RLang: A Declarative Language for Expressing Prior Knowledge for Reinforcement Learning

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Abstract
Communicating useful background knowledge to reinforcement learning (RL) agents is an important and effective method for accelerating learning. We introduce RLang, a domain-specific language (DSL) for communicating domain knowledge to an RL agent. Unlike other existing DSLs proposed by the RL community that ground to single elements of a decision-making formalism (e.g., the reward function or policy function), RLang can specify information about every element of a Markov decision process. We define precise syntax and grounding semantics for RLang, and provide a parser implementation that grounds RLang programs to an algorithm-agnostic partial world model and policy that can be exploited by an RL agent. We provide a series of example RLang programs, and demonstrate how different RL methods can exploit the resulting knowledge, including model-free and model-based tabular algorithms, hierarchical approaches, and deep RL algorithms (including both policy gradient and value-based methods).

1 Introduction
Reinforcement learning (RL) algorithms have seen important successes such as agents that learn to play the Atari games from pixels (Mnih et al. 2013) and learning to play Go, chess and shogi (Silver et al. 2017, 2018; Schrittwieser et al. 2020); demonstrating the capabilities of deep RL methods. However, they require a great amount of experience and, thus, learning in such tabula rasa setting quickly becomes impractical. Moreover, to develop generalist learning agents, we cannot expect them to learn every task they will face without instruction and task-specific knowledge. In fact, it is reasonable to assume that we would communicate to the agent useful task-specific knowledge, e.g., the rules of a game, relevant permitted actions and features of the observation such as relevant observed game pieces, before they begin learning a policy. This information will be oftentimes partial and the agent will need to improve and complete its knowledge in the usual RL loop, but the given prior information should nonetheless improve the learning performance.

Languages, both formal and natural, have been used in various ways to add prior knowledge into decision-making (Luketina et al. 2019). Formal languages benefit from unambiguous syntax and semantics, and can therefore be reliably used to represent knowledge. These have proven useful in specifying advice to agents in the form of hints about actions (Maclin and Shavlik 1996) or policy structure (Andreas, Klein, and Levine 2017). Communicating such knowledge using natural language would be more intuitive, though this approach would require converting natural language sentences into grounded knowledge usable by the agent; most of the approaches in this area restrict the possible grounding by translating natural language into expressions of a restricted grammar. For example, for describing task objectives (Artzi and Zettlemoyer 2013; Patel, Pavlick, and Tellex 2020), or other individual components of decision-making systems such as rewards (Goyal, Niekum, and Mooney 2019; Sumers et al. 2021) and policies (Branavan, Zettlemoyer, and Barzilay 2010). All of the above approaches provide information about a single component of a chosen decision-making formalism; there exists no unified framework able to express information about all the components of a task.

We therefore introduce RLang, a domain-specific language (DSL) with precise syntax and semantics to express information about every component of a Markov decision process (MDP), including flat and hierarchical policies, state factors and features, transition functions, and reward functions. Moreover, we release the RLang Parser1 that interprets RLang programs and produces grounded partial models in Python to be used by any learning algorithm. We then demonstrate RLang’s versatility through a series of example programs that express different types of domain knowledge and how such knowledge improves learning performance.

2 Background

Domain-Specific Languages Domain-specific languages (DSLs) are formal languages designed to specify information relevant to a target domain. Compared to general-purpose programming languages like Python (Van Rossum and Drake Jr 1995) and C (Kernigham and Ritchie 1973), DSLs typically contain a smaller set of narrower semantics that are well-suited to a specific application. That is, DSLs sacrifice computational expressivity for ease-of-use within a particular domain. Commonly-used DSLs include the Standard Query Language (SQL) used for querying relational databases and the Planning Domain Definition Language

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1RLang source code, documentation, and examples are available at rlang.ai
(PDDL; Ghallab et al. 1998) for defining planning tasks.

Decision-Making Formalisms Reinforcement learning tasks are typically modeled as Markov Decision Processes (MDPs; Puterman 1990), which are defined by a tuple \((S, A, R, T, \gamma)\), where \(S\) is a set of states, \(A\) is a set of actions, \(T: S \times A \times S \rightarrow [0, 1]\) is a transition probability distribution, \(R : S \times A \times S \rightarrow \mathbb{R}\) is a reward function, and \(\gamma \in (0, 1)\) is a discount factor. A solution to an MDP is a policy \(\pi: S \times A \rightarrow [0, 1]\) that maximizes the expected discounted return \(\mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t]\), where \(r_t\) is the reward obtained at time step \(t\). The value function \(V^\pi : S \rightarrow \mathbb{R}\) for a policy \(\pi\) captures the expected return an agent would receive from executing \(\pi\) starting in a state \(s\). The action-value function \(Q^\pi : S \times A \rightarrow \mathbb{R}\) of a policy is the expected return from executing an action \(a\) in a state \(s\) and following policy \(\pi\) thereafter.

Hierarchical Decision-Making Solving MDPs with high-dimensional state and action spaces can be difficult, especially in domains where long sequences of actions are required to achieve a goal. In these environments, hierarchical reinforcement learning (Barto and Mahadevan 2003) may be more applicable, as temporally-extended actions can reduce the complexity of the space of solution policies. The options framework (Sutton, Precup, and Singh 1999) formalizes this notion by modeling high-level actions as options: closed-loop policies defined by a tuple \((I, \pi, \beta)\), where \(I \subseteq S\) is a set of states in which the option can be executed, \(\pi\) is an option policy, and \(\beta: S \rightarrow [0, 1]\) describes the probability that the option will terminate upon reaching a given state. Let \(O\) be the set of options the agent can execute, then the MDP tuple is extended to \((S, A \cup O, R, T, \gamma)\) in the hierarchical setting.

3 RLang: Expressing Prior Knowledge about Reinforcement Learning Tasks

If RL is to become widely used in practice, we must reduce the infeasible amount of trial-and-error required to learn to solve a task from scratch. One promising approach is to avoid tabula rasa learning by including the sort of background knowledge that humans typically bring to a new task. Such background knowledge is often easy to obtain—in many cases, it is simply obvious to anyone: try not to fall off cliffs!—and need not be perfect or complete in order to be useful.

Unfortunately, however, there is no standardized approach to communicating such background knowledge to an RL agent. In most cases, the same person who implements the learning algorithm also hand-codes the background knowledge, typically in the same general-purpose programming language in which the algorithm is implemented, typically in an ad-hoc fashion. This has two primary drawbacks. First, prior knowledge is often task-specific, and the lack of a medium to express it hinders the development of general-purpose learning algorithms that can exploit varying types and degrees of background knowledge. Second, this approach is not accessible to end-users or other consumers of RL agents, who do not write the algorithms themselves and cannot necessarily be expected to master the relevant programming languages and mathematical details, but who might nevertheless wish to accelerate learning.

The alternative is to design a standardized, human-interpretable DSL for expressing prior knowledge about reinforcement learning tasks. Such a DSL should have two important properties, which are not present in existing DSLs (Maclin and Shavlik 1996; Denil et al. 2017; Sun, Wu, and Lim 2020). First, it should be agnostic of the learning algorithm used. Separating the question of how to express prior knowledge from how that knowledge is exploited by a learning algorithm introduces a standardized interface that can be used to inform a wide variety of RL agents, even ones based on algorithms that have not yet been developed. Second, it should be complete: able to express all the information that could possibly be informative about a particular task. We therefore propose RLang, a new DSL designed to fulfill these criteria.

RLang can be used to prescribe features of the state space (using Features and Propositions), specify one or more goal states (using Goals), define abstract actions (using Options), describe solution policies and hierarchical policy structure (using Policies), restrict the action space (using ActionRestrictions), provide partial models of the world (using Effects, which ground to reward functions and transition functions), and shape reward (also using Effects). RLang programs can be parsed using the RLang Parser2 into an algorithm-agnostic data structure (see

2Our landing page, which includes installation instructions, can be found at rlang.ai
Table 1: RLang declarations for corresponding MDP elements. The first column shows a component of the MDP, the second shows an RLang expression that can inform it, while the last column contains a description of the expression.

| MDP Component | RLang Declaration | Natural Language Interpretation |
|---------------|-------------------|--------------------------------|
| State Feature \( \phi: \mathcal{S} \rightarrow \mathbb{R}^n \) | Feature inventory.value := 5 * gold + 2 * iron | The value of your inventory is 5 for each gold you have plus 2 for each iron. |
| Proposition \( \sigma: \mathcal{S} \rightarrow \{\top, \bot\} \) | Proposition at_workbench := position in workbench_locations | You are at a workbench if your position is one of the workbench locations. |
| Policy \( \pi: \mathcal{S} \times \mathcal{A} \rightarrow [0, 1] \) | Policy build_bridge: if at_workbench: Execute use | If you are at a workbench, craft using it. |
| Option \( (\sigma_1, \pi, \sigma_2) \) | Option build_axe: init(wood >= 1 and iron >= 1) Execute build_axe_policy until(axe >= 1) | When you have at least one wood and one iron, you can build axes until you have at least one. |
| Reward and Transition Function \( (R_e: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}, T_e: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]) \) | Effect resource_consumption: if wood >= 1 and A == use: stick' -> stick + wood wood' -> 0 Reward wood | Crafting will convert your wood into sticks. You will also be rewarded 1 for every wood you have. |

Section [3.2] that can be integrated into nearly any reinforcement learning algorithm. In this section, we present the main RLang elements and their syntax. As we will show, RLang’s syntax is inspired by Python to ensure readability and ease-of-use, and a full formal specification of the syntax in Backus-Naur Form (BNF) and the grounding semantics implemented by the RLang Parser are in Appendix A.

3.1 RLang Elements

An RLang program consists of a set of declarations, where each one grounds to one or more components of an \((\mathcal{S}, \mathcal{A}, O, R, T, \pi)\) tuple. More specifically, every RLang Element grounds to a function with a domain in \(\mathcal{S} \times \mathcal{A} \times \mathcal{S}\) and a co-domain in \(\mathcal{S}, \mathcal{A}, \mathbb{R}^n\) where \(n \in \mathbb{N}\), or \(\{\top, \bot\}\). We describe the main RLang element types in the rest of this section and summarize them in Table 1.

**State Factors** In Factored MDPs (Boutilier, Dearden, and Goldszmidt 2000), the state space is a collection of conditionally independent variables: \(\mathcal{S} = X_1 \times \ldots \times X_n\). Some learning algorithms might find it useful to reference these variables individually. For example, consider a 2-D version of Minecraft, as represented in Figure 2, where an agent has to collect ingredients to craft new tools and objects. In this environment the state is the concatenation of a position vector, a flattened map representation, and an inventory vector: \(s = (\text{pos}, \text{map}, \text{inventory})\). Factors can be used to reference these independent state variables:

- **Factor** position := \(S[0:2]\)
- **Factor** map := \(S[2:250]\)
- **Factor** inventory := \(S[250:270]\)

\(S\) is a reserved keyword referring to the current state. \(A\) and \(S'\) are also keywords which refer to the current action and the next state, respectively. Factors can be further sliced and indexed:

- **Factor** iron := inventory[0]

**Propositions** Propositions in RLang, which are functions of the form \(\mathcal{S} \rightarrow \{\top, \bot\}\), identify states that share relevant characteristics:

- **Proposition** workbench_locations := [[1, 0], [1, 3]]
- **Proposition** at_workbench := position in workbench_locations
- **Proposition** have_bridge_material := iron >= 1 and wood >= 1

**Goals** Goals can be used to specify goal states given by a proposition. For example, **Goal** get_gold := gold >= 1 encodes that the agent must collect at least one gold unit.

**Markov Features** Markov Functions like the action-value function or transition function take the form \(\mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}\). We extend the co-domain of this function class to \(\mathbb{R}^n\), where \(n \in \mathbb{N}\), and introduce Markov Features, which allow users to compute features on an \((s, a, s')\) experience tuple. The following Markov Feature represents a change in inventory elements:

- **Markov Feature** inventory_change := inventory' - inventory

The prime (‘) operator references the value of an RLang name when evaluated on the next state.

**Policies** Policy functions can also be specified in RLang using conditional expressions:

- **Policy** main:

  - if iron >= 2:
if at_workbench:
    Execute Use # This is an action
else:
    Execute go_to_workbench # This is a policy
else:
    Execute collect_iron

The Execute keyword can be used to execute an action or call another policy. The above policy instructs the agent to craft iron tools at a workbench by first collecting iron and then navigating to the workbench. Policies can also be probabilistic:

Policy random_move:
    Execute up with P(0.25)
    or Execute down with P(0.25)
    or Execute left with P(0.25)
    or Execute right with P(0.25)

Users can specify multiple policy functions in an RLang program and can designate a primary policy by naming it `main`.

Options Temporally-extended actions can be specified using `Options`, which include initiation and termination propositions:

Option build_bridge:
    init have_bridge_material and at_workbench
    Execute craft_bridge
    until bridge in inventory

Action Restrictions Restrictions to the set of possible actions an agent can take in a given circumstance can be specified using `ActionRestrictions`:

ActionRestriction dont.get.burned:
    if (position + [0, 1]) in lava_locations:
        Restrict up

Effects Effects provide an interface for specifying partial information about the transition and reward functions. When using a factorized MDP, RLang can also be used to specify factorized transition functions (i.e., transition functions for individual factors):

Effect movement_effect:
    if x.position >= 1 and A == left:
        x.position' -> x.position - 1
    Reward -0.1

The above Effect captures the predicted consequence of moving left on the x.position factor, stating that the x position of the agent in the next state will be 1 less than in the current state. This Effect also specifies a -0.1 step penalty regardless of the current state or action. In simpler MDPs, predictions can be made about the whole state vector:

Effect tic_tac_toe:
    if three_in_a_row:
        S' -> empty_board # Board is reset

Effects can reference previously defined effects using similar syntax:

Effect main:
    -> movement_effect
    -> crafting_effect

A main Effect designates the primary environment dynamics, and grounds to a partial factored world model \((T, \mathcal{R})\). Similar to policies, Effects can be made probabilistic using `with`.

Finally, it is important to note that RLang, as we have seen across these examples, does not require the specification of Effects and Policies to be complete (i.e., known for every element transition \((s, a, s')\) or state-action pair \((s, a)\), respectively). Therefore, a user is not constrained to provide extensive and complex programs to fully specify the MDP—although this is a possibility with RLang—in order to accelerate learning. Therefore, RL agents are meant to learn to fill the missing pieces and improve over the provided knowledge.

3.2 Accessing Parsed RLang Knowledge

Using the RLang’s Python API, users can parse RLang programs into the following queryable knowledge Python objects, which can be integrated directly into a learning algorithm: (1) the **Dynamics and Task Knowledge** object contains a queryable model of the environment and the task (i.e., transition dynamics \(T\) and reward function \(R\)) that are derived from the `Effect` `main` declaration and the collection of defined goals; (2) the **Solution Knowledge** object that contains information about the collection of newly defined options \(O\) and the `main` policy \(\pi\). Moreover, these knowledge objects are implemented as partial functions and, hence, when querying for a element of the domain where the RLang programs provides no knowledge, it returns an unknown flag.

3.3 Specifying Complex Groundings with a Vocabulary File

RLang comes built-in with a set of simple arithmetic, Boolean, and set operations in addition to `if`, `elif`, `else` conditional statements which can be used in various RLang object declarations. However, we recognize that users may want to include more complex grounding functions in their RLang programs. For instance, when dealing with problems with high-dimensional observation spaces (e.g. pixel frames), we might require to provide groundings that abstract away low-level details of the problem. To accommodate these needs, we have made it possible to define RLang objects using our RLang’s Python API which can be imported and referenced in an RLang program. By specifying a **vocabulary file** (in JSON format) and a corresponding **grounding file** (a Python file defining RLang objects), users can construct RLang objects using the full features of Python and reference them directly in RLang programs. This allows users to provide complex expert groundings or, more generally, learned groundings that hold the necessary semantic information to derive **new** grounded knowledge easily with RLang programs.

4 Demonstrations

In this section, we demonstrate RLang use-cases, focusing on examples that show how different types of prior information that can be concisely and easily expressed, for varying degrees of environment complexity and different fami-
lies of RL methods. We therefore provide examples of information about policy hierarchical structure, policy priors and transition dynamics, and explore how this information can be exploited with RL methods suitable to the type of information provided.\footnote{This section does not provide new algorithmic contribution. Instead, it focuses in showing the advantage of providing such diverse kind of (partial) knowledge to an RL agent and showcases RLang as an algorithm-agnostic medium to express such knowledge.}

We design simple and effective RLang-informed agents based on model-free and model-based tabular RL methods such as Q-Learning \cite{watkins1992}, policy gradient methods such as PPO \cite{schulman2017} and REINFORCE \cite{williams1992} and hierarchical RL methods based on options and DDQN \cite{van2016}.

**Hierarchical Policy Structure: 2D Minecraft** We first consider a 2D version of Minecraft based on \cite{andreas2017}, consisting of a gridworld (see Figure 2) that contains workbenches where the agent can craft new objects, and raw materials like wood, stone and gold. To build an item, the agent must have the required ingredients and be in the correct workbench. The agent has the action `use` to interact with elements, and actions to move in the cardinal directions.

We show how providing the sub-policy structure of the task improves performance. Specifically, we provide the agent with initiation and termination conditions for a few options (to collect wood, to go to the three different workshops, and to build the required elements), leaving the agent to learn the policy over options. The following program concisely defines 3 options fully and 4 options with uninformative policies. This is an example of a simple RLang program that conveys partial hierarchical structure that can effectively help the agent improve learning.

```plaintext
1 Option go_to_workshop_0:
2    init (any):
3        Execute
4          go_to_workshop_0_learnable_policy
5        until (at_workshop_0)
6 Option go_to_workshop_1:
7    init (any):
8        Execute
9          go_to_workshop_1_learnable_policy
10        until (at_workshop_1)
11 Option get_wood:
12    init (there_is_wood):
13        Execute
14          get_wood_learnable_policy
15 until delta_learnable_policy
```

To exploit this information, the agent must learn both the policy over options to maximize reward, and the option policies that achieve each option's termination condition. For both the high-level and low-level agents, we use the DDQN algorithm \cite{van2016} (implementation details are in Appendix B.3).

Figure 3a show the average return of RLang-informed hierarchical DDQN \cite{van2016} vs. the uninformed (flat) performance of a DDQN agent. The results show that providing a concise program partially describing a hierarchical solution was sufficient to successfully learn to solve the task, in stark contrast with the uninformed DDQN agent.

**Policy Prior: Lunar Lander** Next, we consider programs that provide prior policy knowledge. Such policy information need not be optimal or complete, but it can still improve learning performance. We first consider the Lunar Lander environment \cite{brockman2016}, which requires learning an optimal control policy to gently land a ship on the moon. The environment has a dense reward signal encoding both the goal of the system and cost constraints, a continuous state space, and four discrete actions that either do nothing, fire the main engine, or fire the left or right thruster. We provide the agent with an initial policy using the following RLang program:

```plaintext
1 Policy land:
2    if (left_leg_in_contact == 1.0) or
3      (right_leg_in_contact == 1.0)
4      if (velocity_y/2 * -1.0) > 0.05:
5        Execute main_engine
6      else:
7        Execute do_nothing
8    elif remaining_hover >
9      remaining_angle and remaining_hover
10     > -1 * remaining_angle and
11     remaining_hover > 0.05:
12        Execute main_engine
13    elif remaining_angle < -0.05:
14        Execute right_thruster
15    elif remaining_angle > 0.05:
16        Execute left_thruster
17    else:
18        Execute do_nothing
```

We implemented an RLang-informed agent using PPO \cite{schulman2017}, a policy gradient method, as our base method. We probabilistically mixed the RLang-defined advice policy with a learnable policy network using mixing parameter $\beta \in [0, 1]$, following Fernández and Veloso \cite{fernandez2006}.
This mixing parameter is annealed during learning process. In this way, the RLag policy and the learnable policy shared control stochastically.

```plaintext
Policy gain_momentum:
if velocity < 0:
    Execute go_left
else:
    Execute go_right
```

Figure 3b shows the average return curves resulting from an uninformed PPO agent (Schulman et al. 2017) and the RLag-informed version. The informed agent is able to leverage the initial performance of the given policy and learn how to improve it further, resulting in clearly better return.

We also considered two classic control problems: CartPole and Mountain Car. For CartPole, we obtain analogous results using REINFORCE (Williams 1992, as the base method (Appendix B.4). In Mountain Car, a hard exploration problem in RL, a very concise RLag policy results in near-optimal performance; the simple program on the right gets a −119 average return over 100 episodes, where the task is considered solved with a −110 average return.

```plaintext
Effect moving_effect:
if A == up:
    x' = x + 1
    y' = y
elsif A == down:
    x' = x - 1
    y' = y
elsif A == left:
    x' = x
    y' = y - 1
elsif A == right:
    x' = x
    y' = y + 1
Effect dynamics:
if at_wall:
    S' = S
else:
    => moving_effect
Effect reward:
if in_lava:
    Reward -l
elsif at_goal:
    Reward 1.
```

Average return curves for an RLag-informed Q-Learning agent (blue) that leverages hierarchical information vs. standard (flat) DDQN (red) in 2D-Minecraft. Figure(b) shows average return for Lunar Lander in which an RLag-informed PPO agent (blue) leverages an initial advice policy (with average performance shown in yellow). Figure(c) shows the average return curves for RLag-informed Q-Learning with information about the reward and dynamics in Lava-Gap.

5 Related Work

There has been a recent surge of interest in methods that use language to inform RL agents (Luketina et al. 2019). These fall under methods that use natural language to instruct, or to reward, agents as a form of supervision, or methods that use
formal languages to represent goals or an MDP component.

**Formal Languages in Reinforcement Learning** In classical planning it is standard to use the Planning Domain Description Language (PDDL; Ghallab et al. 1998) and its probabilistic extension PDDPL (probabilistic PDDL; Younes and Littman 2004) to specify the complete dynamics of a factored-state environment. RLang is inspired by these but it is intended for a fundamentally different task: providing partial knowledge to a learning agent, where the knowledge might correspond to any component of the underlying MDP. The Relational Dynamic Influence Diagram Language (RDDL; Santer 2010) extends PDDPL capabilities to compactly express factored MDPs grounded on Dynamic Bayesian Networks (DBNs) to allow for correlated effects, concurrent actions and partial observability. However, it lacks expressivity for partial specifications, options and policies which hinders its application in the RL setting.

Maclin and Shavlik (1996) propose an RL paradigm in which the agent may request advice, as provided through a DSL that uses propositional statements to provide policy hints. Similarly, Sun, Wu, and Lim (2020) propose to learn a policy conditioned on a program from a DSL. Andreas, Klein, and Levine (2017) use a simple grammar to represent policies as a concatenation of primitives (sub-policies) to provide RL agents with knowledge about the hierarchical structure of the tasks.

Other languages include linear temporal logic (LTL; Littman et al. 2017), and propositional formulas to reward functions for the agent. Note that LTL formulas easily express non-Markov tasks and grounding methods modify the state space to cope with this. RLang assumes that the state space is already Markov.

RLang expands on all of these DSLs to include information beyond the policy and the reward function, thus allowing a wider array of information to be parsed and interpreted by the agent. Table 2 summarizes existing DSLs for RL and shows their relative expressive power: no existing DSL is sufficiently powerful to express the wide range of information that can be used by an RL agent.

**Natural Language Grounding and Learning Methods** There is a significant amount of work that attempts to ground the semantic meaning of language instructions to information usable by RL agents (Luketina et al. 2019). Some approaches learn to ground natural language advice to a single grounding function type (e.g., reward function) directly from data. For example, for the game of Civilization II, RL agents can be taught to ground linguistic information to features that allow better estimation of the Q-function (Branavan, Silver, and Barzilay 2012). Other work shows that grounding textual specifications of goals and dynamics, allows learning a language-conditioned policy (Zhong, Rocktäschel, and Grefenstette 2019). In instruction-following, some approaches learn to map instructions directly to reward functions (Misra, Langford, and Artzi 2017; Bahdanau et al. 2018; Goyal, Niekum, and Mooney 2020), while others translate natural language to an intermediate formal language that represents rewards (Artzi and Zettlemoyer 2013; Patel, Pavlick, and Tellex 2020). In general, these languages are restricted grammars that can be easily mapped to the desired grounded element. For example, some methods translate instructions to sequences of primitive actions (Misra and Artzi 2015) or to LTL formulae (Williams et al. 2018; Gopalan et al. 2018; Patel, Pavlick, and Tellex 2020). In future work, we plan to use RLang as the semantic representation language, since it has a higher expressive power.

### 6 Conclusion and Future Work

RLang is a precise, concise and unambiguous domain-specific language designed to enable a human to provide prior knowledge to an RL agent. It provides syntax and semantics tailored for MDPs and the RL setting where partial information can significantly improve learning performance of established RL methods, as shown in our experiments. Moreover, these experiments highlight the main assumption in current RL algorithm design: agents must learn tabula rasa and, therefore, we were required to design ad-hoc informed variations in our examples. In future work, RL methods must also consider informed formulations in which humans can provide information about the task definition, the relevant dynamics and policy/action advice. We envision RLang to enable research in more general agents that exploit the structure of programs to automatically decide how to best exploit the knowledge provided. RLang is algorithm-agnostic by design and we expect it to be a standard interface that will enable research in such general informed agents.

### Table 2: Comparison of DSLs proposed for RL agents and the types of expressible MDP information

| RL Language | Policy Hint | Action Structure | Policy Constraints | State Structure | Rewards | Transition Dynamics |
|-------------|-------------|------------------|--------------------|-----------------|--------|---------------------|
| ALisp       | ✓           | ✓                | ✓                  | ✓               | ✓      | ✓                   |
| Advice RL   | ✓           | ✓                | ✓                  | ✓               | ✓      | ✓                   |
| Program-guided Agent | ✓ | ✓              | ✓                  | ✓               | ✓      | ✓                   |
| Programable Agents | ✓ | ✓              | ✓                  | ✓               | ✓      | ✓                   |
| Policy sketches | ✓ | ✓              | ✓                  | ✓               | ✓      | ✓                   |
| GLTL        | ✓           | ✓                | ✓                  | ✓               | ✓      | ✓                   |
| SPECTRL     | ✓           | ✓                | ✓                  | ✓               | ✓      | ✓                   |
| RLang       | ✓           | ✓                | ✓                  | ✓               | ✓      | ✓                   |
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A  RLang: Grammar and Semantics

In this section, we define the semantics of the expressions that compose RLang.

A.1 Grammar

\[
\begin{align*}
\langle \text{program} \rangle & ::= \text{import} \langle \text{declarations} \rangle \\
\langle \text{declaration} \rangle & ::= \langle \text{constant} \rangle \\
& \quad | \langle \text{action} \rangle \\
& \quad | \langle \text{factor} \rangle \\
& \quad | \langle \text{proposition} \rangle \\
& \quad | \langle \text{goal} \rangle \\
& \quad | \langle \text{feature} \rangle \\
& \quad | \langle \text{markov_feature} \rangle \\
& \quad | \langle \text{option} \rangle \\
& \quad | \langle \text{policy} \rangle \\
& \quad | \langle \text{effect} \rangle \\
& \quad | \langle \text{action_restriction} \rangle \\
\langle \text{constant} \rangle & ::= \text{Constant} \langle \text{identifier} \rangle ::= \langle \text{arithmetic_expression} \rangle \\
\langle \text{action} \rangle & ::= \text{Action} \langle \text{identifier} \rangle ::= \langle \text{arithmetic_expression} \rangle \\
\langle \text{factor} \rangle & ::= \text{Factor} \langle \text{identifier} \rangle ::= \langle \text{special_variable} \rangle \\
\langle \text{proposition} \rangle & ::= \text{Proposition} \langle \text{identifier} \rangle ::= \langle \text{boolean_expression} \rangle \\
\langle \text{goal} \rangle & ::= \text{Goal} \langle \text{identifier} \rangle ::= \langle \text{boolean_expression} \rangle \\
\langle \text{feature} \rangle & ::= \text{Feature} \langle \text{identifier} \rangle ::= \langle \text{arithmetic_expression} \rangle \\
\langle \text{markov_feature} \rangle & ::= \text{MarkovFeature} \langle \text{identifier} \rangle ::= \langle \text{arithmetic_expression} \rangle \\
\langle \text{policy} \rangle & ::= \text{Policy} \langle \text{identifier} \rangle ::= \langle \text{policy_statement} \rangle \\
\langle \text{policy_statement} \rangle & ::= \langle \text{execute_statement} \rangle \\
& \quad | \langle \text{conditional_policy_statement} \rangle \\
& \quad | \langle \text{probabilistic_policy_statement} \rangle \\
\langle \text{execute_statement} \rangle & ::= \text{Execute} \\
& \quad \langle \text{arithmetic_expression} \rangle \\
\langle \text{option} \rangle & ::= \text{Option} \langle \text{identifier} \rangle ::= \langle \text{policy_statement} \rangle \\
\langle \text{option_init} \rangle & ::= \text{init} \langle \text{boolean_expression} \rangle \\
\langle \text{option_until} \rangle & ::= \text{until} \langle \text{boolean_expression} \rangle \\
\langle \text{effect} \rangle & ::= \text{Effect} \langle \text{identifier} \rangle ::= \langle \text{effect_statement} \rangle \\
\langle \text{effect_statement} \rangle & ::= \langle \text{reward} \rangle \\
& \quad | \langle \text{prediction} \rangle \\
& \quad | \langle \text{effect_reference} \rangle \\
& \quad | \langle \text{conditional_effect_statement} \rangle \\
& \quad | \langle \text{probabilistic_effect_statement} \rangle \\
\langle \text{reward} \rangle & ::= \text{Reward} \langle \text{arithmetic_expression} \rangle \\
\langle \text{prediction} \rangle & ::= \langle \text{identifier} \rangle' \rightarrow \langle \text{arithmetic_expression} \rangle \\
\langle \text{effect_reference} \rangle & ::= \rightarrow \langle \text{identifier} \rangle \\
\langle \text{action_restriction} \rangle & ::= \text{ActionRestriction} \langle \text{identifier} \rangle ::= \langle \text{restrict Statements} \rangle
\end{align*}
\]

A.2 Semantics: Basic Syntactic Elements

RLang allows to express information that grounds to functions defined over the State-Action space of an MDP. Moreover, these functions have to be Markov, in the MDP sense, allowing to define functions with domain \( X \) that can be \( S \times A \times S \) and, its simplifications, \( S, A, S \times A, S \times S \). The range of these functions can include real vectors \( \mathbb{R}^d \) (with \( d \in \mathbb{N} \)), Booleans \( \{\top, \bot\} \) and sets. The following are the basic expressions that are used to build the MDP specific elements of RLang.

- **Real Expressions** \( \langle \text{arithmetic_expression} \rangle \) are functions of the form \( f : X \rightarrow \mathbb{R}^d \) for some dimension \( d \). Syntactically, RLang allows element-wise arithmetic operations (+, -, *, /), numeric literals, and references to previously defined real functions to define new functions. These functions are Markov and defined over the State-Action Space of the MDP, i.e. \( X \in \{S, A, S \times A, S \times S, S \times A \times S\} \).

- **Constant expressions** \( \langle \text{identifier} \rangle \) allows to bind a name \((\langle \text{identifier} \rangle)\) to literal value or a list of literal values.

- **Boolean Expressions** \( \langle \text{boolean_expression} \rangle \) Analogous to Real Expressions, these are functions of the form \( f : X \rightarrow \{\top, \bot\} \) with domain \( X \in \{S, A, S \times A, S \times S, S \times A \times S\} \). In order to define new Boolean expressions, RLang allow for logical operators (and, or, not) and order relations of the real numbers (\( i.e., i=, i<=, i=\)).

- **Relations and Partial Functions** A relation of domains \( X \) and \( Y \) are a subset \( R \subseteq X \times Y \). Partial functions are specifications of functions of the form \( f : X \rightarrow Y \). A partial function is, then, a relation such that

\[
PF := \{(x, y) \in X \times Y \text{ and } \forall (x, y), (x', y') \mid x = x' \implies y = y'\}.
\]
A.3 Semantics: RLang Expressions

Core RLang Type Definitions are necessary in order to derive new information from the base vocabulary.

- **State Space Definitions** allows to define important features and set of states for the agent.
  1. **State Features** (feature) These ground to functions of the form \( \phi : S \rightarrow \mathbb{R}^d \). Hence, given the base vocabulary and using real expressions, we can derive new features;
  2. **State Factors** (factor) In the particular case the state space is \( S \subseteq \mathbb{R}^n (n \in \mathbb{N}) \) and factored, we have specific state features that correspond to the State Factors whose definition is given by a list of integers that correspond to the positions in the state vectors that are part of the factor. A factorization of the state correspond to a set of disjoint factors whose union is the full state vector;
  3. **Propositions** (proposition) ground to Boolean functions with domain in \( S \) that represents a set of states \( S_\sigma := \{ s \in S \text{ and } s \models \sigma \} \).

- **Action Definition** (action) names a particular action. Consider that the action space \( A \subseteq \mathbb{R}^d \) with \( d \in \mathbb{N} \). Then, an action definition grounds to a point in \( A \).

- **Option Definition** (option) allows to define an temporally-abstracted action based on the options framework (Sutton, Precup, and Singh [1999]). Therefore, the statement directly maps to the triple \( (I, \pi_o, \beta) \), where \( I \) is the initiation proposition defined by the syntactical element \( \langle \text{option_init} \rangle \), \( \beta \) is the termination proposition defined by \( \langle \text{option_until} \rangle \) and \( \pi_o \) is the policy function defined by a policy statement (policy_statement)

- **Markov Feature Definition** (markov_feature) allow to derive real-value features of a transition tuple \((s, a, s')\) of the MDP. These expressions ground to real functions of the form \( f : S \times A \times S \rightarrow \mathbb{R}^n \) with \( n \in \mathbb{N} \). These are the more general grounding function within RLang and it allows to compose information regarding all important elements of an MDP (e.g., rewards, transitions, value functions).

Core MDP Expressions are related to specifications of the main functions of the MDP:

- **Transition Dynamics and Rewards** represented syntactically by \( \langle \text{effect_statement} \rangle \). Such statements ground to tuples \( (R, T) \) of reward functions and next-state probabilities. More precisely, grounding functions are \( R : S \times A \times S \rightarrow \mathbb{R} \) and \( T : S \times A \times S \rightarrow [0, 1] \). The following are the semantics of possible effect expressions.

- **Reward** (reward) statement allows to specify a reward value using real expressions. A reward statement grounds to a function \( R : S \times A \times S \rightarrow \mathbb{R} \) defined by scalar arithmetic expressions.

- **Next State Prediction** (prediction) ground to functions \( T : S \times A \times S \rightarrow [0, 1] \) that gives a probability of transitioning to the next state \( s' \) after executing action \( a \) at state \( s \). The following are possible groundings:
  1. **Null Effect**: \( s' \rightarrow s \). This grounds to
     \[
     T(s', a, s) = \begin{cases} 
     1 & \text{if } s' = s \\
     0 & \text{otherwise} 
     \end{cases}
     \]
  2. **Singleton Prediction**: \( s' \rightarrow \langle \text{constant} \rangle \). Let the constant ground to a valid state vector \( \hat{s} \in S \). Thus, the expression grounds to
     \[
     T(s', a, s) = \begin{cases} 
     1 & \text{if } s' = \hat{s} \\
     0 & \text{otherwise} 
     \end{cases}
     \]
  3. **Real Prediction**: \( s' \rightarrow \langle \text{arithmetic_expression} \rangle \). Let the \( \langle \text{arithmetic_expression} \rangle \) ground to a real function of the form \( e : S \times A \rightarrow \mathbb{R} \). Then, the prediction expression grounds to
     \[
     T(s', a, s) = \begin{cases} 
     1 & \text{if } s' = e(s, a) \\
     0 & \text{otherwise} 
     \end{cases}
     \]
  4. **Factor Prediction**: \( \text{factor_name} \rightarrow \langle \text{arithmetic_expression} \rangle \). Let \( \text{factor_name} \) ground to the factor \( \phi : S \rightarrow \mathbb{R}^d \) where \( d \in \mathbb{N} \) is the dimension of the factor. Let the \( \langle \text{arithmetic_expression} \rangle \) ground to \( e_{\phi} : S \times A \rightarrow \mathbb{R}^d \). Then, a factored prediction grounds to the function
     \[
     T_{\phi}(\phi(s'), a, s) = \begin{cases} 
     1 & \text{if } \phi(s') = e(s, a) \\
     0 & \text{otherwise} 
     \end{cases}
     \]
     A collection of factor predictions for a set of disjoint factors \( \{ \phi_i \}_i \) that partition the state vector can ground to a full transition function
     \[
     T(s', a, s) = \prod_i T_{\phi_i}(\phi_i(s'), a, s)
     \]
  5. **Probabilistic Effect Statements**: \( \langle \text{probabilistic_effect_statement} \rangle \) allows to explicitly indicate probabilities for a collection of predictions. Consider that the probabilistic statement is a collection of tuples \( \{(T_i, p_i)\}_i \) where \( T_i \) is the grounding function of the prediction and \( p_i \) a probability, subject to the correctness of the probabilities \( \sum_i p_i \leq 1 \) and for all \( p_i \geq 0 \). Thus, it grounds to
     \[
     T(s', a, s) = \sum_i p_i T_i(s', a, s)
     \]
     If \( \sum p_i < 1 \), then the remaining probability is construed to be assigned to unknown.
     In the case of Factor predictions for a given factor, the grounding function \( T_{\phi} \) is defined analogously.

- **Conditional Effect Statements**: \( \langle \text{conditional_effect_statement} \rangle \). The conditional context allows to define subsets of the domain \( D \subseteq S \times A \times S \) through a \( \langle \text{boolean_expression} \rangle \).
that defines when a particular Execute statement is valid. Hence, a (conditional_policy_statement) grounds to partial functions \( R = \{(D_i, R_i)\}_i \), where each tuple is the result of a branch from the parsing of if-elif-else blocks. Analogously, for the grounding of dynamics information of the statement \( T = \{(D_i, T_i)\}_i \), where the \( D_i \) are disjointed subsets of the domain defined by the Boolean expressions, the order of the conditional branches and the \( T_i \) and \( R_i \) are defined by reward and prediction statements defined above.

7. Effect References (effect_reference) allows to refer to previously defined effect statements to compose new ones. Each referred effect is tuple of \((R_i, T_i)\) of groundings for rewards and transition dynamics. A collection of effect references ground to:

\[
\text{Rewards} \quad R(s, a, s') = \sum_{i \in \{(s, a, s')\}} R_i(s, a, s')
\]

where \( I(s, a, s') \) is the set of referred effects that have information for rewards in the tuple \((s, a, s')\). Hence, rewards are composed additively.

Transition Dynamics Let \( S'_i(s, a) = \{s' \in S : T_i(s', a, s) > 0\} \) be the set of next states from state-action pair \((s, a)\) about which \( T_i \) provide knowledge. Thus, a set of effect references are well-defined if \( \bigcap_i S'_i(s, a) = 0 \) and \( \sum_{s' \in \bigcup_i S'_i(s, a)} T(s', a, s) \leq 1 \) for all \((s, a)\). Hence, the grounding function is

\[
T(s', a, s) = \sum_i T_i(s', a, s).
\]

Policies (policy) ground to policy functions \( \pi: S \times A \rightarrow [0, 1] \). The simplest expression to specify a policy is an execute statement (execute_statement). The name after the Execute keyword represents either an (action) \( a' \in A \) and, hence, the statement grounds to

\[
\pi(s, a) = \begin{cases} 1 & \text{if } a = a' \\ 0 & \text{otherwise} \end{cases}
\]

or it can refer to a previously defined (policy) that grounds to \( \pi \) and, then, the statement grounds to \( \pi = \pi'. \) Therefore, the (execute_statement) functions analogously to a return statement in function definitions in imperative programming languages: when an action name is found, it maps the querying state \( s \) to the first action referenced by an execute statement.

Probabilistic policy expressions (probabilistic_policy_statement): Probability statements allow to extend the execute statement with explicit probability values. Therefore, a probabilistic policy statement grounds to a collection of execute statements-probability pairs \( \{(\pi_i, p_i)\}_i \). In this way, probabilistic policy statements ground to

\[
\pi(s, a) = \sum_i p_i \pi_i(s, a)
\]

If \( \sum_i p_i < 1 \), then the remaining probability is construed to be assigned to unknown.

Conditional Policy Expressions (conditional_policy_statement): The conditional context allows to define subsets of the domain \( S' \subseteq S \) through a (proposition) that defines when a particular execute statement is valid. Hence, a (conditional_policy_statement) grounds to a partial function \( \pi': \{(S_i, \pi_i)\}_i \) where each pair \((S'_i, \pi_i)\) the result of a branch from the parsing of if-elif-else blocks. The \( S'_i \) are disjointed and they are the result of the (proposition), the order of the statements and the returning semantics of the execute statements. The \( \pi_i \) are defined by execute statements or probabilistic policy statements.

Action Restrictions (action_restriction) are defined analogously to conditional policy statements. They reduce the possible set of actions to consider in a given situation. They ground to functions of the form \( A: S \rightarrow A \) that defines then subset of prohibited actions to take in state \( s \)—i.e., \( A(s) \subseteq A \).

Goals (goal) ground to set of states that are considered goal states for the MDP, i.e. terminating and highly rewarding. RLang represents goals through propositions.

B Experimental Details and Additional Results

In this section, we extend the discussion on the implementation details of RLang demonstrations in Section A. We provide details about the implementation of the RLang-informed variations of the RL algorithms, descriptions of the environments and the hyperparameters used.

For each of the experiments below we report average return curves over 5 different random seeds and report 95% confidence intervals. Moreover, we use a running average with window size of 50.

B.1 Lava-Gap

Lava-Gap is a 6 × 6 grid-world with coordinates \( x, y \in \{1, 6\} \). There is a wall in position \((3, 1)\) and 4 lava pits in locations \((3, 2), (1, 4), (2, 4), (2, 5)\). The goal position is \((5, 1)\). The agent has 4 discrete actions that allows it to move in one of the cardinal directions by 1 step. Each action has a probability of failure of 1/3 that would move the agent to a random neighboring position (in the cardinal directions). The state \( s_i \) at time \( t \) is represented by the \( x \) and \( y \) coordinates of the position at time \( t \). The agent receives a reward of −1 for falling in a lava pit and the episode terminates. Similarly, the agent receives a reward of 1 for reaching the goal and the episode terminates. In any other case, the reward is 0. At the start of every episode, the agent begins executing at position \((1, 1)\). We use a discount factor of \( \gamma = 0.95 \). We use simple_r1’s implementation (Abel 2019) of this gridworld and of the RMax and Q-Learning algorithms. Experiments were run in a personal MacBook Pro with a 2.4 GHz Quad-Core Intel Core i5.

RLang-informed Q-Learning In the RLang-informed example for Lava-gap, we leverage the transition and reward information from the RLang program to initialize the Q-table for Q-Learning and R-Max. We compute the Q-table by executing value iteration considering in the state pairs
where transition information is available. In Algorithm 1 we show how the Q-table of a Q-Learning agent is initialized using the information provided in a RLang program given as input as the RLangKnowledge objects. The UpdateValue function computes the new value using the standard TD-error.

Algorithm 1: Q-Table Initialization

```c
function InitQTable(RLangKnowledge, QAgent)
    for (s,a) ∈ S × A do
        if RLangKnowledge.Reward(s,a) is known then
            QAgent.Q(s,a) ← RLangKnowledge.Reward(s,a)
        end if
    end for
    for N iterations do
        for (s,a,s') ∈ S × A × S do
            if RLangKnowledge.Transition(s,a) is known then
                T(s,a,s') ← RLangKnowledge.T(s,a)
                R(s,a,s') ← RLangKnowledge.Reward(s,a)
                QAgent.Q(s,a) ← UpdateValue(s,a,s', T(s,a,s'), QAgent)
            end if
        end for
    end for
end function
```

RMax Results In Figure 4b we show the average return curves for an RMax agent informed with the program below, in which we see consistent results with the results obtained for an RLang-informed Q-Learning agent.

B.2 Taxi

We use simple rl’s implementation of the Taxi environment (Dietterich 1998) with 2 passengers in a 5 × 5 grid. The state vector has the position of the agent and a binary variable that is 0 when the taxi does not carry a passenger and 1 otherwise. Moreover, it has the current position of the passengers, the destination of the passenger and a binary variable that indicates if the passenger is in the taxi. The agent has 4 movement actions and a special action for picking up a passenger that is at the same position than the agent and another for dropping off the passenger currently in the taxi. The reward function is 1 when all passenger are in destination and 0 otherwise. The discount factor γ = 0.95. Experiments were run in a personal MacBook Pro with a 2.4 GHz Quad-Core Intel Core i5.

RLang-informed hierarchical Q-Learning In this experiment, we use a hierarchical RL agent based on the options framework. In this particular case, we use Q-Learning to learn both the policy over options and the intra-option policies. We consider that an RLang-defined option is learnable if the policy function is not provided, i.e. only initiation and termination conditions are specified. We use such termination condition as a goal represented by a pseudo-reward function that is 1 when the termination condition is achieved and 0 otherwise that the inner agent uses to learn the intra-option policy. We initialize the intra-option learning agents of those learnable options defined in the input RLang program with the procedure in Algorithm 2.
Hyperparameters For our Q-Learning baseline, we use an exploration $\epsilon = 0.1$ and a step size of $\alpha = 0.1$. For our hierarchical Q-Learning agents, we have a Q-Learning agent for each subpolicy to be learnt with $\epsilon = 0.1$ and $\alpha = 0.1$ and a Q-Learning agent to learn the policy over options with $\epsilon = 0.01$ and $\alpha = 0.5$. We implemented our hierarchical Q-Learning agent as Sutton, Precup, and Singh.

Results In Figure 5a, we show the average return curves for Taxi. The RL contains shown below, defines the options given to the agent—a simple variation of this program is provided to the agent that needs to learn the intra-option policies. The plot shows the most-informed agent, i.e. extra-option policies are provided and it only needs to learn the policy over options, is represented in blue, the RL-informed agent that only knows the initiation and termination conditions of the options (in red) and an uninformed Q-Learning agent. We observe that both of the informed agents are able to exploit the knowledge to gain a steeper learning curve with respect to the uninformed agent.

Option pick_up_passenger0:
init(not(pasenger_in_taxi) and not(pasenger_0_in_dest))
Execute pick_up_passenger0
until passenger_0_in_taxi

Option drop_off_passenger0:
init(pasenger_0_in_taxi)
Execute drop_off_passenger0
until passenger_0_in_dest and not(passenger_0_in_taxi)

Option pick_up_passenger1:
init(not(pasenger_in_taxi) and not(pasenger_1_in_dest))
Execute pick_up_passenger1
until passenger_1_in_taxi

Option drop_off_passenger1:
init(pasenger_1_in_taxi)
Execute drop_off_passenger1
until passenger_1_in_dest and not(passenger_1_in_taxi)

B.3 2D Minecraft

2D Minecraft is a crafting environment based on Andreas, Klein, and Levine implemented as a $10 \times 10$ grid. The state vector includes a map of the environment, an inventory vector and the change on inventory with respect to the previous time step. The map is represented by $10 \times 10 \times 22$ tensor that represent with a one-hot vector the element at position $(x, y)$. The agent has 4 actions to move in the cardinal directions by one position and a special action use to interact with the element in front, i.e., given the current position and orientation of the agent, the position with which the agent interacts in the one the agent is facing. If such element is a primitive, the agent adds it to its inventory; if the element is a workbench and it has any of the primitive elements to build an object in the workbench, then those objects are built and added to the inventory (any primitive element used is removed from the inventory); if the agent is in front of water and has a bridge, it can use it and cross the water. If the agent has to interact with stone, it needs an axe in inventory. This is a goal-oriented environment; when the agent has the goal object in inventory, it receives a reward of 1 and the episode terminates. When an episode starts, the agent is randomly placed in any free cell of the grid. We use a discount factor $\gamma = 0.99$. Experiments were run on a single GPU NVIDIA GeForce RTX 3090 Ti.

RLang-informed hierarchical DDQN Agent To solve this environment, analogously to the Taxi environment, we use a hierarchical agent based on options. We use DDQN (van Hasselt, Guez, and Silver 2016) as the algorithm to learn the both the policy over options and intra-option policies. Algorithm 2 is used to initialized the intra-option policies. To implement DDQN and its hierarchical variation based on options, we based it on the Autonomous Learning Library (Nota 2020).

Neural Network architecture and parameters We use a CNN with 4 ReLU-activated layers with filter banks of size 32, 32, 32, 64, a kernel size of 3 and stride of 2 (padding was used to keep the dimension $10 \times 10$). The inventory and inventory change were processed with a ReLU MLP with hidden layer of size 32 and output size 32. These two vectors are concatenated and passed through a linear layer of size 256 (for the flat DDQN) and 64 for the agents in the hierarchical DDQN implementation. Finally, this output vector is passed through a ReLU MLP with a hidden layer of size 64 to get the value predictions for each action.

Hyperparameters For DDQN, we use a linear schedule for $\epsilon$-greedy exploration with start with $\epsilon = 1$ and $\epsilon = 0$ and final exploration step 10000. We use a learning rate 0.001 and mini-batch of size 64. We use a Prioritized replay buffer of size 10000. The target network update frequency is 100 steps. We set a time of 1000 steps.

For hierarchical DDQN:

- Outer Agent (policy over options): we use a linear schedule for $\epsilon$-greedy exploration with start with $\epsilon = 1$ and $\epsilon = 0$ and final exploration step 60000. We use a learning rate $10^{-5}$ and mini-batch of size 64. We use a Prioritized replay buffer of size 10000. The target network update frequency is 100 steps. This outer agent had a timeout of 10000 steps;
- Inner Agents (intra-option policies): we use a linear schedule for $\epsilon$-greedy exploration with start with $\epsilon = 1$ and $\epsilon = 0.001$ and final exploration step 30000. We use a learning rate $10^{-4}$ and mini-batch of size 128. The target
network update frequency is 100 steps. We use a Prioritized replay buffer of size 10000. Each subpolicy had a timeout of 100 steps.

B.4 Classic Control

Environments In this section, we consider Cartpole and Lunar Lander, two classic environments for RL research that have continuous state-space and discrete action space. For both environments, we use OpenAI Gym’s implementations (Brockman et al. 2016), i.e. CartPole-v0 and LunarLander-v2.

Cartpole (Barto, Sutton, and Anderson 1983) consists of an underactuated pole attached to a cart. At the beginning, the pole starts in a vertical position (0 degrees) and the agent has to learn a policy to keep it within 15 degrees. The state consists of the position and the velocity of the cart, and the angle and angular velocity of the pole. The action space is to apply momentum to move the cart to the right or to the left. An episode ends when the pole absolute angle is greater than 15 degrees, the position of the cart is greater than 2.4 units or after 200 time steps. The agent gets a reward of 0 if the main engine is fired. The ν1 has to learn a policy to keep it within 0 degrees.)

Lunar Lander simulates the task of landing a ship in a landing pad on the moon. The state consists of the ship’s position and velocity, angle and angular velocity, and Boolean flags that indicate if the ship’s leg is in contact with the ground. The actions are to fire the main engine, the right orientation engine, the left orientation engine and doing nothing. The agent gets a reward of −100 if the ship crashed and +100 if it lands correctly. It receives +10 for each leg that touches the ground and −0.3 if the main engine is fired. The task is solved with a return of at least 195 over 100 episodes.

In the case of Lunar Lander and PPO, we use a policy network based on an MLP with hidden size 64 and Leaky ReLU activations (Maas et al. 2013) with parameter 0.2. As a value network, we use an MLP with hidden size 64 and Tanh activations.

Hyperparameters For Cartpole, we use PFRL’s REINFORCE implementation (Fujita et al. 2021). We use an initial mixing parameter β = 0.7 and a decay rate α = 0.99. For REINFORCE, we use a learning rate of 0.001 and a batch size of 5. In Lunar Lander, we use PFRL’s PPO implementation and use a mixing parameter β = 0.5 and a

RLang-informed Policy Gradient Agent To solve these environments, we provided non-optimal policies through RLang programs and use policy gradients methods to leverage this knowledge while learning. Algorithm 3 is derived from (Fernández and Veloso 2006), in which, we probabilistically share control between the learning policy πθ and the RLang-provided policy ˆπ. At each time step, we choose which policy to follow by drawing a sample from a Bernoulli distribution with parameter β. We use such probabilistic mixing to collect trajectories and then optimize, θ, using policy gradient methods. We use REINFORCE (Williams 1992) for Cartpole and PPO (Schulman et al. 2017) for Lunar Lander. The mixing parameter β is annealed exponentially using a decay rate α.

Algorithm 3: Hierarchical Agent Initialization

1: function PolicyMixing(RLangKnowledge, decay_rate)
2:   Trajectories ← Rollout(Env, πθ, π, β)
3:   θ ← PolicyGradient(Trajectories, πθ)
4:   β ← β * decay_rate
5: end function

Neural Network architecture and parameters For Cartpole and REINFORCE, we use a policy network using an MLP with hidden size 64 and Leaky ReLU activations (Maas et al. 2013) with parameter 0.2.

Figure 5: Average return curves for Taxi and Craftworld when information about the hierarchical structure of the problem is provided using RLang. We provide the agents with a program that specifies the initiation and termination conditions of the options required to solve the problem and the RLang-informed agent learns the intra-option policies and policy over options. In the particular case of Taxi, we also include the learning curve when we also provide the intra-option policies.
Figure 6: Average return curves for classic control tasks with continuous state spaces. We use RLang to provide the agent with an initial policy (non-optimal) that the agent can leverage to improve learning performance. We compare with the uninformed counterparts.

For PPO, we used a learning rate of 0.0002.

**Cartpole Results** For Cartpole, we provide the RLang program below with a very simple prior policy. In Figure 6a, we show the average return curves for RLang-informed REINFORCE and its uninformed performance, which show a jump-start performance gain for the agent then improves through experience.

```python
1  Policy balance_pole:
2    if pole-angular_velocity > 0:
3      Execute move_right
4  else:
5      Execute move_left
```