AI Planning Annotation for Sample Efficient Reinforcement Learning

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Abstract

AI planning and Reinforcement Learning (RL) both solve sequential decision-making problems under the different formulations. AI Planning requires operator models, but then allows efficient plan generation. RL requires no operator model, instead learns a policy to guide an agent to high-reward states. Planning can be brittle in the face of noise whereas RL is more tolerant. However, RL requires a large number of training examples to learn the policy. In this work, we aim to bring AI planning and RL closer by showing that a suitably defined planning model can be used to improve the efficiency of RL. Specifically, we show that the options in the hierarchical RL can be derived from a planning task and integrate planning and RL algorithms for training option policy functions. Our experiments demonstrate an improved sample efficiency on a variety of RL environments over the previous state of the art.

Introduction

While both AI planning and reinforcement learning (RL) solve sequential decision-making problems, the approach they take is quite different. AI planning primarily solves shortest path problems in large-scale state transition systems, concisely declared by symbolic languages, and it can quickly solve large tasks. RL primarily addresses discounted reward Markov Decision Process (MDP) problems in model-free setting, and combined with deep neural networks, Deep RL (DRL) solves problems with large-scale unstructured state spaces. However, model-free DRL is sample inefficient when the reward is sparse, or the underlying model has zero-length cycles or dead-ends. This sample inefficiency greatly limits its applicability to real-world applications (Dulac-Arnold, Mankowitz, and Hester 2019).

Hierarchical reinforcement learning (HRL) (Barto and Mahadevan 2003) aims to address the curse of dimensionality by exploiting the task structure in the state and action space. Earlier works in HRL presented basic frameworks that exploit state and action abstraction with task decomposition from domain knowledge. Dean and Littman (1995) presented an MDP decomposition method that induces aggregate states and macro actions from sub-MDPs, and Parr and Russell (1998) showed a hierarchical MDP framework using hierarchical abstract machines that inject domain knowledge into a finite state machine. Sutton, Precup, and Singh (1999) formalizes the hierarchy of executing sub-routines by extending the high-level control being semi MDP (SMDP) in the options framework. Dayan and Hinton (1992) proposed Feudal RL that introduces a hierarchy of control through subgoals for the lower-level control agents.

More recent work focused on learning state aggregation functions (Ravindran and Barto 2004; Li, Walsh, and Littman 2006), temporal abstraction of actions or the sub-tasks (McGovern and Barto 2001; Stolle and Precup 2002; Castro and Precup 2011; Simsek and Barreto 2008). Often implemented with DRL methods (Bacon, Harb, and Precup 2017; Machado, Bellemare, and Bowling 2017; Bagaria and Konidaris 2019). Recent hierarchical DRL agents share a common architecture, where a higher level controller generates intrinsic rewards (Singh, Barto, and Chentanez 2004) for the lower level controllers to learn subgoal policies (Vezhnevets et al. 2017; Kulkarni et al. 2016; Nachum et al. 2018). To deal with sparse rewards, hindsight samples relabeling as subgoals was suggested in continuous robotics control domains (Andrychowicz et al. 2017; Eysenbach, Salakhutdinov, and Levine 2019; Epoft et al. 2019). When the problem involves complex task structures, e.g., as in combined task and motion planning (Eppe, Nguyen, and Wermer 2019; Garrett et al. 2021) or in the RL environments originated from AI planning domains (Ilyas et al. 2018; Groshef et al. 2018; Shen, Trevizan, and Thiebaux 2020), integrated AI planning and RL approach is a more natural choice. The reason for that is that it's not clear how to define sub-goals between sub-tasks in the RL state space, and we often have access to domain knowledge that captures the task structure for defining symbolic planning problems (Illeses et al. 2020; Yang et al. 2018; Lyu et al. 2019).

In this work, we present Planning annotated RL (PaRL), an integrated AI planning and RL architecture for HRL. PaRL links the state abstraction in AI planning and temporal abstraction in RL. In the integrated architecture, a planning agent have access to symbolic AI planning task so that it can plan in an abstract symbolic state and action space, and control the lower-level RL agents. The contributions of the paper are summarized as follows: (1) We present a method for deriving options from the planning task. Unlike earlier approaches that require a manual process for mapping the symbolic planning tasks to options, we allow an arbitrary planning task to annotate the underlying RL model. (2) We...
design a general method for injecting intrinsic rewards to RL agents from the planning task by reformulating the underling decomposed MDPs with constraints visible to planning agents. (3) We show the improvement in sample efficiency due to decomposition and characterize the sufficient conditions when an arbitrary annotating task can solve the underlying RL model.

Background

RL and Options Framework

In reinforcement learning, we assume that an agent interacts with a goal oriented MDP $M = (S, A, P, r, s_0, G, \gamma)$ with a set of states $S$, a set of actions $A$, a state transition function $P : S \times A \times S \to [0, 1]$, a reward function $r : S \times A \to \mathbb{R}$, an initial state $s_0 \in S$, a set of goal states $G \subseteq S$, and a discounting factor $\gamma \in (0, 1)$ for the rewards. In this goal oriented environment, we are interested in the sparse reward task where the $r(s, a)$ is a constant step cost when $s \not\in G$ and zero in a goal state, and the objective is to learn a stationary policy $\pi \in \Pi$.

A value function $V_{\pi}^s(s)$ is the expected sum of the discounted reward in each state $s \in S$, and $V_{\pi}^s(s) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t|s_0]$, where $s_0$ is the initial state, and $\pi(s)$ is a stochastic policy $\pi : S \times A \to [0, 1]$. A value function $V^*(s)$ is the expected sum of the discounted reward in each state $s \in S$,

$$V^*(s) = \sum_{a \in A} \pi(a|s) [r(s, a) + \gamma \sum_{s' \in S} P(s'|s, a) V^*(s')]$$

The action-value function gives the value of executing an action $a \in A$ in state $s \in S$ under the policy $\pi$,

$$Q^*(s, a) = r(s, a) + \gamma \sum_{s' \in S} P(s'|s, a) V^*(s')$$

The optimal value function $V^*(s)$ and action-value function $Q^*(s, a)$ can be found by $V^*(s) = \max_{\pi} V_{\pi}^s(s)$ and $Q^*(s, a) = \max_{\pi} Q_{\pi}(s, a)$.

A set of options $O$ formulates the temporally extended actions that defines a semi-MDP (SMDP) over the original MDP $M$. A Markovian option $O \in O$ is a triple $\langle O, \pi_O, \beta_O \rangle$, where $O$ is the initiation set in which $O$ can begin, the $\pi_O$ is a stationary option policy $\pi_O : S \times A \to [0, 1]$, and $\beta_O$ is a termination set in which $O$ terminates. We follow the call-and-return option execution model, where an agent selects an option $O$ using an option level policy $\mu(s)$ in state $s$ at time $t$, and generates a sequence of actions according to the option policy $\pi_O(a|s)$. The execution of an option $O$ continues up to $k$ steps until reaching the $\beta_O$ and it returns the option reward $R(s, O)$ accumulated from $t + 1$ to $t + k$ with a discounting factor $\gamma$,

$$R(s, O) = \mathbb{E}[\sum_{t'=t+1}^{t+k} \gamma^{t'-t-1} r_{t'}|E(O, s, t)]$$

where $E(O, s, t)$ denotes the event of an option $O$ being selected in state $s$ at time $t$, and $r_{t'}$ denotes the reward obtained at time $t'$. The state transition probability from a state $s$ to a state $s'$ under the execution of an option $O$ can be written as

$$P(s'|s, O) = \sum_{j=0}^{\infty} \gamma^j P_r(k = j, s_{t+j}|E(O, s, t))$$

In SMDP, the value function $V^\mu(s)$ under the option level policy $\mu$ can be written as

$$V^\mu(s) = \sum_{O \in O} \mu(O|s) \left[ R(s, O) + \sum_{s' \in S} P(s'|s, O) V^\mu(s') \right]$$

and the option-value function $Q^\mu(s, O)$ is

$$Q^\mu(s, O) = R(s, O) + \sum_{s' \in S} P(s'|s, O) \sum_{O \in O} \mu(O|s) Q^\mu(s', O).$$

Given a set of learned options $O$, an off-policy learning methods such as Q-learning (Watkins and Dayan 1992) and SMDP Q-learning (Sutton, Precup, and Singh 1999) can learn the option value function by reformulating the unification training, and the SMDP learning, to the online end-to-end approach (Bacon, Harb, and Precup 2017).

AI Planning

In order to formally represent planning tasks, we follow the notation of SASS+ planning tasks (Bäckström and Nebel 1995). In SASS+, a planning task $\Pi$ is given by a tuple $\langle V, O, s_0, s_*$, $\rangle$, where $V$ is a finite set of state variables, and $O$ is a finite set of operators. Each state variable $v \in V$ has a finite domain $dom(v)$ of values. A pair $\langle v, \theta \rangle$ with $v \in V$ and $\theta \in dom(v)$ is called a fact. A (partial) assignment to $v$ is called a (partial) state, with the full state $s_0$ being the initial state and the partial state $s_a$ being the goal state. We denote the variables of a partial assignment $p$ by $V(p)$. It is convenient to view a partial state $p$ as a set of facts with $\langle v, \theta \rangle \in p$ if and only if $p[v] = \theta$. A partial state $p$ is consistent with state $s$ if $p \subseteq s$.

We denote the set of states of a planning task by $S_*$. Each operator $o \in O$ is a pair $\langle pre(o), eff(o) \rangle$ of partial states called preconditions and effects. The (possibly empty) subset of operator precondition that does not involve variables from the effect is called prevail condition, $prv(o) = \{ \langle v, \theta \rangle | \langle v, \theta \rangle \in pre(o), v \notin eff(o) \}$. An operator $o$ is applicable in a state $s \in S_*$ if and only if $pre(o) \subseteq s$. Applying $o$ changes the value of $v$ to $eff(o)[v]$, if defined. The resulting state is denoted by $s[\theta]$. An operator sequence $\pi = \langle o_1, \ldots, o_k \rangle$ is applicable in $s$ if there exist states $s_0, \ldots, s_k$ such that (1) $s_0 = s$, and (2) for each $1 \leq i \leq k$, $o_i$ is applicable in $s_{i-1}$ and $s_i = s_{i-1}[o_i]$. We denote the state $s_k$ by $s[\pi]$. $\pi$ is a plan for $s$ if $\pi$ is applicable in $s$ and $s_* \subseteq s[\pi]$.

A transition graph of a planning task $\Pi = \langle V, O, s_0 \rangle$ is a triple $T_\Pi = (S, T, s_0)$, where $S$ are the states of $\Pi$, the $T_\Pi \subseteq S \times O \times S$ is a set of labelled transitions, and $s_0 \subseteq S$ is the set of goal states. An abstraction of the transition graph $T$ is a pair $\langle T', \alpha \rangle$, where $T' = \langle S', T', s_0 \rangle$ is an abstract transition graph and $\alpha : S \mapsto S'$ is an abstraction mapping, such that $\langle s, o, s' \rangle \in T$ for all $\langle s, o, s' \rangle \in T'$, and $\alpha(s) \in S'$ for all $s \in S$.

Annotating RL with Planning

In this section, we formulate an HRL framework when we are given a symbolic description of the underlying MDP. The
The basic idea is to link the AI planning task and the RL MDP task by viewing the AI planning task as an abstraction of the RL MDP task, and mapping each state transition in the AI planning task to a temporal abstraction encapsulated in the RL option (Sutton, Precup, and Singh 1999). We extend the frame concept in the AI planning to the options framework to characterize the conditions that regulate the MDP task to behave like a given planning task. Then, under the assumption that the annotating task simulates the MDP task and the MDP transitions are constrained under the frame constraints, we show that the options framework derived from the AI planning task can decompose the MDP task to smaller sub-MDPs. Nevertheless, the annotating planning task is a mere side-information, and we cannot constrain the MDP transitions. Therefore, we introduce intrinsic rewards as a penalty for violating the frame constraints and regulate the option learning agent to restrict its exploration within the state space relevant to the planning task, which improves the sample efficiency in the empirical evaluations.

**PaRL Task**

We start by defining a Planning annotated RL (PaRL) task and present the options framework derived from a symbolic planning task.

**Definition 1** A PaRL task is a triple \( \langle M, \Pi, L \rangle \), where \( M := \langle S, A, P, r, s_0, G, \gamma \rangle \) is a goal-oriented MDP over RL states \( S \), \( \Pi := \langle V, O, s'_0, s_* \rangle \) is a planning task over planning states \( S' \), and \( L : S \rightarrow S' \) is a surjective mapping from the states of the MDP \( S \) to planning states \( S' \) satisfying \( s'_0 = L(s_0) \) and \( s_* \) consistent with \( L(s) \) for all \( s \in G \). We denote the pre-image of \( s' \in S' \) under the \( L \), \( \{ s \in S | L(s) = s' \} \) by \( L^{-1}(s') \).

The generic definition of PaRL task is a mixed blessing. On the one hand, it does not pose any constraints on the connection between the \( M \) and the \( \Pi \) beyond the consistency of the initial state and the goal under the \( L \). On the other hand, if the two tasks are unrelated, it is not clear what is the benefit of connecting these tasks together. We formulate the connection by extending the definition of abstraction to PaRL tasks.

**Definition 2** Let \( E = \langle M, \Pi, L \rangle \) be a PaRL task and \( T_{\Pi} = \langle S', T_{\Pi}, S_* \rangle \) be the transition graph of \( \Pi \). We say that \( \langle M, \Pi \rangle \) is an abstraction of \( M \) if for all \( \langle s, o, t \rangle \) we have \( P(t|s,a) > 0 \), iff \( (L(s), o, L(t)) \in T_{\Pi} \) for some \( o \in O \) or \( L(s) = L(t) \). We call such PaRL tasks proper.

The idea behind the definition of PaRL task is to allow the specification of some of the functionality of the reinforcement learning task in a declarative way. In what follows, we only consider proper PaRL tasks. Next, we link the RL task \( M \) and the planning task \( \Pi \) by an options framework.

**Definition 3** For a PaRL task \( E := \langle M, \Pi, L \rangle \), plan options are: (1) for each operator \( o \in O \) in \( \Pi \), an operator option \( O_o := \langle T_{O_o}, \pi_{O_o}, \beta_{O_o} \rangle \) with \( T_{O_o} := \{ s \in S | (prv(o) \subseteq L(s)) \} \) and \( \beta_{O_o} := \{ s \in S | (prv(o) \cup \text{eff}(o) \subseteq L(s)) \} \), and (2) a single goal option \( O_* := \langle T_{O_*}, \pi_{O_*}, \beta_{O_*} \rangle \) with \( T_{O_*} := \{ s \in S | s \in L(s) \} \) and \( \beta_{O_*} := G \).

Previous attempts in the literature have suggested using planning operators to define options (Lyu et al. 2019, Illasses et al. 2020). However, earlier works assume an additional domain knowledge associating planning operators with conditions over propositional variables. Here, we do not require such an additional input, relying solely on the planning task.

Denoting by \( O_M \), a set of plan options induces an SMMDP \( M' := \langle S, O_M, P, r, s_0, G, \gamma \rangle \), where we replace the primitive actions \( A \) in \( M \) with \( O_M \). Next, we define a transition graph \( T_{M'} \) in which a multi-step state transition of an option \( O_o \) is collapsed to a single labelled transition that connects each state \( s \in T_{O_o} \) to the states \( t \in \beta_{O_o} \).

**Definition 4** Given a PaRL task \( E := \langle M, \Pi, L \rangle \), a transition graph of the SMMDP \( M' := \langle S, O_M, P, r, s_0, G, \gamma \rangle \) is a triple \( T_{M'} := \langle S, T_{M'}, G \rangle \), where \( S \) is the states of \( M \), \( T_{M'} \) is a set of non-deterministic labelled transitions \( \{ (s, o, t) \mid s \in T_{O_o}, t \in \beta_{O_o}, P(t|s, o) > 0 \} \), and \( G \) is the goal states in \( M \).

**Frames and Decompositions in Plan Options**

Although we do not assume to have exact model of the \( M \), it is desirable to have an annotating planning task \( \Pi \) that behaves similar to the \( M \). To characterize the similarity between the two tasks, we introduce a context and frame of an option \( O_o \) in an RL state \( s \) to capture the subset of facts in the planning task that prevail when applying a planning operator \( o \) to the planning state \( L(s) \), namely \( L(s) \cap L(s)[o] \).

**Definition 5** For an operator \( o \) and its option \( O_o \), we define the context of an operator option in state \( s \in S \) by \( C_{O_o}(s) := L(s) \backslash (\text{prv}(o) \cup \text{eff}(o)) \). The frame of an operator option in state \( s \in S \) is \( F_{O_o}(s) := \text{prv}(o) \cup C_{O_o}(s) \). A partial frame of an option in \( s \), \( F_{O_o}(s) \), is a subset of \( F_{O_o}(s) \).

We say that a PaRL task \( E \) with a set of plan options \( O_M \) is frame preserving if \( F_{O_o}(s) = F_{O_o}(t) \) for every \( (s, o, t) \in T_{M'} \) and operator \( o \in O \).

**Theorem 1** If a PaRL task \( E \) with plan options \( O_M \) is frame preserving, then \( T_{\Pi} \) and \( T_{M'} \) are bisimilar.

**Proof:** Consider a binary relation \( \{ (s, t) \in S \times S \mid L(s) = L(t) \} \). For each \( o \in O \), every \( (s, o, t) \in T_{M'} \) satisfies \( L(t) = L(s) \cup (\text{prv}(o) \cup \text{eff}(o)) \) and \( L(t) = L(s) \cup (\text{prv}(o) \cup \text{eff}(o)) \). For a transition \( (t, o, t') \in T_{M'} \) such that \( L(t) = L(s), L(t') = L(t)[o] = L(s)[o] \).

The desiderata in HRL is that a task hierarchy in the \( M \) captures the decomposition into sub-MDP tasks that are easier to solve in a local state space, and those sub-tasks are reusable in similar problems. It is often claimed that HRL will improve sample efficiency, and a sub-problem analysis in (Wen et al. 2020) shows that HRL methods can improve the sample efficiency as well as the computational complexity if the total sum of the size of each partitioned state space is smaller than the size of the original state space. Following the intuition behind the MDP decomposition in HRL, we now characterize the sub-problem decomposition imposed by the frame constrained option MDPs.

Note that the bisimilarity in PaRL task \( E \) is a very strong property. However, it still does not guarantee that the state
space of each sub-MDP of a plan option \( O_o \) is restricted to a local state space, common in the options framework. To see this, consider a full trajectory \( \langle s_0, s_1, s_2, \ldots, t \rangle \) of \( \langle s, o, t \rangle \in T_{M'} \). If there exists an MDP transition \( \langle s_i, a, s_j \rangle \in T_{M} \) such that \( \mathcal{F}_{O_o} \not\subseteq L(s_j) \) given some option policy \( \pi_{O_o}(a|s_i) > 0 \), the exploration in RL can visit the state space outside of the the pre-image of \( \mathcal{F}_{O_o} (s) \).

Let’s consider a fictitious sub-MDP of each Markov option in the \( M' \), where the state space is localized subject to the frames due to the fictitious constraints that enforcing the successor states remain in local state space.

**Definition 6** Given a PaRL task \( E := \langle M, \Pi, L \rangle \) and a plan option \( O_o := \langle \mathcal{O}_{O_o}, \pi_{O_o}, \beta_{O_o} \rangle \), a frame constrained option MDP is an MDP for a Markovian option \( O_o \), defined as

\[
M_{\text{con}, o} := \langle S_{\mathcal{F}_{O_o}(s_0)}, A, P_{\mathcal{F}_{O_o}(s_0)}, r, \delta_{O_o}, \mathcal{D}_{\mathcal{F}_{O_o}(s_0)}, \gamma \rangle
\]

where \( S_{\mathcal{F}_{O_o}(s_0)} \) is the local states, the \( P_{\mathcal{F}_{O_o}(s_0)} \) is a constrained state transition probability, the initial state \( s_0 \) is a state in the \( \mathcal{O}_o \), the \( \beta_{O_o} \) is the goal states, and the \( \mathcal{D}_{\mathcal{F}_{O_o}(s_0)} \) is a set of fictitious transition constraints \( \{ \mathcal{F}_{O_o}(t)_i = \mathcal{F}_{O_o}(s_0) | \forall (s, a, t) \in T_{M_{\text{con}, o}}, \pi_{O_o}(a|s) > 0 \} \), enforcing the state transitions preserve the \( \mathcal{F}_{O_o}(s_0) \).

Note that we modified the \( P_{\mathcal{F}_{O_o}(s_0)} \) in \( M_{\text{con}, o} \) from the original \( P \) in \( M \) so that all the transitions don’t violate \( \mathcal{D}_{\mathcal{F}_{O_o}(s_0)} \). Namely, for all \( (s, a, t) \in T_{M_{\text{con}, o}} \) such that \( \mathcal{F}_{\mathcal{D}_o}(s_0) \not\subseteq L(t) \), assign \( P_{\mathcal{F}_{O_o}(s_0)}(t,s,a) = 0 \) and normalize conditional probability. Introducing the frame constraints to each option MDP reduces the size of the state space subject to the number of facts in the frame of the option.

**Theorem 2** Given a PaRL task \( E := \langle M, \Pi, L \rangle \) and two frame constrained option MDPs \( M_{\text{con}, o_1} \) and \( M_{\text{con}, o_2} \) induced by partial frames \( \mathcal{F}^p_{O_o}(s_0) \) and \( \mathcal{F}^q_{O_o}(s_0) \), if \( \mathcal{F}^p_{O_o}(s_0) \subseteq \mathcal{F}^q_{O_o}(s_0) \), the states of the \( M_{\text{con}, o_1} \) is a super-set of the states of the \( M_{\text{con}, o_2} \).

**Proof:** Let \( S_p \) and \( S_q \) denote the states of the \( M_{\text{con}, o_1} \) and \( M_{\text{con}, o_2} \). For every \( s \in S_q \), we can see that \( s \in S_p \) since \( \mathcal{F}^p_{O_o}(s_0) \subseteq \mathcal{F}^q_{O_o}(s_0) \subseteq L(s) \).

If each option MDP is frame constrained and a PaRL task is frame preserving, we have two advantages using it in HRL: (1) improved sample efficiency due to the reduction in the size of the state space for learning options, and (2) re-usability of options by composing them solely relying on the symbolic annotation.

### Intrinsic Rewards for Plan Options

In practice, we don’t assume that the annotating planning task \( \Pi \) simulates the underlying \( M \), and furthermore, it is impossible to constrain the transitions in the MDP task in RL. Therefore, we relax all the constraints in the frame constrained option MDPs and absorb those constraints in the objective function as an intrinsic reward to the option learning agent.

**Definition 7** Given a PaRL task \( E := \langle M, \Pi, L \rangle \) and a plan option \( O_o := \langle \mathcal{O}_{O_o}, \pi_{O_o}, \beta_{O_o} \rangle \), a frame penalized option MDP is a tuple \( \mathcal{M}_{\text{con}, o_0} := \langle S, A, P, T, S_0, \beta_{O_o}, \gamma \rangle \), where we replace the reward function, the initial state, and the goal of the MDP task \( M \) with an intrinsic reward \( \tau \), an initial state \( s_0 \in \mathcal{O}_{O_o} \), and the \( \beta_{O_o} \), respectively. Under the objective that maximizes the expected sum of discounted rewards, the intrinsic reward \( \tau := S \to R \) is given by

\[
\tau(s) := \sum_{v \in \mathcal{V}} c_1 \cdot I(v[s] \not\in \mathcal{F}_{O_o}(s)) + c_2 \cdot I(s \not\in \beta_{O_o}),
\]

where \( I \) is an indicator function and \( c_1 \) and \( c_2 \) are negative rewards.

Note that the state space of the frame penalized option MDP can be as large as the original state space. We only hope that the intrinsic reward obtained in the planning space guides the option policy learning agent to visit states that are more likely to preserve the frame of an option. Here, we lose the theoretical guarantee on the improvement in the sample efficiency, but we empirically show that the planning annotation with the intrinsic reward improves the sample efficiency.

In the absence of knowledge about the underlying dynamics of the \( M \), an SMDP task \( M' \) induced by the plan options also solves the \( M \) yet with a lower expected return if the \( \Pi \) does not have a dead-end. Namely, if the \( M \) reaches the goal in discounted stochastic shortest path model (Bertsekas 2018), the \( M' \) will reach the goal with a finite yet larger number of steps. If the \( M \) has dead-ends and maximizes the probability of reaching the goal (Kolobov, Mausam, and Weld 2012), the \( M' \) will also reach the goal with a lower yet non-zero probability.

### Solving PaRL Task

In this section, we present HRL algorithms for solving PaRL tasks \( E := \langle M, \Pi, L \rangle \). Namely, algorithms for learning the SMDP policy \( \mu(O|s) \) and the option policies \( \pi_{O_o}(a|s) \) for \( O_o \in \mathcal{O}_M \). For any pair of initial state \( s_0 \in S \) and a goal \( s_g \in G \in M \), we can generate a sequence of options \( \{O_{o_1}, O_{o_2}, \ldots, O_{o_n}\} \) from a plan in \( \Pi \) that reaches the goal state \( L(s_g) \in S' \) from the initial state \( L(s_0) \in S' \). Therefore, we can invoke AI planners in two ways, either precompute those option-level plans offline or generate plans while training option policies online. In the offline approach, the overall process of solving a PaRL task can be divided into three steps: First, identify relevant options for solving the \( M \) by selecting operators, hence options, appearing in the plans. Second, train each option policy with a frame constrained option MDP. Third, train the SMDP policy with the fully trained set of options and primitive actions. Most of the option discovery algorithms in the literature follows the offline approach (Stoie and Precup 2002, Machado, Bello-mare, and Bowling 2017, Ramesh, Tomar, and Ravindran 2019).

When we solve a PaRL task offline, we identify relevant options for solving an MDP task, reaching \( G \) from \( s_0 \) using AI planner. Note that, in the absence of annotation, selecting relevant options or skills purely from learning algorithm is not at all trivial.
Algorithm 1: Online Option Learning with a PaRL Task

Require: PaRL task \( E(\mathcal{M}, \Pi, L) \).
Ensure: SMDP policy \( \mu(O|s) \), option policies \( \pi_{O_o}(a|s) \).
1: Initialize trajectory buffer \( B \)
2: Initialize a set \( D \) for storing options
3: Initialize option level policy \( \mu \)
4: while \( iter < N \) do
   5:    rollout samples from the current policies
   6:       \( s \leftarrow \) current state
   7:       Select an option \( O_o \) using \( \mu \) or AI planner
   8:       if \( O_o \notin D \) then
   9:          Create \( O_o \), Initialize \( \pi_{O_o}, \) Add \( O_o \) to \( D \)
   10:      while \( iter_{rollout} < N_{rollout} \) do
   11:        Sample \( (s, a, r_e, t) \) using \( \pi_{O_o} \)
   12:        Compute intrinsic reward \( r_i \)
   13:        Store \((O_o, s, a, r_e, r_i)\) to buffer \( B \)
   14:      end while
   15:      for each option \( O_o \in D \) do
   16:         Update option policy function \( \pi_{O_o} \)
   17:      end for
   18:      Update SMDP policy function \( \mu \)

Online Option Learning with PaRL Task

AI planning algorithms and RL algorithms are coupled more tightly into an HRL agent in the online approach. Algorithm 1 shows the outline of a generic HRL agent that learns options online with a PaRL task. The algorithm alternates the rollout phase and the training phase until the iteration limit. In the rollout phase, the HRL agent samples an option \( O_o \) using the SMDP policy \( \mu \). If the \( O_o \) was never selected before, we create the option and initialize the policy \( \pi_{O_o} \) and add it to a container. Next, the sample trajectories are generated by using the \( \pi_{O_o} \) until it terminates. After sampling one-step state transition, we compute the intrinsic reward following Definition 7. Then, the HRL agent updates the option policy and the SMDP policy using the samples stored in the buffer in the training phase.

We can specialize the above generic scheme by introducing algorithms from AI planning and RL. Thus, we can directly use an AI planner to prescribe a sequence of relevant options for solving the MDP problem. Algorithm 2 shows an online learning approach with Proximal Policy Optimization (PPO) for on-policy option training. We used PPO (Schulman et al. 2017) in our evaluation since it showed robust performance over discrete RL environments. In lines 8-13, we see that an AI planner directly rolls out options at the current state and skip training SMDP policy \( \mu \). In lines 15-19, we use selected option policy \( \pi_{O_o} \) to generate on-policy samples and store those transition to the buffer. While training each option in lines 21-23, we only train options that are generated during the rollout and skip updating the policy if the average success ratio is 1.0 and the average length is less than some limit \( K \).

Implementing Online Option Learning

Algorithm 2 shows an online learning approach with Proximal Policy Optimization (PPO) for on-policy option training. We used PPO (Schulman et al. 2017) in our evaluation since it showed robust performance over discrete RL environments. In lines 8-13, we see that an AI planner directly rolls out options at the current state and skip training SMDP policy \( \mu \). In lines 15-19, we use selected option policy \( \pi_{O_o} \) to generate on-policy samples and store those transition to the buffer. While training each option in lines 21-23, we only train options that are generated during the rollout and skip updating the policy if the average success ratio is 1.0 and the average length is less than some limit \( K \).

Experiments

We implemented the PaRL framework on Stable baselines3 (Kafifin et al. 2019). To empirically evaluate the proposed approach, we conducted experiments on the three goal-oriented MDP environments, (1) the rooms navigation domain extending the 4-rooms domain (Sutton, Precup, and Singh 1999), (2) the logistics classical planning domain, and (3) Montezuma’s revenge domain as modified in (Le et al. 2018). We also constructed the PaRL task \( E = (\mathcal{M}, \Pi, L) \) by modeling a planning task based on the domain knowledge with an appropriate state mapping function \( L \). (In the
Appendix, we show all the planning task descriptions in PDDL. We compared the HRL configuration that implements Algorithm 2 (plan-HRL) with existing baselines in each problem domain and report the success rate and the average number of actions for reaching the goal from given initial states.

Rooms Domain

The N-rooms domain modifies the classic 4-rooms domain by increasing the number of rooms and varying the size of the grids. We also created a hard version of each N-rooms domain by removing the corridors between rooms until all the rooms can only be connected by a single path. In this problem, an agent moves on a grid, separated into N rooms, with narrow corridors connecting the adjacent rooms. The agent needs to move from a given location on the grid (in a given room) to a goal location (in a goal room). The annotating planning task of the N-rooms domain captures the movement between rooms by abstracting away the precise location of the agent on the grid. In a four rooms domain, the PaRL task captures total 16 options from the 16 ground planning operators that define all the movements from one room to its adjacent corridor.

Baseline comparison: Figure 1 shows the average number of actions from PPO, plan-HRL with PPO, DQN (Mnih et al. 2015), and the Hindsight Experience Replay (HER) with DQN (Andrychowicz et al. 2017) in a 16 rooms domain on the 50 x 50 grid. In Figure 1a and 1b, we can see that plan-HRL converged to close to optimal trajectories (lower the number of actions, closer to the optimal trajectory) with a lower variance than other methods, while PPO converged in the easy environment with higher variance but it failed to reach the goal in the hard environment. In Figure 1c, the result from DQN and HER shows that both methods failed to reach the goal in the easy environment.

Scaling up the grid environment: Figure 2 shows the result from the grid environment scaled up to 100 x 100. We see that plan-HRL reaches the goal with the success rate 1.0 in both easy and hard 16 rooms domain. In the N rooms domain, the plan options decompose the original MDP into sub-MDPs such that each sub-MDP only solves the state space comprised of a single room and the corridors adjacent to it. In addition, the intrinsic reward derived from the frame penalized option MDP will regularize the RL transitions that deviate toward undesired locations such as the corridors opposite from the termination set. Therefore, the training of the plan options is robust to modifying the connectivity of rooms, and the intrinsic reward derived from the frame penalized option MDP can handle the side-effects of the RL transitions from a planner perspective.

Switching the initial and goal locations: Figure 4 shows the improvement in the sample efficiency in a smaller 16 x 16 grid environment with 12 rooms. In this configuration, PPO can converge on many instances even if only a single path connects all the rooms. In Figure 4a, we see that PPO failed to converge on the 17 out of 32 problem instances within 10^6 samples. On the other hand, plan option training for plan-HRL solved all problem instances. Figure 4b shows the improvement in the sample efficiency by showing the ratio of the accumulated number of samples between PPO and plan-HRL. When we use on-policy RL algorithms such as PPO in the online option learning setting, we must generate fresh samples from the option policy networks under training to update the network parameters, which is often costly if the number of desired options increases. In Figure 4b, the sample efficiency curve drops when plan-HRL should train new options since planner requested to use new plan options while solving the 7-th, 9-th, and 25-th instances.

Logistics Domains

We show the experiment results from a task having 4 packages, 2 cities, 2 trucks, and 1 airplane. We first examine typical options derived from the PaRL task. In the logistics domain, the objective is to move packages from the initial lo-
Baseline Algorithms

Figure 3: The average number of actions in the logistics domain with 4 packages from DQN, PPO, HER, and plan-HRL: the x-axis shows the number of samples up to $10^7$, and the y-axis shows the length of the trajectory.

Impact of intrinsic rewards: Figure 3b shows the results from plan-HRL with and without intrinsic rewards that penalizes the side-effects while executing the option policy. On the left, we see that the number of actions converges close to the optimal length. We still see that one trajectory deviates around 60 actions more than other trajectories. On the right, we see much higher variance in the length of the trajectory due to the absence of the intrinsic rewards.
a model-free on-policy algorithm, HIRL algorithms based on the results shown in Table 1 since PPO et al. (2018). Note that it is not fair to evaluate three algorithms reported by Schulman et al. (2017) and Le of sample interactions and the score achieved in the base-
cations that are easy to achieve. Table 1 shows the number
return to the door by introducing intermediate subgoal lo-
ging the different pixels in the selected bounding boxes and
and the pixels around the agent as shown in Figure 5. The an-
notating planning task guides the agent to move from the
initial location to reach the door after obtaining the key in the
planning state space with the predicates, init, chain, flu, 
lcm, lrd, lld, ltu, key, lcm, and door. The planning task guides
the agent to move from the initial location to the key and then
return to the door by introducing intermediate subgoal loca-
tions that are easy to achieve. Table 1 shows the number of sample interactions and the score achieved in the baseline algorithms reported by Schulman et al. (2017) and Le et al. (2018). Note that it is not fair to evaluate three algorithms based on the results shown in Table 1 since PPO is a model-free on-policy algorithm, HIRL (Le et al. 2018) is an imitation learning approach with the off-policy DQN, and the online on-policy plan-HRL requires the planning task that annotates the RL task. Nevertheless, we can observe that plan-HRL improves sample efficiency compared with its flat RL counter part PPO and used 20% more samples than HIRL, which uses the demonstrations and the samples stored in the replay buffer.

Table 1: Baseline comparison.

|                | plan-HRL | PPO   | HIRL   |
|----------------|----------|-------|--------|
| samples        | 2,904,000| 4,000,000 | 2,400,000 |
| score          | 400      | 42    | 400    |

Figure 5: The state mapping from image to planning state in Montezuma’s revenge domain.

Montezuma’s Revenge

Unlike previous two problem domains that we can easily de-
fine the state mapping function between the RL task and the
planning task, the state mapping function in the Montezuma’s revenge domain requires a mapping from an image to a symbolic state representation. For the state mapping, we used the RL environment modified in (Le et al. 2018) that captures the location of the agent in the image by counting the different pixels in the selected bounding boxes and the pixels around the agent as shown in Figure 5. The annotating planning task guides the agent to move from the initial location to reach the door after obtaining the key in the planning state space with the predicates, init, chain, flu, lcm, lrd, lld, ltu, key, lcm, and door. The planning task guides the agent to move from the initial location to the key and then return to the door by introducing intermediate subgoal locations that are easy to achieve. Table 1 shows the number of sample interactions and the score achieved in the baseline algorithms reported by Schulman et al. (2017) and Le et al. (2018). Note that it is not fair to evaluate three algorithms based on the results shown in Table 1 since PPO is a model-free on-policy algorithm, HIRL (Le et al. 2018) is an imitation learning approach with the off-policy DQN, and the online on-policy plan-HRL requires the planning task that annotates the RL task. Nevertheless, we can observe that plan-HRL improves sample efficiency compared with its flat RL counter part PPO and used 20% more samples than HIRL, which uses the demonstrations and the samples stored in the replay buffer.

Related Work

Some of the relevant works that attempt to combine sym-

bolic planning and RL include PEORL (Yang et al. 2018),
SDRL (Lyu et al. 2019), and Taskable RL (Illanes et al.

Conclusions and Future Work

In this work, we have presented a simple general framework for annotating reinforcement learning tasks with planning tasks, to facilitate the transfer of planning based techniques into the field of reinforcement learning. Our framework links the state abstraction in AI planning and temporal abstraction in RL, providing a way to decompose the MDP into sub-MDPs by specifying options initiation set and termination condition based on planning operator definitions. We design a general method for injecting intrinsic rewards to RL agents from the abstract planning task by reformulating the underlying decomposed sub-MDPs with constraints visible to planning agents. Learning only the (intra-option) policies for these sub-MDPs is shown to work well in practice on various problems, significantly improving sample efficiency.

This, however, is not the end of the road. While this work focused on temporal abstractions, our framework is more general, allowing to inject knowledge from the annotated planning task into the MDP. One example of such knowledge is goal distance estimates that can be used for reward shaping (Gehring et al. 2021). Another example is landmarks (Porteous, Sebastian, and Hoffmann 2001) (logical formula that must occur on all plans), that can be used as sub-goals. Planning research has been focusing for years on automatically extracting knowledge from the planning task description. We believe that injecting this knowledge into the MDP can greatly improve the performance of RL agents.

References

2017. Proc. ICML 2017.
2020. Proc. ICAPS 2020.
Andrychowicz, M.; Wolski, F.; Ray, A.; Schneider, J.; Fong, R.; Welinder, P.; McGrew, B.; Tobin, J.; Abbeel, P.;
Zaremba, W. 2017. Hindsight experience replay. In Proc. NIPS 2017, 5055–5065.

Bäckström, C.; and Nebel, B. 1995. Complexity Results for SAS* Planning. Computational Intelligence, 11(4): 625–655.

Bacon, P.; Harb, J.; and Precup, D. 2017. The Option-Critic Architecture. In Proc. AAAI 2017, 1726–1734.

Bagaria, A.; and Konidaris, G. 2019. Option discovery using deep skill chaining. In Proc. ICLR 2019.

Barto, A. G.; and Mahadevan, S. 2003. Recent advances in hierarchical reinforcement learning. DEDS, 13(1): 41–77.

Bertsekas, D. 2018. Abstract dynamic programming. Athena Scientific.

Castro, P. S.; and Precup, D. 2011. Automatic construction of temporally extended actions for mdps using bisimulation metrics. In European Workshop on Reinforcement Learning, 140–152. Springer.

Dayan, P.; and Hinton, G. E. 1992. Feudal Reinforcement Learning. In Proc. NIPS 1992, 271–278.

Dean, T.; and Lin, S.-H. 1995. Decomposition techniques for planning in stochastic domains. In IJCAI, volume 2, 3.

Dulac-Arnold, G.; Mankowitz, D.; and Hester, T. 2019. Challenges of Real-World Reinforcement Learning. arXiv preprint arXiv:1904.12901

Ecoffet, A.; Huizinga, J.; Lehman, J.; Stanley, K. O.; and Clune, J. 2019. Go-explore: a new approach for hard-exploration problems. arXiv preprint arXiv:1901.10995

Eppe, M.; Nguyen, P. D.; and Wernter, S. 2019. From semantics to execution: Integrating action planning with reinforcement learning for robotic causal problem-solving. Frontiers in Robotics and AI, 6: 123.

Eysenbach, B.; Salakhutdinov, R.; and Levine, S. 2019. Search on the replay buffer: Bridging planning and reinforcement learning. arXiv preprint arXiv:1906.05253

Garrett, C. R.; Chitnis, R.; Holladay, R.; Kim, B.; Silver, T.; Kaelbling, L. P.; and Lozano-Pérez, T. 2021. Integrated task planning and motion planning. Ann Rev Control, 4: 265–293.

Gehring, C.; Asai, M.; Chitnis, R.; Silver, T.; Kaelbling, L. P.; Sohrabi, S.; and Katz, M. 2021. Reinforcement Learning for Classical Planning: Viewing Heuristics as Dense Reward Generators. Planning and Reinforcement Learning PRL Workshop at ICAPS.

Groshev, E.; Tamar, A.; Goldstein, M.; Srivastava, S.; and Abbeel, P. 2018. Learning generalized reactive policies using deep neural networks. In 2018 AAAI Spring Symposium Series.

Helmert, M.; Haslum, P.; and Hoffmann, J. 2007. Flexible Abstraction Heuristics for Optimal Sequential Planning. In Proc. ICAPS 2007, 176–183.

Illanes, L.; Yan, X.; Icarte, R. T.; and McIlraith, S. A. 2020. Symbolic Plans as High-Level Instructions for Reinforcement Learning. In Proc. IJCAI 2020, 540–550.

Kolobov, A.; Mausam; and Weld, D. 2012. A Theory of Goal-oriented MDPs with Dead Ends. In Proc. UAI 2012, 438–447.

Kulkarni, T. D.; Narasimhan, K.; Saeedi, A.; and Tenenbaum, J. 2016. Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. In Proc. NIPS 2016, 3675–3683.

Le, H.; Jiang, N.; Agarwal, A.; Dudik, M.; Yue, Y.; and Daumé, H., III. 2018. Hierarchical Imitation and Reinforcement Learning. In Proc. ICML 2018, 2917–2926.

Li, L.; Walsh, T. J.; and Littman, M. L. 2006. Towards a Unified Theory of State Abstraction for MDPs. ISAIM, 4: 5.

Lyu, D.; Yang, F.; Liu, B.; and Gustafson, S. 2019. SDRL: Interpretable and Data-efficient Deep Reinforcement Learning Leveraging Symbolic Planning. In Proc. AAAI 2019, 2970–2977.

Machado, M. C.; Bellemare, M. G.; and Bowling, M. 2017. A Laplacian Framework for Option Discovery in Reinforcement Learning. In Proc. IJCAI 2017, 2295–2304.

Mausam; and Kolobov, A. 2012. Planning with Markov Decision Processes: An AI Perspective. Synthesis Lectures on Artificial Intelligence and Machine Learning. Morgan & Claypool Publishers.

McGovern, A.; and Barto, A. G. 2001. Automatic discovery of subgoals in reinforcement learning using diverse density. Computer Science Department Faculty Publication Series.

Niu, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; et al. 2015. Human-level control through deep reinforcement learning. nature, 518(7540): 529–533.

Nachum, O.; Gu, S. S.; Lee, H.; and Levine, S. 2018. Data-Efficient Hierarchical Reinforcement Learning. Advances in Neural Information Processing Systems, 31: 3303–3313.

Parr, R.; and Russell, S. 1998. Reinforcement learning with hierarchies of machines. In Proc. NIPS 1998, 1043–1049.

Porteous, J.; Sebastia, L.; and Hoffmann, J. 2001. On the Extraction, Ordering, and Usage of Landmarks in Planning. In Proc. ECP 2001, 174–182.

Raffin, A.; Hill, A.; Ernestus, M.; Gleave, A.; Kanervisto, A.; and Dormann, N. 2019. Stable baselines3.

Ramesh, R.; Tomar, M.; and Ravindran, B. 2019. Successor Options: An Option Discovery Framework for Reinforcement Learning. In Proc. IJCAI 2019, 3304–3310.

Ravindran, B.; and Barto, A. 2004. Approximate Homomorphisms : A framework for non-exact minimization in Markov Decision Processes. In Proc. KBCS 2004.

Schulman, J.; Wolski, F.; Dhariwal, P.; Radford, A.; and Klimov, O. 2017. Proximal Policy Optimization Algorithms. CoRR, abs/1707.06347.

Shen, W.; Trevizan, F.; and Thiébaux, S. 2020. Learning Domain-Independent Planning Heuristics with Hypergraph Networks. In IJCAI 2020, 574–584.

Simsek, O.; and Barreto, A. S. 2008. Skill characterization based on betweenness. In Proc. NIPS 2008, 1497–1504.

Singh, S.; Barto, A. G.; and Chentanez, N. 2004. Intrinsically motivated reinforcement learning. In Proc. NIPS 2004, 1281–1288.
Stolle, M.; and Precup, D. 2002. Learning Options in Reinforcement Learning. In Proc. SARA 2002, 212–223.

Sutton, R. S.; Precup, D.; and Singh, S. P. 1999. Between MDPs and Semi-MDPs: A Framework for Temporal Abstraction in Reinforcement Learning. AIJ, 112(1-2): 181–211.

Toyer, S.; Trevizan, F.; Thiébaux, S.; and Xie, L. 2018. Action Schema Networks: Generalised Policies with Deep Learning. In Proc. AAAI 2018, 6294–6301.

Vezhnevets, A. S.; Osindero, S.; Schaul, T.; Heess, N.; Jaderberg, M.; Silver, D.; and Kavukcuoglu, K. 2017. Feudal networks for hierarchical reinforcement learning. In (icml 2017), 3540–3549.

Watkins, C. J.; and Dayan, P. 1992. Q-learning. Machine learning, 8(3–4): 279–292.

Wen, Z.; Precup, D.; Ibrahimi, M.; Barreto, A.; Van, B. R.; and Singh, S. 2020. On Efficiency in Hierarchical Reinforcement Learning. In Proc. NeurIPS 2020, 6708–6718.

Yang, F.; Lyu, D.; Liu, B.; and Gustafson, S. 2018. PEORL: Integrating Symbolic Planning and Hierarchical Reinforcement Learning for Robust Decision-Making. In Proc. IJCAI 2018, 4860–4866.
A Appendix

A.1 Planning Annotations

This section summarizes the planning annotations for the three domains that we evaluated in the experiment section.

N-rooms  The RL environment maintains N x N grids with the location of rooms, hallways and walls. Therefore, a planning state obtained from an RL state through the state mapping function is the name of each room associated with the location. The PDDL domain file used for the n-rooms problem is described in what follows.

(define (domain rooms)
  (:requirements :strips :typing)
  (:types
    room - object
  )
  (:predicates
    (in-room ?r - room)
    (CONNECTED-ROOMS ?r - room ?s - room)
  )
  (:action move-room
    :parameters (?r - room ?s - room)
    :precondition (and
      (CONNECTED-ROOMS ?r ?s)
      (in-room ?r)
    )
    :effect (and
      (not (in-room ?r))
      (in-room ?s)
    )
  )
)

Logistics  The RL environment maintains the states of the grounded logistics planning domain. In the experiment, we define a planning task as an abstract planning task that is defined over the subset of the predicates and actions in the grounded logistics planning task. Therefore, the state mapping function is a projection of logical variables from an RL state to its planning state. The PDDL domain file used for the RL task is described as follows.

(define (domain logistics-rl)
  (:requirements :strips :typing)
  (:types truck
    airplane - vehicle
    package vehicle - physobj
    airport location - place
    city place physobj - object
  )
  (:predicates (IN-CITY ?loc - place ?city - city)
    (at ?obj - physobj ?loc - place)
    (in ?pkg - package ?veh - vehicle))
  (:action LOAD-TRUCK
    :parameters (?pkg - package ?truck - truck ?loc - place)
    :precondition (and (at ?truck ?loc) (at ?pkg ?loc))
    :effect (and (not (at ?pkg ?loc)) (in ?pkg ?truck)))
  (:action LOAD-AIRPLANE
    :parameters (?pkg - package ?airplane - airplane ?loc - place)
    :precondition (and (at ?pkg ?loc) (at ?airplane ?loc))
    :effect (and (not (at ?pkg ?loc)) (in ?pkg ?airplane)))
  (:action UNLOAD-TRUCK
    :parameters (?pkg - package ?truck - truck ?loc - place)
    :precondition (and (at ?truck ?loc) (in ?pkg ?truck))
    :effect (and (not (in ?pkg ?truck)) (at ?pkg ?loc)))
  (:action UNLOAD-AIRPLANE
    :parameters (?pkg - package ?airplane - airplane ?loc - place)
    :precondition (and (in ?pkg ?airplane) (at ?airplane ?loc))
    :effect (and (not (in ?pkg ?airplane)) (at ?pkg ?loc)))
The PDDL domain file used for the planning task is described as follows.

```
(define (domain logistics-pl)
 (:requirements :strips :typing)
 (:types
  truck - vehicle
  package vehicle - physobj
  airport location - place
  city place physobj - object)
 (:predicates
  (AT-CITY ?tru - truck ?cit - city)
  (IN-CITY ?pla - place ?cit - city)
  (at ?obj - package ?loc - place)
  (in ?obj - package ?veh - vehicle)
 )
 (:action LOAD-TRUCK
  :parameters (?pkg - package ?tru - truck ?pla - place ?cit - city)
  :precondition (and (at ?pkg ?pla) (AT-CITY ?tru ?cit) (IN-CITY ?pla ?cit))
  :effect (and (not (at ?pkg ?pla)) (in ?pkg ?tru))
 )
 (:action UNLOAD-TRUCK
  :parameters (?pkg - package ?tru - truck ?pla - place ?cit - city)
  :precondition (and (in ?pkg ?tru) (AT-CITY ?tru ?cit) (IN-CITY ?pla ?cit))
  :effect (and (at ?pkg ?pla) (not (in ?pkg ?tru)))
 )
 (:action LOAD-AIRPLANE
  :parameters (?pkg - package ?apn - airplane ?apt - airport)
  :precondition (and (at ?pkg ?apt))
  :effect (and (not (at ?pkg ?apt)) (in ?pkg ?apn))
 )
 (:action UNLOAD-AIRPLANE
  :parameters (?pkg - package ?apn - airplane ?apt - airport)
  :precondition (and (in ?pkg ?apn))
  :effect (and (not (in ?pkg ?apn)) (at ?pkg ?apt))
 )
)

Montezuma’s Revenge The RL environment maintains the images obtained from the arcade learning environment, and we selected bounding boxes in the image to generate planning states from the RL state. Figure 5 shows the bounding boxes we used. The PDDL domain file used for the planning task is described as follows.

```
(define (domain montezuma)
 (:requirements :strips :typing)
 (:types
  location - object
 )
 (:predicates
  (CONNECTED ?x ?y - location)
  (at ?l - location)
 )
)
From each bounding box, we assign a location object and ground predicates by assigning objects to the variables in the PDDL domain definition. The PDDL problem file used for the planning task is described as follows.

(define (problem montezuma-room1)
  (:domain montezuma)
  (:objects
    INI LRD LCM LRU DOOR LLU LLD CHA - location
  )
  (:init
    (CONNECTED INI CHA)
    (CONNECTED CHA LRU)
    (CONNECTED LRU LRD)
    (CONNECTED LRD LLD)
    (CONNECTED LLD LLU)
    (CONNECTED LLU LLD)
    (CONNECTED LRD LRD)
    (CONNECTED LRU LRD)
    (CONNECTED LCM DOOR)
    (key-at LLU)
    (at INI)
  )
  (:goal (and
    (holding-key)
    (at DOOR)
  )
  )
)
B Implementation Notes

In this section, we provide implementation details on Algorithm 2 and selection of hyperparameters.

B.1 Hierarchical RL with Online Option Planning

We implemented Algorithm 2 using python language by extending RL agents in stable-baselines 3 and using pyperplan as AI planner. For simplicity, we didn’t train option level policy function. This choice leaves only use to train intra option policy learning by PPO.

B.2 Hyperparameters

We used the following hyperparameters for the PPO.

N-rooms and logistics domain

- learning rate: 1e-4
- gae: 0.95
- clip: 0.1
- vf coeff: 0.5
- max episode length: 256 / 512 / 1024 / 2048
- rollout length: 256 / 512 / 1024 / 2048
- batch size: 128
- network dimension: [64, 64] / [256, 256] / [400, 300] / [256, 256, 256]
- gamma: 0.999
- epochs: 10
- entropy coefficient: 1e-5
- step cost: -0.01
- context intrinsic cost: -0.1 per mismatch
- reward: +1

Montezuma’s revenge domain

- learning rate: 2.5e-4
- gae: 0.95
- clip: 0.1
- vf coeff: 1
- max episode length: 1024
- rollout length: 1024
- batch size: 64
- network dimension: CNN based architecture as shown in (Minh, 2015).
- gamma: 0.99
- epochs: 4
- entropy coefficient: 0.01
- step cost: -0.01
- reward: +1

Hardwares We used two types of hardwares for evaluation. For the N-rooms and logistics domain, we used CPU only machines with 56 cores of 2 GHz CPUs and for the Montezuma’s revenge domain, we used P100 GPU for the training.