Hierarchical Reinforcement Learning with Abductive Planning

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Abstract

One of the key challenges in applying reinforcement learning to real-life problems is that the amount of train-and-error required to learn a good policy increases drastically as the task becomes complex. One potential solution to this problem is to combine reinforcement learning with automated symbol planning and utilize prior knowledge on the domain. However, existing methods have limitations in their applicability and expressiveness. In this paper we propose a hierarchical reinforcement learning method based on abductive symbolic planning. The planner can deal with user-defined evaluation functions and is not based on the Herbrand theorem. Therefore it can utilize prior knowledge of the rewards and can work in a domain where the state space is unknown. We demonstrate empirically that our architecture significantly improves learning efficiency with respect to the amount of training examples on the evaluation domain, in which the state space is unknown and there exist multiple goals.

1 Introduction

Reinforcement learning (RL) is a class of machine learning problems in which an autonomous agent learns a policy to achieve a given task through trial and error. Automated planning is an area of artificial intelligence that studies how to make efficient plans for achieving a given task with predefined knowledge. Reinforcement learning and automated planning are complementary to each other and various methods to combine them have been proposed [Partalas et al., 2008; Grzes and Kudenko, 2008; Branavan et al., 2012; Konidaris et al., 2014; Konidaris et al., 2015; Leonetti et al., 2016; Andersen and Konidaris, 2017].

Partalas et al. [2008] classified those methods into two categories: reinforcement learning to speed up automated planning and reinforcement learning to increase domain knowledge for automated planning. In this paper, we focus on the former, and, more specifically, address the problem of hierarchical reinforcement learning with symbol-based planning. We are motivated by the fact that the lack of efficiency in the learning process is an essential problem which has hampered application of reinforcement learning to complicated domains in the real world.

We argue that there are problems with the automated planners employed by existing hierarchical reinforcement learning frameworks if they are to be used in real-life applications. First, most of the widely used planners and inference models are based on the Herbrand theorem and thus need a set of constants as input to generate a Herbrand universe. Therefore, the meaning representation used in planning by such planners must satisfy the condition that, for each term of the predicates, there exists a finite sequence of constant terms. This condition restricts the available meaning representations and often hampers the application of symbolic planners to domains modeled by a partially observable Markov decision process (POMDP). Second, to the best of our knowledge, existing symbolic planners cannot deal with pre-defined knowledge about rewards and hence cannot evaluate the expectations of rewards in planning. Real-life problems often have several goals with different priorities. For instance, the AI controller of a plant may need to consider multiple goals in planning (e.g., safety operation vs profit maximization). Third, classical planners (e.g., STRIPS) can only deal with rules that define actions. Those planners cannot utilize other types of knowledge, such as relationships of a subordinate concept to a main concept. In order to address the above problems, we propose a new symbolic planner that employs ILP-formulated abduction as its symbolic planner. Abduction is a form of inference that is used to find the best explanations to a given observation. The development of efficient inference techniques for abduction in recent years warrants the application of abduction with large knowledge bases to real-life problems. We show that our model can overcome the above issues through experiments on a Minecraft-like evaluation task.

This paper consists of six sections. In Section 2, we introduce the formalism of reinforcement learning and automated reasoning in abduction, and review some previous work on symbolic planning-based hierarchical reinforcement learning. Section 3 describes our abduction-based hierarchical reinforcement learning framework. Section 4 describes our evaluation domain. In Section 5, we report the results of experiments. The final section concludes the paper.
2 Background

This section reviews related work on hierarchical reinforcement learning with symbolic planning and abduction.

2.1 Reinforcement Learning

Reinforcement Learning is a subfield of machine learning that studies how to build an autonomous agent that can learn a good behavior policy through interactions with a given environment. A problem of RL can be formalized as a 4-tuple $<S, A, T, R>$, where $S$ is a set of propositional states, $A$ is a set of available actions, $T(s, a, s') \rightarrow [0, 1]$ is a function which defines the probability that taking action $a \in A$ in state $s \in S$ will result in a transition to state $s' \in S$, and $R(s, a, s') \rightarrow \mathbb{R}$ defines the reward received when such a transition is made.

The problem is called a Markov Decision Process (MDP) if the states are fully observable; otherwise it is called a Partially Observable Markov Decision Process (POMDP).

The learning efficiency of RL decreases as the state space in the target domain becomes larger. This is a major problem in applying RL to large real-life problems. Although various approaches to solve this problem have been proposed, we focus on methods that utilize symbolic automated planners to improve the learning efficiency.

In automated planning, prior knowledge is used to produce plans which would lead the world from its current state to its goal state. Specially, Symbolic Automated Planning methods deal with symbolic rules and generate symbolic plans.

Grounds & Kudenko [2007] proposed PLANQ to improve the efficiency of RL in large-scale problems. In PLANQ, a STRIPS planner defines the abstract (high-level) behavior and a RL component learns low-level behavior. PLANQ contains multiple Q-learning agents for each high-level action. Each Q-learning agent learns the behavior to achieve the abstract action corresponding to itself. The authors have shown that a PLANQ-learner learns a good policy efficiently through interactions with a given environment. Typically, there exist several hypotheses $H$ that explain $O$. We call each of them a candidate hypothesis. The goal of abduction is to find the best hypothesis among candidate hypotheses according to a specific evaluation measure. Formally, we find $H = \arg \max_{H \in H} \text{Eval}(H)$, where $\text{Eval}(H)$ is a function $H \rightarrow \mathbb{R}$, which is called the evaluation function. The best hypothesis $H$ is called the solution hypothesis.

Although abduction on first-order logic or similarly expressive formal systems is computationally expensive, inference techniques developed in recent years have improved its computational efficiency. Inoue and Inui [2011], Inoue and Inui [2012], Yamamoto et al. [2015], Inoue and Gordon, [2016]. Specially, Inoue et al. [2011, 2012] proposed a method (called ILP-formulated Abduction) to formulate the process of finding the solution hypothesis as a problem of Integer Linear Programming (ILP) and showed that their method significantly improves the computational efficiency of abduction. In addition, since ILP-formulated abduction is based on the directed acyclic graph representation for abduction [Charniak and Shimony, 1990] and thus generates a set of candidate hypotheses in the manner similar to graph generation, it does not need the grounding process. This is a strong advantage in comparison to other inference models based on the Herbrand theorem (e.g. Answer Set Programming, Markov Logic Networks, Richarison and Domingos, 2006). More specifically, a candidate hypothesis is expressed as a directed graph in which each node corresponds to a logical atom, where each candidate hypothesis corresponds to a subset of nodes in the directed graph. In the process to enumerate candidate hypotheses, ILP-formulated abduction constructs the directed graph by applying two kinds of operations to the observation: backward chaining and unification. Backward chaining is an operation that applies a rule backward (i.e. consider that the presupposition may be true if the consequence is true) and adds atoms in the presupposition to the graph. Unification is an operation that unifies two atoms having the same predicate and makes the assumption that each term of an atom is equal to the corresponding term of the other atom. See Inoue and Inui [2011] for details.

Abduction has been applied to various real-life problems such as discourse understanding [Inoue et al., 2012], Ovchinnikova et al. [2013], Sugita et al. [2013], Gordon, 2016, question answering [And et al., 2001], Sasaki, 2003 and automated planning [Shanahan, 2000; do Lago Pereira and de Barros, 2004]. Many planning tasks can be formulated as problems of abductive reasoning by giving an observation consisting of the initial state and the goal state. Abduction will find the solution hypothesis explaining why the goal state has been achieved by starting from the initial state. Then the solution hypothesis can be interpreted a plan from the initial state to the goal state.

Find: A hypothesis (explanation) $H$ such that $H \lor B \models O$, $H \lor B \not\models \perp$, where $H$ is a set of first-order logical formulas.
Figure 1: An example of a solution hypothesis generated by ILP-formulated abduction. Capitalized terms (e.g. $M$ and $T1$) are logical constants and the others (e.g. $u1$ and $t3$) are logical variables. Atoms in a square are conjunctive (i.e. $\text{have}(M) \land \text{money}(M)$) and atoms in gray squares are observations. An equality between terms represents a relation between time points corresponding to the terms. Each solid, directed edge represents an operation of backward-chaining in which the tail atoms are hypothesized from the head atoms. Each dotted, undirected edge represents a unification. Each label on a unification edge such as $M = u1$ is an equality between arguments led by the unification.

Figure 2 shows an example of a solution hypothesis by ILP-formulated abduction in automated planning. A solution hypothesis is expressed as a directed acyclic graph and thus we can obtain richer information about the inference than one of other inference frameworks. From this graph, we can obtain the plan to get an apple, namely go a grocery and buy an apple.

3 Proposed Architecture

This section describes abduction-based hierarchical reinforcement learning.

Figure 2: The basic structure of our architecture.

Using a predefined knowledge base, the abduction-based symbolic planner generates plans at the abstract level. The planner based on a reinforcement learning model interprets the plans made by the symbolic planner as a sequence of subgoals (options) and plans a specific action on the next step. This structure is similar to existing hierarchical reinforcement learning methods based on symbolic planners, such as PLANQ. Following previous work, we call the abstraction level on which the symbolic planner works high-level and the abstraction level on which the planner based on the reinforcement learning model works low-level. We use the term the high-level planner to refer to the planner based on abduction, and the term the low-level planner the planner based on the reinforcement learning model.

Here we describe the algorithm for choosing an action. First, the system converts the current state and the goal state into an observation in first-order logic for abduction. Next, the system performs abduction for this observation and then makes a high-level plan to achieve the goal state. We use a modified version of the evaluation function in Weighted Abduction [Hobbs et al., 1993] in order to obtain a good plan. We describe the details of this evaluation function in Section 3.1. Finally, the system decides the next action by considering the nearest subgoal in the high-level plan. Following hierarchical-DQN [Kulkarni et al., 2016], the system gives intrinsic rewards to the low-level component when the subgoal is completed, and thus the low-level component will learn the behavior to achieve subgoals by considering the intrinsic rewards.

One can use an arbitrary method to make a high-level plan from a solution hypothesis in our architecture. In this paper, assuming that the graph structure corresponds to the time order, we make a high-level plan from actions sorted by distance from the goal state. For example, actions in the solution hypothesis shown in Figure 1 may be get-apple, buy-apple, have-money and go-grocery. Sorting them by distance from the goal state, we can obtain a high-level plan \{go-grocery, buy-apple, get-apple\}. The action have-money is excluded from the high-level plan because it has already satisfied by the current state.

Using ILP-formulated abduction as the high level planner has several benefits. First, since ILP-formulated abduction does not need a set of constants as input, our architecture can deal with a domain in which the size of state space is unpredictable. In other words, there is no need to consider whether the state space made from the current meaning representation is a closed set or not. When using other logical inference models, it is often hard to find which meaning representation is appropriate for the target domain. This difficulty can be sidestepped by ILP-formulated abduction. Second, this advantage gives our architecture another benefit, namely the ability to make plans of an arbitrary length. This is an advantage over existing logical inference models (e.g. Answer Set Programming). Third, an advantage over classical planners is the ability to use types of knowledge other than action definitions. For instance, in STRIPS, one cannot define rules of relations between objects (e.g. coal($x$) $\Rightarrow$ fuel($x$)). Finally, ILP-formulated abduction provides directed graphs as the solution hypothesis. Compared with other logical inference models which just return sets of logical symbols as outputs, abduction can provide more interpretable outputs.

3.1 Evaluation Function

In this section, we describe the evaluation function used in the abductive planner of our architecture.

In general abduction, evaluation functions are used to eval-
uate the plausibility of each hypothesis as the explanation for the observation. For instance, the evaluation function of probabilistic abduction (e.g., Etcetera Abduction [Gordon, 2016]) is the posterior probability \( P(H|O) \), where \( H \) is a hypothesis and \( O \) is the observation.

However, what we expect abduction to find in this work is not the most probable one, but the most promising one as a high-level plan. In other words, our evaluation function needs to consider not only the possibility of a hypothesis but also the reward that the agent will receive by completing the plan made from the hypothesis.

Therefore, we add a new term of expected reward to the standard evaluation function:

\[
Eval(H) = E_0(H) + E_R(H),
\]

where \( E_0(H) \) is some evaluation function in an existing abduction model, such as Weighted Abduction and Etcetera Abduction. \( E_R(H) \) is the task-specific function that evaluates the amount of reward on completing a plan in hypothesis \( H \). More specifically, in this paper, we use an evaluation function based on Weighted Abduction:

\[
Eval(H) = -\text{Cost}(H) - r_H
\]

where \( \text{Cost}(H) \) is the cost function in Weighted Abduction and \( r_H \) is the amount of reward of completing a plan in hypothesis \( H \).

Although we employ Weighted Abduction as a base model due to the availability of an efficient reasoning engine, a different abduction model could be used. For instance, using a probabilistic abduction model, one can define an evaluation function to evaluate the exact expectation of reward, namely \( Eval(H) = \log(P(H|O)) + \log(r_H) \).

4 Evaluation Domain

This section describes the domain we used for evaluating our abduction-based RL method.

In this paper, we use a domain of grid-based virtual world based on Minecraft. Each grid cell is either of land or lava and can contain materials or utilities. The player can move around the world, pick up materials and craft objects with utilities. Each episode will end when the player arrives at the goal position, when the player walks into a lava-grid, or when the player has executed 100 actions.

In order to examine the effectiveness of our approach empirically, we set up the problem so that it has types of complexity that tend to exist in real-world problems: partial observability, multiple goals, delayed reward and multitask.

Partial Observability The player at the initial state does not have any knowledge of the environment. More specifically, he does not know the size of the grid world, where he is, what items there are, or the positions of materials and utilities in the grid world. He can detect the existence of an object in the world when he gets close to it. For example, the gray area around the player in Figure 3 shows the range of his sensing. Therefore, he knows nothing about the outside of this area at the initial state.

Multiple Goals and Delayed Reward The player receives a reward only when he arrives at the goal position. The amount of the reward depends on what he can craft on arriving at the goal. The reward will be high if he can craft an object made from many materials. For instance, the reward given to a player who has enough materials to cook rabbit-stew is much higher than that for a player who has only collected rabbit.

Multitask In this domain, the layout of the grid world is randomized on every episode. Specifically, the player’s starting position, the goal position, the arrangement of lava, the width of the grid-world, the variation of materials and their positions vary randomly. The range of the width of the grid-world \( w \) is \( 12 \leq w \leq 15 \). Each grid world contains \( 4 \sim 9 \) kinds of materials and is always surrounded by lava.

It should be noted that, since the variation of materials in the world may change, it is possible that the player cannot craft the optimal object in some episodes. In other words, the optimal goals of different episodes are different. Therefore, the player needs to judge which goal is the most appropriate in each episode. For example, the player will receive the highest reward when he can cook rabbit-stew, which is made from rabbit, bowl, mushroom, potato, carrot and some fuel to use a furnace. Therefore, the player cannot cook it if any of its materials does not exist in the world.

These characteristics make it difficult to apply existing reinforcement learning models to this evaluation domain. The state space in this domain is unpredictable and thus existing first-order symbolic planners based on Herbrand’s theorem, such as Answer Set Programming and STRIPS, are not straightforwardly applicable to this domain.

Let us discuss in more detail the difficulty of applying Herbrand’s theorem-based planners to this domain. Since those planners need a set of constants to make a Herbrand universe, one must define predicates so that one can enumerate all possible arguments in advance. However, most of the objects in this domain (e.g., grid cells, materials and time points) are not enumerable; that is, one cannot define closed sets of arguments corresponding to those objects in advance. Therefore...
one cannot avoid giving a huge set of constants to deal with all possible cases or abstracting predicates so that its argument set is known in advance. The former may be computationally intractable and the latter may be too time-consuming and difficult for human.

Following the conditions in General Game Playing [Gene-sereth et al., 2005], we had conducted evaluation on the following presuppositions. First, the player can use prior knowledge of the dynamics of the target domain. That includes knowledge of crafting rules and the amount of reward for each object. Second, the player cannot use the knowledge of task-specific strategies for the target domain. In other words, we do not add any knowledge of how to move for getting higher rewards.

5 Experiments

We evaluated our approach in the domain described in Section 3. We compared the following three models. First, NO-PLANNER is a RL model without a high-level planner. Second, FIXED-GOAL is the model in which the high-level planner always makes plans so that the player achieve the most ideal goal (i.e. cooking rabbit-stew). We consider this model to correspond to existing symbolic planner-based hierarchical RL models, in which the high-level planners cannot deal with prior knowledge of the rewards. Finally, ABDUCTIVE is our proposed model, in which the high-level planner is based on abduction.

We employed Proximal Policy Optimization algorithm (PPO) [Schulman et al., 2017] as the low-level component for each model. PPO is a state-of-the-art policy gradient RL algorithm, and is relatively easy to implement.

In order to perform abduction based on our evaluation function proposed in Section 3, we implemented a modified version of Phillip, a state-of-the-art engine for ILP-formulated abductive reasoning, and used it for the high-level planner of ABDUCTIVE. In order to improve the time efficiency of planning, we cached the inference results for each observation and reused them whenever possible.

We manually constructed the prior knowledge of the evaluation domain for the high-level planner. The knowledge base contains 31 predicates and 125 rules. As stated in Section 3, these rules consist of only the ones for the dynamics of the domain, such as crafting rules and properties of objects. We describe examples of the rules in Figure 4.

We used roughly three types of actions as elements in high-level plans, namely finding a certain object, picking up a certain material and going to a certain place. Each of them takes one argument (e.g. get-rabbit) and thus we actually used 20 actions in a high-level plan. For instance, a high-level planner in this experiment may generate high-level plans like {find-coal, get-coal, get-rabbit, go-furnace, go-goal}.

As stated previously, the content of each task is generated randomly. Since we use the number of episodes as the range

Figure 4: Examples of rules that we used.

Figure 5: The performance of three models.

As we can see, ABDUCTIVE obtained much more rewards than other models and learned more efficiently with respect to the number of training examples. Learning efficiency is important when RL is applied to real-life problems. In such domains, the time required for trial and error can be prohibitively long because of the computational cost of a simulator or necessity of manual operations.

Figure 6 is an example of solution hypotheses made by the abductive planner in the evaluation domain. Our architecture may convert this into a subgoal sequence — pick up rabbit, go to furnace and go to goal. As we can see, since it is described as a graph how the planner inferred the plan, our system can improve interpretability of the content of the inference. From this proof graph, we can see that our planner can make plans of an arbitrary length and can use types of
knowledge other than action definitions.

One limitation of our architecture is the large variance in CPU time required per time step. Most of the action selections can be made in a few milliseconds, but when the high-level planner needs to perform abductive planning, the selection may take a few seconds. For this issue, there are several directions of future work to reduce the frequency of performing abduction. One is to improve the algorithm for finding reusable cached results. Our current implementation uses cached results only when exactly the same observation is given. The computational cost of high-level planning could be significantly reduced if the high-level planner can reuse a cache for similar observations as well.

6 Conclusion

We proposed an architecture of abduction-based hierarchical reinforcement learning and demonstrated that it improves the efficiency of reinforcement learning in a complex domain.

Our ILP-formulated abduction-based symbolic planner is not based on the Herbrand theorem and thus can work in domains where the state space is unknown. Moreover, since it can deal with various evaluation functions including user-defined ones, we can easily allow an abductive planner to utilize prior knowledge about rewards.

In future work, we plan to employ machine learning methods for abduction. In recent years, some methods for machine learning of abduction have been proposed [Yamamoto et al., 2013; Inoue et al., 2012]. Although we manually made prior knowledge for the experiments in this work, we could apply these methods to our architecture. Specifically, if we could divide the errors into the high-level component’s errors and the low-level component’s errors, we can update the weights of symbolic rules used in the abductive planner discriminatively when the high-level planner fails.

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