha_{\text{bottom}} \in [\alpha_{\text{min height}}, \alpha_{\text{max height}}]$ |
| obstacle_max_height | 0.99 | |
| obstacle_min_dist | 0.5 | The x-coordinate center of the obstacle: $\alpha_{\text{center}} \in [\alpha_{\text{min dist}}, \alpha_{\text{max dist}}]$ |
| obstacle_max_dist | 0.75 | |

Table 9: Parameters used for the cart-pole with obstacle environment. Non-stated parameters were not altered. Angles given in degrees.

**Lunar lander with obstacle**

| Episode Conditions | | |
|--------------------|---|---|
| max_steps          | 600 | Steps before episode termination. |
| terminate_on_collision | True | Episode ends if lander collides with ground or with obstacle. |
| x_limit            | 1.0 | Episode ends if $|x| \geq x_{\text{limit}}$. |
| Note: there is no $y_{\text{limit}}$. |

**Reward Parameters**

| x_target          | 0.0 | The lander’s ideal goal. |
|-------------------|-----|------------------------|
| x_target_tol      | 0.15| Goal area. $G = \{(x, 0) : |x - x_{\text{target}}| \leq x_{\text{target(tol)}} \}$ |
| theta_target      | 0.0 | The lander’s most comfortable angle. |
| theta_conf        | $\pi/3$ | Comfort limit. $|\theta - \theta_{\text{target}}| \leq \theta_{\text{conf}}$ |

**Initial Conditions**

| x_offset          | 0.1 | Lander’s starting x-position. $x_{\text{offset}} \in [-x_{\text{offset}}]$ |
|-------------------|-----|--------------------------|
| obstacle_left     | 0.0 | |
| obstacle_right    | 0.2 | |
| obstacle_bottom   | 0.53| |
| obstacle_top      | 0.46| |

Obstacle size and position is fixed.

Table 10: Parameters used for the lunar lander with obstacle environment. Non-stated parameters were not altered. Angles given in radians. Spatial coordinates normalized with default environment resolution.
### Bipedal Walker

#### Episode Conditions

| Parameter                  | Value |
|----------------------------|-------|
| `max_steps`                | 500   |
| Steps before episode terminiation. |
| `terminate_on_collision`   | True  |
| Episode ends if walker’s hull makes contact with the ground or an obstacle. |

#### Reward Parameters

| Parameter                  | Value |
|----------------------------|-------|
| `lidar_offset`             | 0.225 |
| Since the LiDAR origin is inside the hull, a constant offset is considered. $l \leftarrow l - l_{\text{offset}}$ |
| `theta_target`             | 0.0   |
| The hull’s most comfortable angle. |
| `theta_comf`               | 0.436 |
| Comfort limit. $|\theta - \theta_{\text{target}}| \leq \theta_{\text{comf}}$ |
| `theta_dot_target`         | 0.0   |
| The hull’s most comfortable angular velocity. |
| `theta_dot_comf`           | 0.25  |
| Comfort limit. $|\dot{\theta} - \dot{\theta}_{\text{target}}| \leq \dot{\theta}_{\text{comf}}$ |
| `y_dot_target`             | 0.0   |
| The hull’s most comfortable $y$-velocity. |
| `y_dot_comf`               | 0.1   |
| Comfort limit. $|\dot{y} - \dot{y}_{\text{target}}| \leq \dot{y}_{\text{comf}}$ |

Table 11: Parameters used for the bipedal walker environments. Non-stated parameters were not altered. Angles given in radians. Spatial coordinates normalized with default environment resolution.