Knowledge-Based Sequential Decision-Making
Under Uncertainty

Daoming Lyu
Auburn University, Auburn, AL 36849, USA
daoming.lyu@auburn.edu

Abstract. Deep reinforcement learning (DRL) algorithms have achieved great success on sequential decision-making problems, yet is criticized for the lack of data-efficiency and explainability. Especially, explainability of subtasks is critical in hierarchical decision-making since it enhances the transparency of black-box-style DRL methods and helps the RL practitioners to understand the high-level behavior of the system better. To improve the data-efficiency and explainability of DRL, declarative knowledge is introduced in this work and novel algorithm is proposed by integrating DRL with symbolic planning. An experimental analysis on publicly available benchmarks validates the explainability of the subtasks and shows that our method can outperform the state-of-the-art approach in terms of data-efficiency.

1 Introduction
As shown in AlphaGo or self-driving car, it is critical to making sequential decisions. Recently, deep reinforcement learning (DRL) algorithms have made a lot of achievements on sequential decision-making problems involving high-dimensional sensory inputs such as Atari games[14]. Though this approach can learn policies that were able to surpass the overall performance of a professional human player, it usually requires millions of data samples or more, which would be less efficient. In addition, learning behavior based on the black-box deep neural network is nontransparent. This fails to explain the internals of a system in a way that is understandable to humans. In real applications of decision-making, however, it is crucial to enable the system behavior to be explainable, in order to gain the confidence from the user and provide insights for their decision-making process [5] with reasonable less data samples.

To improve the data-efficiency and explainability of DRL, we propose a Symbolic Deep Reinforcement Learning (SDRL) framework that integrates symbolic planning with a hierarchical approach of DRL. Symbolic Planning (SP) can perform reasoning and planning on explicitly represented knowledge. SP has been used for task planning of mobile robots which usually co-inhabit with human, perform tasks for human and communicate with human [6,2], all requiring high-level explainability of their behavior. Different from reinforcement learning, a planning agent carries prior symbolic knowledge of objects, properties and how they are changed by executing actions in the dynamic system, represented
in a formal, logic-based language such as PDDL \cite{13} or an action language \cite{4} that relates to logic programming under answer set semantics (answer set programming) \cite{10}. The agent utilizes a symbolic planner, such as a PDDL planner \textsc{FastDownward} \cite{7} or an answer set solver \textsc{Clingo} \cite{3} to generate a sequence of actions based on its symbolic knowledge, executes the actions to achieve its goal, perform execution monitor and replan to handle execution failure and domain uncertainty. Due to the white-box algorithms of planning and reasoning with predefined and human-readable symbolic knowledge, the explainability of the agent’s behavior can be achieved. In addition, recent work on integrating symbolic planning with reinforcement learning \cite{15,11} shows that symbolic plans with prior knowledge can guide reinforcement learning for meaningful exploration, which can lead to improvement on data efficiency for decision-making.

2 SDRL Framework

Symbolic Deep Reinforcement Learning (SDRL) framework features a planner–controller–meta-controller architecture, as shown in Fig.1, which takes charge of subtask scheduling, data-driven subtask learning, and subtask evaluation, respectively.

![Fig. 1: Architecture of SDRL](image)

We assume a symbolic structure, i.e., a set of causal rules that captures objects, fluents and how their values are changed by executing subtasks, is given by human experts. While a pre-defined symbolic representation requires some work, we build it for general-purpose so that the symbolic formulation for one problem can be easily applied to another, by instantiating a different set of objects or adding a few more rules. The laborious effort of crafting an accurate symbolic model is neither necessary nor useful.

Next, we define the workflow as follows. With a symbolic representation given by the human expert, a symbolic planner generates high-level plans, i.e.,
a sequence of subtasks, to meet its intrinsic goal. An intrinsic goal is a measurement on plan quality, which approximates how much cumulative reward the plan may achieve. In other words, intrinsic goal is an internal desire that enables the reward-driven symbolic planning. Besides, we assume a pre-trained mapping function can associate each sensory input with a symbolic state, i.e., performing symbol grounding, so that a set of subtasks on the problem MDP can be induced based on symbolic states and the mapping function. We extend the reward structure of core MDP by introducing intrinsic reward and extrinsic reward to facilitate two levels of learning tasks. The sub-policies for the action level are learned using DRL algorithms based on intrinsic reward. Intrinsic reward can be used to encourage the agent to learn skills to achieve each subtask, which is a pseudo-reward crafted by human. As DRL continues, a metric is used to evaluate the competence of learned sub-policies, such as the success ratio. Success ratio is defined as the average rate of successfully accomplishing the subtask over certain episodes, from which extrinsic rewards is derived. When the sub-policy is learned and reliably achieves the subtask, the extrinsic reward is equivalent to the environmental reward. Using extrinsic rewards, meta-controller performs evaluation on the subtask learning that reflects the long-term average reward and gains the reward of selecting each subtask. The learned values are returned to the symbolic planner and are used to measure plan quality and propose new intrinsic goals for the planner to improve the plan, by either exploring new subtasks or by sequencing learned subtasks that supposedly can achieve higher rewards in the next iteration.

In this process, the components of planner, controllers, and meta-controller cross-fertilize each other and eventually converge to an optimal symbolic plan along with the learned subtasks. While our framework is generic enough so that various planning and DRL techniques can be used, we instantiate our framework using action language $BC$ for planning and R-learning for meta-controller learning.

### 3 Experiment

The proposed approach is evaluated on Taxi domain [11] and Montezuma’s Revenge [14]. Due to the space limitation, we skip the description of experimental settings and the complete results. Here we only show some results of Montezuma’s Revenge. The interested readers are referred to [12] for more details.

As shown in Fig.2 and Fig.3, we formulated domain knowledge of Montezuma’s Revenge in action language $BC$ based on 6 pre-defined locations or objects: middle platform ($mp$), right door ($rd$), left of rotating skull ($ls$), lower left ladder ($lll$), lower right ladder ($lrl$), and key ($key$). All 13 subtasks are pre-defined and shown in Table 1. Actually, during the experiment, subtasks 1–10 can be successfully learned, but only 7 of them (1–7) were selected in the final solution. This can be explained by the extrinsic rewards derived from training performance. For subtasks 11 – 13, they were shown to be too difficult to learn in our experiments and discarded by the planner due to poor extrinsic rewards.

...
Fig. 2: Pre-defined Locations or Objects

% object declaration
location(mp;rd;ls;lll;lrl;key).
% dynamic causal law declaration
move(L) causes loc=L if location(L).
move(L) causes cost=L+Z if rho((at(L1)),move(L))=Z,
   loc=L1, picked(key)=false.
move(L) causes cost=L+Z if rho((at(L1),picked(key)),
   move(L))=Z, loc=L1, picked(key)=true.
 inertial loc. inertial quality.
% static causal law declaration
picked(key)=true if loc=key.
nonexecutable move(key) if picked(key).
default rho((at(L1)),move(L))=10.
default rho((at(L1),picked(key)),move(L))=10.

Fig. 3: Montezuma’s Revenge in BC

| No. | subtask                  | policy learned | in optimal plan |
|-----|--------------------------|----------------|-----------------|
| 1   | MP to LRL, no key        | ✓              | ✓               |
| 2   | LRL to LLL, no key       | ✓              | ✓               |
| 3   | LLL to key, no key       | ✓              | ✓               |
| 4   | key to LLL, with key     | ✓              | ✓               |
| 5   | LLL to LRL, with or without key | ✓ | ✓ |
| 6   | LRL to MP, with or without key | ✓ | ✓ |
| 7   | MP to RD, with key       | ✓              | ✓               |
| 8   | LRL to LS, with or without key | ✓ | ✓ |
| 9   | LS to key, with or without key | ✓ | ✓ |
| 10  | MP to RD, no key         | ✓              | ✓               |
| 11  | key to LRL, with key     | ✓              | ✓               |
| 12  | LRL to LRL, with key     | ✓              | ✓               |
| 13  | LRL to RD, with key      | ✓              | ✓               |

Table 1: Subtasks for Montezuma’s Revenge

In Fig.4 (Learning Curve), our method (SDRL) is compared with state-of-the-art approach, hierarchical DQN (hDQN) [9]. The learning curve of SDRL shows that the agent first discovered the plan of collecting key after 0.5M samples
by sequencing subtasks 1–3. Intrinsically motivated planning encourages exploring untried subtasks, and by learning more subtasks to move to other locations, the agent finally converges to the maximal cumulative external reward of 400 around 1.5M samples by sequencing subtasks 1–7 (Fig.4 (Final Solution)). By comparison, hDQN cannot reliably achieve the score of 400 around 2.5M samples. The shadow of the curves in Fig.4 (Learning Curve) represents the variance among multiple runs, which shows our SDRL has a small variance and can lead to more robust and stable learning.

4 Conclusion

This work demonstrates that by integrating symbolic planning with DRL for decision-making, explicitly represented symbolic knowledge can be used to perform high-level symbolic planning based on intrinsic goal which leads to improved task-level interpretability for DRL and data-efficiency. This framework makes the final solution converge to an optimal symbolic plan along with the learned subtasks, bringing together the advantages of long-term planning capability with symbolic knowledge and end-to-end reinforcement learning. In the future work, one promising direction is to investigate on subtask discovery and we are working on this.

References

1. Barto, A., Mahadevan, S.: Recent advances in hierarchical reinforcement learning. Discrete Event Systems Journal 13, 41–77 (2003)
2. Chen, K., Yang, F., Chen, X.: Planning with task-oriented knowledge acquisition for a service robot. In: IJCAI. pp. 812–818 (2016)
3. Gebser, M., Kaufmann, B., Schaub, T.: Conflict-driven answer set solving: From theory to practice. Artificial Intelligence 187-188, 52–89 (2012)
4. Gelfond, M., Lifschitz, V.: Action languages. Electronic Transactions on Artificial Intelligence (ETAI) (1998)
5. Gilpin, L.H., Bau, D., Yuan, B.Z., Bajwa, A., Specter, M., Kagel, L.: Explaining explanations: An approach to evaluating interpretability of machine learning. arXiv preprint arXiv:1806.00069 (2018)
6. Hanheide, M., Göbelbecker, M., Horn, G.S., et al.: Robot task planning and explanation in open and uncertain worlds. Artificial Intelligence (2015)
7. Helmert, M.: The fast downward planning system. Journal of Artificial Intelligence Research 26, 191–246 (2006)
8. Khandelwal, P., Zhang, S., Sinapov, J., Leonetti, M., Thomason, J., Yang, F., Gori, I., Svetlik, M., Khante, P., Lifschitz, V., Stone, P.: Bwibots: A platform for bridging the gap between ai and human–robot interaction research. The International Journal of Robotics Research 36(5-7), 635–659 (2017)
9. Kulkarni, T.D., Narasimhan, K., Saeedi, A., Tenenbaum, J.: Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. In: Advances in Neural Information Processing Systems. pp. 3675–3683 (2016)
10. Lifschitz, V.: What is answer set programming? In: Proceedings of the AAAI Conference on Artificial Intelligence. pp. 1594–1597. MIT Press (2008)
11. Lu, K., Zhang, S., Stone, P., Chen, X.: Robot representation and reasoning with knowledge from reinforcement learning. arXiv preprint arXiv:1809.11074 (2018)
12. Lyu, D., Yang, F., Liu, B., Gustafson, S.: Sdrl: Interpretable and data-efficient deep reinforcement learning leveraging symbolic planning. In: AAAI (2019)
13. McDermott, D., Ghalab, M., Howe, A., Knoblock, C., Ram, A., Veloso, M., Weld, D., Wilkins, D.: Pddl-the planning domain definition language (1998)
14. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., et al.: Human-level control through deep reinforcement learning. Nature 518(7540), 529–533 (2015)
15. Yang, F., Lyu, D., Liu, B., Gustafson, S.: Peorl: Integrating symbolic planning and hierarchical reinforcement learning for robust decision-making. In: International Joint Conference of Artificial Intelligence (IJCAI) (2018)