Creativity of AI: Automatic Symbolic Option Discovery for Facilitating Deep Reinforcement Learning

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Abstract
Despite of achieving great success in real life, Deep Reinforcement Learning (DRL) is still suffering from three critical issues, which are data efficiency, lack of the interpretability and transferability. Recent research shows that embedding symbolic knowledge into DRL is promising in addressing those challenges. Inspired by this, we introduce a novel deep reinforcement learning framework with symbolic options. This framework features a loop training procedure, which enables guiding the improvement of policy by planning with action models and symbolic options learned from interactive trajectories automatically. The learned symbolic options alleviate the dense requirement of expert domain knowledge and provide inherent interpretability of policies. Moreover, the transferability and data efficiency can be further improved by planning with the action models. To validate the effectiveness of this framework, we conduct experiments on two domains, Montezuma’s Revenge and Office World, respectively. The results demonstrate the comparable performance, improved data efficiency, interpretability and transferability.

Introduction
Deep Reinforcement Learning (DRL) has achieved tremendous success in complex and high dimensional environments such as Go (Silver et al. 2016, 2017) and Atari Games (Mnih et al. 2015). It interacts with environments and improves its policy with the collected experience, by maximizing the long term reward. Recent criticism on DRL mostly focuses on the lack of transferability, interpretability, and data efficiency. The policy learnt from an environment often fails in another unseen environment. Due to the use of black-box neural networks for function approximation, the intrinsic lack of interpretability issue naturally raises in DRL, which disables the agent to explain its actions in a human-understandable way and earn people’s trust in critical areas such as autonomous driving (Aradi 2020) and chemical engineering (Zhou, Li, and Zare 2017). Besides, DRL often requires a large amount of data to learn a satisfying policy in complex environments. The process of collecting experiences for learning is time-consuming and the sample efficiency is low.

To alleviate those issues, researchers have investigated the combination of h-DRL and symbolic planning to improve transferability, interpretability, and data efficiency (Parr and Russell 1997, Ryan 2002, Hogg, Kuter, and Muñoz-Avila 2010, Leonetti, Iocchi, and Stone 2016, Yang et al. 2018, Lyu et al. 2019, Illanes et al. 2020, Sarathy et al. 2020). In this structure, the original MDP is divided into two levels. The higher level utilizes a symbolic planner with a given action model to generate plans for selecting options, while the lower-level interacts with the environment to accomplish the selected options. This two-level structure helps alleviating the sparse reward issue, and improves sampling efficiency with the help of generated plans. In those work, they require the action models have been provided by domain experts. In many real-world applications, however, it is often difficult to create action models by hand, especially when the environment is complicated. A more realistic idea is to automatically learn action models from training data (Zhuo and Kambhamettu 2017, Yang, Wu, and Jiang 2007, Ng and Petrick 2019, Martinez et al. 2016, James, Rosman, and Konidaris 2020) and exploit the learnt action models to generate plans for guiding the exploration of options. Although there is indeed an approach (Sarathy et al. 2020) proposed to learn action models automatically, they still need to manually define a major part of the models in advance. Besides, the planning goal in this approach is kept unchanged while it is dynamically adapted to maximize the external reward in our framework.

Figure 1: State Mapping Function in Montezuma’s Revenge

In this work, we propose a novel framework, namely SORL, which stands for Symbolic Options for Reinforcement Learning, to learn action models to help the exploration of actions in reinforcement learning. We assume that there exists a function $F$, mapping high dimensional states to symbolic states and enabling us to learn symbolic action models and...
options. As shown in Figure 1, we extract the position of the man in red and the key from the high-dimensional state to obtain the corresponding symbolic state. When the agent walks from the middle ladder to the right ladder, the key still exists and the environment does not give any feedback (e.g., zero reward). This can be seen as a symbolic transition and we will generate the corresponding action model as shown in Figure 2. Then, we use a planner with the learned action models and a planning goal as inputs to generate a plan and use it to instruct the learning of the agent.

**Figure 2: An Action model in Montezuma’s Revenge**

Based on the assumption, SORL features a two-level structure, of which the higher level is a symbolic planner and a meta-controller, and the lower level is an RL agent interacting with the environment. The higher level utilizes the collected trajectories from the lower level to learn action models and symbolic options with minimum human knowledge. After that, the meta-controller chooses an option according to the plan generated from the planner with the learned action models and assigns it to the lower level. By interacting with the environments, the lower level learns a policy to reach the goal state. This cross-fertilization structure not only helps alleviating the sparse and delayed reward problem but also improves the data efficiency.

Different from previous action model learning approaches (Zhuo and Kambhampati 2017; Yang, Wu, and Jiang 2007), which assume the number of action models to be learnt is known beforehand, our SORL does not know exactly “how many” and “what” action models to be learnt from the environment. We expect the agent continuously creates new action models via the interactions with the environment, and exploits both new and old action models to guide the exploration of actions to build policies creatively—we consider this as the creativity property of an AI agent. We claim that an agent with such creativity can build better policies with respect to transferability, interpretability, and data-efficiency.

We summarize our contribution as below:

- Our work is the first one to learn action and option models automatically without being told any knowledge of these models and simultaneously learn RL policies.
- We propose a symbolic reinforcement learning framework capable of providing transferability, interpretability, and improved data-efficiency.
- The symbolic option learned by SORL is more general, which can correspond to more than one action model.

In this chapter, we establish relevant notation and briefly introduce key aspects of symbolic planning and reinforcement learning.

**Symbolic Planning with PDDL**

In PDDL language, states are represented as set of propositions and we call it symbolic states throughout the paper to distinguish them from states in RL. Propositions represent the properties of the world and in the symbolic state $s$, proposition $p \in s$ if $p$ is true otherwise (not $p$) $\in s$. An action description called action model is a tuple $(\text{name}, \text{pre}^+, \text{pre}^-, \text{eff}^+, \text{eff}^-)$, where name is the name of the action, $(\text{pre}^+, \text{pre}^-)$ are the preconditions and $(\text{eff}^+, \text{eff}^-)$ are the effects. As shown in Fig 2, the action model describes that when the agent walks from the middle ladder to the right ladder, the key keeps still and the reward remains unchanged. If $\text{pre}^+ \subset s$ and $s \cap \text{pre}^- = \emptyset$, then we can execute action $a$ and obtain the next state

$$s' = ((s - \text{eff}^-) \cup \text{eff}^+).$$

The planning domain $D = (P, A)$ includes the proposition set $P$ and the action set $A$, which describe the state space and the action space, respectively. A tuple $(s, a, s')$ describes a symbolic transition from state $s$ to state $s'$ after executing action $a$. We define a planning problem denoted as a triple $(I, P, A, G)$, of which $I$ is an initial state and $G$ is a goal state. The solution to this problem is called a plan $\pi$, which is a sequence of actions. After executing the plan, we can obtain a symbolic transition trace from $I$ to $G$. To obtain such a plan with the maximum reward, we use a planner called Metric-FF (Hoffmann 2002), which can handle planning problems with continuous metrics.

**Reinforcement Learning**

A Markov Decision Process (MDP) is defined as the tuple $(\tilde{S}, \tilde{A}, P_{\tilde{a}}, \tilde{r}^s_\tilde{a}, \gamma)$ where $\tilde{S}$ and $\tilde{A}$ denote the state space and action space, respectively. $P_{\tilde{a}}^{s\tilde{a}}$ provides the transition probability of moving from state $\tilde{s} \in \tilde{S}$ to state $\tilde{s}' \in \tilde{S}$ after taking action $\tilde{a} \in \tilde{A}$. $\tilde{r}^s_\tilde{a}$ is the immediate reward obtained after performing action $\tilde{a}$ at state $\tilde{s}$ and $\gamma \in (0, 1)$ is a discount factor. The task of RL is to obtain a policy $\pi: \tilde{S} \rightarrow \tilde{A}$ that maximizes the expected return

$$V_{\pi}(\tilde{s}) = \mathbb{E}_{\pi} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \mid \tilde{s}_0 = \tilde{s} \right]$$

where $r_t$ is the reward at time step $t$ received by following $\pi$ from state $\tilde{s}_0 = \tilde{s}$. The state-action value function is defined as follows:

$$Q_{\pi}(\tilde{s}, \tilde{a}) = \mathbb{E}_{\pi} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \mid \tilde{s}_0 = \tilde{s}, \tilde{a}_0 = \tilde{a} \right].$$

| action act0: |
|-------------|
| pre$^+$: (atMiddleLadder)(keyexist) |
| pre$^-$: $\emptyset$ |
| eff$^+$: (atRightLadder) (increase (reward) 0 ) |
| eff$^-$: (atMiddleLadder) |
**Option Framework**

Hierarchical Reinforcement Learning (HRL) extends RL with temporally macro actions that represent high-level behaviors. The option framework [Sutton, Precup, and Singh 1999] models macro actions as options. In particular, an option \( o \) is defined as \((I_o(s), \pi_o(s), \beta_o(s))\), where initiation condition \( I_o(s) \) determines whether the option \( o \) can be executed at state \( s \), termination condition \( \beta_o(s) \) determines whether option execution terminates at state \( s \) and \( \pi_o(s) \) is a policy mapping state \( s \) to a low-level action. In this framework, an agent learns to choose an optimal option to be executed in the higher level, i.e. meta controller level and the lower level, i.e. controller level learns optimal policies to reach the option. An explicit assumption is that the set of options is predefined by human experts.

**The SORL Framework**

We define the reinforcement learning environment by a tuple \((I, G, P, A, F, \tilde{S}, \tilde{A}, \tilde{R}, \tilde{P}, \gamma)\) and divide it into three parts:

- First, we define a high-level symbolic planning problem by \((I, G, P, A)\), where \( I \) is an initial state, and \( G \) is a goal state. \( P \) is a set of propositions represented by planning language PDDL with prior knowledge and it is used to describe symbolic states \( S \), where \( S \subseteq 2^P \). \( A \) is a set of action models that \( \tilde{S} \rightarrow S \) transfer a symbolic state to another. Each action model is learned by meta-controller through symbolic state pairs.

- Second, we define a state mapping function \( F : \tilde{S} \rightarrow 2^P \) mapping a high dimension state \( \tilde{s} \) to a symbolic state \( s \).

- At last, we define an underlying decision-making problem by an MDP tuple \((\tilde{S}, \tilde{A}, \tilde{R}, \tilde{P}, \gamma)\). We denote a symbolic action and state as \( \tilde{a} \) and \( \tilde{s} \) respectively, while the primitive action and state as \( a \) and \( s \). Noted that \( \tilde{a} \) and \( \tilde{s} \) are gained from interacting with the environment.

Taking the Figure 4 as an example, in the game of the Montezuma’s Revenge, the high level dimension state is the picture of the game scene and the symbolic state is composed of the propositions describing the location of the agent and the existence of the key.

This framework aims to learn action models, which can be utilized by logic-based planner to generate a sequence of options and achieve the maximal cumulative reward. As shown in the Figure 3, the SORL framework includes three components: (1) a planner for generating plans, (2) a meta-controller for generating action models, goals and choosing the goal option, and (3) an option set for interacting with the environment. The meta-controller first takes the symbolic state pairs and their external rewards as inputs and outputs action models and a goal. Noted that the state pairs set are empty in the beginning. Then the planner takes the action models as input and computes a plan. Next, the meta-controller receives the plan from the planner and chooses an option. Each option in option set can be regarded as an agent. The chosen agent keeps interacting with the environment until accomplishing the option or reaching the maximal steps, and the low-level state traces will be transformed into symbolic state pairs by the label function \( F \) and sent back to meta controller. The meta-controller continues learning action models and symbolic options from gained symbolic state pairs and external rewards. We repeat these procedures \( num\_episodes \) times. With the proceeding of learning, our approach keeps updating action models and planning goals and the planner is able to generate plans achieving better rewards.

**Option Set**

**Symbolic Option** In this paper, we propose a novel option framework which is called symbolic option. A symbolic option is computed by symbolic state pairs gained from trajectories instead of manual setting in advance, requiring less prior knowledge in our approach. We define a symbolic option by \( so = (pre, \pi, eff) \) is a low-level policy. \( pre \) is an union of preconditions, including \( pre^+ \) and \( pre^- \). It’s created and updated when the meta-controller generates action models. Similarly, \( eff \) is composed of \( eff^+ \) and \( eff^- \), describing the effects of the symbolic option. As for a symbolic option \( so \) and a high-dimension state \( s \), we compute initiation condition \( I_{so}(\tilde{s}) \) by Equation (1) and termination condition \( \beta_{so}(\tilde{s}) \) by Equation (2). A symbolic option can be executed based on \( s \) only if \( I_{so}(\tilde{s}) = True \). Similarly, it terminates only if \( \beta_{so}(\tilde{s}) = True \).

\[
I_{so}(\tilde{s}) = \begin{cases} 
  True & \text{pre}^+ \cap F(\tilde{s}) \cap \text{pre}^- = \emptyset \\
  False & \text{otherwise} 
\end{cases} 
\tag{1}
\]

\[
\beta_{so}(\tilde{s}) = \begin{cases} 
  True & eff^+ \cap F(\tilde{s}) \cap eff^- \cap F(\tilde{s}) = \emptyset \\
  False & \text{otherwise} 
\end{cases} 
\tag{2}
\]

It’s noted that the inherent symbolic propositions of our symbolic option provide better interpretability compared to those approaches based on black-box neural networks. In terms of the low-level policy \( \pi_i \), it can be learned by interacting with the environments with the intrinsic rewards given by the meta-controller.

**Global Option** At the beginning of our algorithm, the option set contains no symbolic options but a global option \( o_G = (I_G(s), \pi, \beta_G(s)) \), where \( I_G(\tilde{s}) = True \), \( \beta_G(\tilde{s}) = True \) if symbolic state changes and \( \pi = \text{random}(A) \). We use \( \text{random}(A) \) to indicate that the global option each time chooses a random action \( \tilde{a} \in A \). Intuitively, the global option is available for any state and it keeps randomly exploring until the symbolic state changes. Hence, in order to discover new action models, the meta-controller outputs the global option when the plan is empty or all action models in the plan has been executed.

**Symbolic State Pair and External Reward** Given an option \( o_j \) under state \( \tilde{s} \), the lower level policy interacts with the environment and output a pair of symbolic states \((s_1, s_2)\) and external reward \( r_e \), denoted by \((s_1, s_2), r_e = \text{ExecuteOption}(\tilde{s}, o_j)\).

If the chosen option \( o_j \) isn’t available for \( \tilde{s} \), i.e., \( I_j(\tilde{s}) = False \), both of the output pair and the reward are \( \text{None} \). Otherwise, if the chosen option \( o_j \) is able to be executed, we
let \( s_1 = F(\tilde{s}) \) and the policy \( \pi_j \) first chooses an action \( \tilde{a} \) and we can obtain the next state \( \tilde{s}' \) and its reward \( \tilde{r} \) by interacting with the environments. Then the controller adds experiences \((\tilde{s}, \tilde{a}, \tilde{s}', \tilde{r})\) to the \( o_j \)’s replay buffer. We keep executing action by following the low-level policy and update the states and rewards until until \( \beta_j(\tilde{s}') = \text{True} \) or reaching the maximum steps, which means the option has been successfully executed or not. Finally, if the option \( o_j \) is successfully executed, we set the output symbolic state pair as \((s_1, s_2)\) of which \( s_2 = F(\tilde{s}') \) and the external reward \( r_{\text{eff}} \) be the accumulated sum of the environment rewards during interacting.

Meta-controller

In this section, we introduce our Meta-controller in detail. Meta-controller takes symbolic state pairs and their external rewards as input, and first generates action models and a planning goal and then chooses an option according to the plan from planner.

Action Model

Given symbolic state pairs and their rewards, meta-controller generates action models by

\[
A, F_{A,O}, O = \text{GenerateActionModels}(R, O, sr).
\]

The function indicates it takes a dictionary \( R \), an option set \( O \) and the success ratio set \( sr \) as inputs, and outputs a generated action set \( A \), a mapping function \( F_{A,O} \) and the updated option set \( O \). Dictionary \( R \) includes mappings from a symbolic state pair to its external rewards. \( F_{A,O} \) transfers action models to options. The success ratio set \( sr \) records the percentage of action models successful executed each 100 times.

As for a symbolic state pair \((s_1, s_2)\) \in R, we can get a corresponding action model

\[
a_i = (\text{name}, \text{pre}^+, \text{pre}^-, \text{eff}^+, \text{eff}^-).
\]

Noted that the action model and a symbolic state pair is a one-to-one match. Given a state pair \((s_1, s_2)\), the name of \( a_i \) is the index of action models, denoted by \( act_i \), and \( \text{pre}^+ = \{p | p \in s_1\} \), \( \text{pre}^- = \{p | p \notin s_1\} \). Next we let \( \text{eff}^+ = s_2 - s_1 \) and \( \text{eff}^- = s_1 - s_2 \), where \( a - b \) is a set subtraction indicating set \( a \) subtracts the intersection of set \( a \) and set \( b \). In order to generate a plan gaining a maximum reward, we use the metric constant \( q \) to denote the cumulative reward of the plan and add the proposition "((increase quality) \( \rho_i \)" into \( \text{eff}^+ \). Finally, we get an action which is called \( act_i \), and we define the gained reward of \( act_i \) by \( \rho_i \). To encourage the planner to generate a plan including the exploring action model, the reward \( \rho_i \) is composed of mean external reward and exploration reward, computed by Equation (3), where \( R((s_1, s_2)) \) is the external rewards list and \( r_{\text{eff}} \) is the exploration rewards. The exploration rewards is computed by Equation (4), where \( c \) is a constant and \( sr[i] \) is the success rate of \( act_i \), which means exploration reward decreases as success rate increases.

\[
\rho_i = \text{mean}(R((s_1, s_2))) + r_{\text{eff}} \tag{3}
\]

\[
r_{\text{eff}} = \begin{cases} c(1 - sr[i]) & \text{act}_i \text{ is being explored} \\ 0 & \text{otherwise} \end{cases} \tag{4}
\]

If there exists a symbolic option \( o_j = (pre_j, \pi_j, eff_j) \) where \( eff_j = eff \) after we attain an action model, we update \( pre_j \) to a union of \( pre^+ \) and \( pre^- \), and \( pre_j \) to a union of \( pre^- \) and \( pre^+ \). Otherwise, we create a new symbolic option \( o_j = (pre, \pi, eff) \) and add it to the option set \( O \). At last, we set the mapping function \( F_{A,O}(act_i) = o_j \). During the exploration, we explore each action model sequentially, in other words, we repeat exploring \( act_i \) until the success rate of \( act_0 \) to \( act_{i-1} \) is higher than the threshold.

Planning Goal

Next Meta-controller outputs a goal to guide planner, aiming at generating a plan with a maximal reward. The goal is a label function \( q > q \), where \( q \) is the cumulative external rewards of the plan gained in the last episode. Intuitively, the function constrains the planner to compute a plan with a largest reward compared with the past plans.

Chosen Option and Intrinsic Reward

After the planner generates a plan \( \Pi = (a_1, a_2, \ldots, a_n) \), as for each action model \( a_i \), the meta-controller selects a symbolic option from option set by \( o_j = F_{A,O}(act_i) \), and we can get an series of options \((o_0, o_1, \ldots, o_n)\). If all action models in \( \Pi \) successfully finish, which indicates the chosen symbolic options are executed sequentially and termination conditions are satisfied , then the meta-controller would choose the global option \( o_G \) to explore the environment thoroughly. For each option \( o_i = (pre_i, \pi_i, \beta_i) \), we refer to [Lyu et al. 2019] to design intrinsic rewards:

\[
r_i(s) = \begin{cases} \phi & \beta_i(s) = \text{True} \\ r & \text{otherwise} \end{cases}
\]

where \( \phi \) is a constant and \( r \) is the reward gained from the environments when reach state \( s \).
Algorithm 1: Planning and Learning algorithm for SORL

**Input:** proposition set $P$, state mapping function $F$, success ratio threshold $\lambda$

1. **Initialization:** option set $O \leftarrow \{o_G\}$, action models set $A \leftarrow \emptyset$, symbolic state pairs’ external rewards dictionary $R \leftarrow \emptyset$, action models’ success ratio set $sr \leftarrow \emptyset$, plan $\Pi_0 \leftarrow \emptyset$, $q \leftarrow 0$

2. for $t=1, 2, \ldots, \text{num\_episodes}$ do
   3. Initialize game, get start state $s_0$, $I \leftarrow F(s_0)$, $\Pi^* \leftarrow \Pi_{t-1}$
   4. $A,F,A,O \leftarrow \text{GenerateActionModels}(R,O,sr)$
   5. $G \leftarrow (\text{quality} > q)$
   6. $\Pi_t \leftarrow \text{metric\_FF\_solve}(I, P, A, G)$
   7. if $\Pi_t = \emptyset$ then $\Pi_t \leftarrow \Pi^*$
   8. $q \leftarrow 0$
   9. for $a_t \in \Pi_t$ do
      10. $o_j \leftarrow F(A, O)[i]$, obtain current state $\overline{s}$
      11. $(s_1, s_2), r_e \leftarrow \text{ExecuteOption}(\overline{s}, o_j)$
      12. append $r_e$ into $R[(s_1, s_2)]$, $q \leftarrow q + r_e$
   13. end for
   14. while env isn’t terminal do
      15. obtain current state $\overline{s}$
      16. $(s_1, s_2), r_e \leftarrow \text{ExecuteOption}(\overline{s}, o_G)$
      17. if $(s_1, s_2) \text{ not in } R$ then
         18. $R[(s_1, s_2)] \leftarrow \text{list}(r_e)$
      19. else
         20. append $r_e$ into $R[(s_1, s_2)]$
      21. end if
   22. end while
   23. train options in $O$ and calculate $sr$
   24. end for

**Planning and Learning**

As shown in Algorithm 1, we firstly initialize an option set $O$ only including $o_G$, an empty action model set $A$, an empty dictionary mapping symbolic state pairs to their external rewards $R$, an empty action models success ratio set $sr$ and an empty plan $\Pi_0$. When an episode $t$ begins, we first get a start state $s_0$ from environment. Then we compute the symbolic initial state $I$ by $F$ and record the best plan $\Pi^*$, which is the plan generate in the last episode. Then meta-controller updates action models $A$, symbolic options set $O$, their mapping function $F_{A,O}$ and the planning goal $G$. Given current action models $A$ and planning goal $G$, Metric-FF planner (Hoffmann, 2002) generates a new plan $\Pi_t$ whose quality is higher than the last plan $\Pi_{t-1}$. If $\Pi_t$ is empty, which indicates Metric-FF couldn’t find a solution to solve the problem, we let $\Pi_t = \Pi^*$.

As for each action model $a_i$ in plan $\Pi_t$, meta-controller chooses a corresponding symbolic option $o_j$ by $F_{A,O}$. Then the controller interacts with environment by performing Deep Q-Learning, executes the action chosen by $o_j$’s inner policy and stores experience into $o_j$’s replay buffer until $o_j$ terminates. After that, we get $o_j$’s initial symbolic state $s_1$ and a terminate symbolic state $s_2$ and an extrinsic reward $r_e$. In this way, we compute symbolic state pairs and their extrinsic rewards by one and record these mappings by a dictionary $R$. Finally, quality $q$ of plan $\Pi_t$ is defined as the accumulated sum of extrinsic rewards.

If the environment isn’t finished after executing $\Pi_t$, the meta-controller chooses the global option $o_G$ to explore new symbolic state pairs in the environment. $o_G$ stops exploring when the computed symbolic state changes and we calculate a symbolic state pair $(s_1, s_2)$ and its external reward $r_e$. If $(s_1, s_2)$ is a new symbolic state pair, we add it into $R$. This process repeats until the environment is terminated. Finally, when an episode ends, we train options in $O$ and calculate success ratio for each action model.

**Experiment**

In this section, we evaluate our approach on two domains, Office World and Montezuma’s Revenge in terms of data-efficiency, interpretability and transferability.

**Office World**

We first evaluate our approach on the Office World (carte et al., 2018) which is a simple multitask environment. In this environment, being initialized at a random location, the agent can move towards one of the four cardinal directions. Actions are valid only if the movement does not go through a wall. The agent can pick up cups of coffee or mails when it reaches the cell marked with blue cups or green envelops, respectively. He can deliver coffee or mail to the office by reaching the cell marked with a purple hand. The symbol * means the place where the agent can not stay or reach.

**Setup** In this environment, the start location of the agent is randomly initialized at every episode. The agent is required to finish three tasks. The first and the second are to deliver a cup of coffee or a piece of mail to the office while the third is to hand both objects to the office. We compared SORL to h-DQN, a goal based h-DRL approach (Kulkarni et al., 2016). Since the state and action space are finite, we choose to implement these two approaches with q-table in both high and low levels.

**Results** We evaluate our approaches in terms of data-efficiency, interpretability and transferability.

- **Data-efficiency** In order to validate the data-efficiency, we train these two approaches in the three tasks and compare the corresponding performance at the same interaction steps. To demonstrate the transferability, we train the agent in task 3 along with the options learned in tasks 1 and 2. To implement our approach, we design the propositions as shown in Fig. 4(c). As shown in Fig 4(b), from Task1 to Task3, SORL can get rewards faster than HRL.

- **Interpretability** Fig 4(d) shows action models and symbolic options learned in each task. Those action models describe the reason of making decisions at each step in a human understandable way. For example, we can explicitly know act1 in task1 can be executed when the agent gets coffee and does not deliver it to the office, and the agent would deliver the coffee to the office and get a reward of 100 when act1 is executed.

- **Transferability** By utilizing the options learned in tasks 1 and 2, we test the transferability of SORL and H-DQN
in Task 3 and denote them as $SORL_t$ and $HRL_t$. As shown in Fig 4(c), the performance of SORL and HRL is improved when transferring the learned knowledge. It verifies that compared to SORL, the converging speed of $SORL_t$ improves dramatically with only half of samples. We conjecture that the SORL is able to transfer the learned knowledge into other unseen environments.

Montezuma’s Revenge

Montezuma’s Revenge is an Atari game with sparse and delayed rewards. It requires the player to navigate through several rooms while collecting treasures. We conduct our experiments based on the first room shown in Fig 5(a). In this room, the player only obtains positive rewards when it fetches the key (+100) or opens a door (+300). Otherwise, the player would not receive any reward signal. The optimal solution is to climb down the ladders to obtain the key, then return back to the platform and open a door, resulting in a maximum reward (+400).

Setup

We compare our approach with HRL (Kulkarni et al. 2016) and SDRL (Lyu et al. 2019) as baselines, where SDRL is an approach that combines symbolic planning and RL with excellent results in complex environments with sparse rewards. SORL can automatically learn the action models while they are pre-defined by experts in SDRL. Besides, the option model can correspond to multiple action models in SORL while one in SDRL. We implement these approaches under an option-based h-DRL framework. In terms of the low level, we follow the network architecture used in (Kulkarni et al. 2016) and train this network with double-Q learning (van Hasselt, Guez, and Silver 2016) and prioritized experience replay (Schaul et al. 2016). Besides, both SORL and SDRL use a planner to generate high level policy while HRL utilizes a neural network. The intrinsic reward follows $\phi = 100$. The maximum steps in an episode and the threshold of success rate are set to be 500 and 0.95, respectively. To describe the environment, we abstract four local propositions (e.g., MiddleLadder, RightDoor, LeftLadder and RightLadder) and an object (Key).

Results

We present the experimental results in Fig 5. It is evident that SORL can achieve the maximum reward (+400) in 0.7M samples while both SDRL and HDQN need more than 1.5M samples, indicating the superior data-efficiency of SORL. However, to pick up the key (reward +100), SORL needs to interact with the environment with more than 0.3M steps, at which SDRL and HDQN fall into the local optimum. This is because SORL randomly explores symbolic options and it is easier to find options closer to the starting point. After finding these options, SORL would train them sequentially instead of directly learning options on the path of getting the key. One option model corresponds to one action model in SDRL while several action models in SORL. The ability of reusing the learned symbolic options enables SORL to converge faster than SDRL. Take Fig 5(c) as an example, the opt1 representing the move from middle ladder to right door, is firstly trained at the beginning when the player does not get the key. After the player picks up the key, SORL only needs a small amount of data to fine-tune opt1 when the player moves from the middle ladder to right door with a key. However, both SDRL and HDQN start training the...
options after the player moves to the middle ladder with a key, consuming more interaction resources. Different from option-based HDQN and SDRL, SORL can learn the initial and termination condition of symbolic options automatically. The action models used in SDRL need to be constructed by human in advance while they are learned from the trajectories in SORL, saving labour resources. We present some of the learned action models in Fig. 5(b) and the effects of symbolic options in Fig. 5(c) Fig. 5(b) describes the preconditions and effects of each action model and we can see that if the player is at LeftLadder and the key exists, then the player can obtain a key and reward (+100) by executing action5. Fig. 5(c) shows the learned options in SORL and the order of options actually does not match the optimal order because SORL randomly explore the environment and options 0-3 are easier to learn. We describe the meaning of all learned action models and their corresponding options in Fig. 5(d) It is easy to see that act7 to act10 correspond to the options explored before, so these options can be reused to improve the data-efficiency.

Conclusions

In this paper, we propose a novel framework SORL which can automatically learn action models and symbolic options from the trajectories and the symbolic planner can instruct RL to explore efficiently in environments with sparse and delayed rewards. Compared with other approaches, the experimental results demonstrate the better sampling efficiency of our approach. Moreover, SORL requires less prior knowledge and provides interpretability and transferability by the learned action models and symbolic options. In the future, it would be interesting to investigate possibility of learning more expressive planning models, such as learning Hierarchical Task Networks (Zhuo and Yang 2014) and PDDL models (Zhuo et al. 2010), as well as different learning mechanisms, such as transfer learning (Zhuo and Yang 2014; Shen et al. 2020).

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