Guided Dyna-Q for Mobile Robot Exploration and Navigation

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Abstract

Model-based reinforcement learning (RL) enables an agent to learn world models from trial-and-error experiences toward achieving long-term goals. Automated planning, on the other hand, can be used for accomplishing tasks through reasoning with declarative action knowledge. Despite their shared goal of completing complex tasks, the development of RL and automated planning has mainly been isolated due to their different modalities of computation. Focusing on improving model-based RL agent’s exploration strategy and sample efficiency, we develop Guided Dyna-Q (GDQ) to enable RL agents to reason with action knowledge to avoid exploring less-relevant states toward more efficient task accomplishment. GDQ has been evaluated in simulation and using a mobile robot conducting navigation tasks in an office environment. Results show that GDQ reduces the effort in exploration while improving the quality of learned policies.

1 Introduction

Robots have been used to conduct a variety of tasks in human-inhabited environments, such as navigation and delivery [Khandelwal \textit{et al.}, 2017; Hawes \textit{et al.}, 2017]. These tasks often demand robots to take actions sequentially. In these domains, modeling world dynamics can be used to help the robots achieve long-term goals under uncertainty. When a world model is available, one can use Markov Decision Process (MDP) algorithms to compute action policies [Puterman, 2014]. In practice, however, world models are frequently unavailable or tend to change over time due to exogenous changes. Reinforcement learning (RL) algorithms have been used to solve sequential decision-making problems, where agents learn action policies toward maximizing long-term (discounted) rewards from the trial-and-error experiences [Sutton and Barto, 2018].

There are various types of RL algorithms. Among them, model-based RL enables agents to learn a world model while learning an action policy to achieve long-term goals [Brafman and Tennenholtz, 2002; Mann and Choe, 2011]. There are at least two advantages of model-based RL. First, one can easily incorporate domain knowledge from a human expert into a process of policy learning by planning. Second, model-based RL is goal-independent so that the learned world model applies to other tasks. We are particularly interested in (improving) model-based RL, due to the characteristics of service robotics domains, such as widely available domain knowledge (e.g., rooms are connected through doors), and diverse service requests.

We focus on addressing the low sample-efficiency challenge of model-based RL algorithms in this research. In this paper, we develop Guided Dyna-Q (GDQ) that, for the first time, integrates model-based RL with declarative action knowledge to help the agent avoid exploring less-relevant states toward more sample-efficient model learning and decision making. In particular, we use Answer Set Programming (ASP) to formulate action language [Lifschitz, 2002; Erdem \textit{et al.}, 2016], and use Dyna-Q for model-based RL [Sutton and Barto, 2018]. It should be noted that we only use widely available action knowledge, such as “To open a door, one has to be in front of it first”, where knowledge acquisition is not a problem. The goal is to consolidate the two classical paradigms of model-based RL and automated planning, and show that GDQ can leverage their complementary features to produce the best performance, as summarized in Figure 1.

We demonstrate and evaluate GDQ both in simulation and using a real mobile robot. Results show that GDQ significantly improves the learning efficiency in comparison to existing model-free and model-based RL methods, such as Q-Learning, Sarsa, Dyna-Q, and RMAX [Sutton and Barto, 2018; Brafman and Tennenholtz, 2002]. In a real-world office environment with more than 20 rooms, GDQ helped a robot learn the optimal solution from only 30 episodes, whereas Dyna-Q could not find a meaningful solution.

2 Related Work

We briefly summarize existing algorithms that used both automated planning with RL methods.

Model-free RL and automated planning have been combined to avoid taking unreasonable actions in exploration, resulting in an algorithm called DARLING [Leonetti \textit{et al.}, 2016]. Leveraging action preconditions and effects, DARLING has been applied to mobile robot navigation, and grid world domains. More recently, researchers have integrated automated planning and Q-learning (a model-free RL
paradigm) focusing on non-stationary domains under uncertainties [Ferreira et al., 2017]. Those algorithms exploited the flexibility of RL approaches and the accuracy of the declarative knowledge from humans. Researchers have developed other algorithms for efficiently guiding the agent to execute tasks and to learn policies under uncertainty [Ferreira et al., 2019; Yang et al., 2018; Lyu et al., 2019; Zhang et al., 2019; Furelos-Blanco et al., 2019]. In these works, researchers exploit the pre-designed models for constraining the state space and dealing with a change of world dynamics of a domain, instead of encouraging the agent to accumulate domain knowledge. The main difference from the above-mentioned methods is that GDQ (ours) uses model-based RL, whereas those methods used model-free RL that is goal-oriented. Our service robotics domain includes potentially many service requests, rendering goal-independent methods (e.g., model-based RL) more suitable.

There is the fundamental “logic-probability” gap between model-based RL and automated planning, where model-based RL relies on probabilistic transition systems, and traditionally automated planning does not model quantitative uncertainty. Aiming at bridging this gap, automated planning researchers have used logical-probabilistic paradigms to represent action knowledge, so as to directly reason about probabilistic transitions for model-based RL. For instance, Ng and Petrick recently developed an algorithm that generates and updates Probabilistic PDDL (PPDDL) [Younes and Littman, 2004] action models of automated planning by using model-based RL [Ng and Petrick, 2019]. Alternatively, researchers have developed new knowledge representation paradigms to help agents simultaneously reason with human knowledge and learn the model through interaction with the environment [Wang et al., 2019; Lu et al., 2018; Sridharan et al., 2019; Veiga et al., 2019; Sanner and Kording, 2010]. The above-mentioned methods require the human developer to manually encode logical-probabilistic knowledge, which requires significant professional skills and might soon become infeasible in large domains. In comparison, GDQ requires the minimum amount of widely available action knowledge, e.g., [Yang et al., 2014], such as “After going through a door, a robot will be on the other side of it,” rendering GDQ more applicable to real-world domains.

3 Background

In this section, we very briefly summarize Markov Decision Process (MDP), and model-based RL.

3.1 Markov Decision Process

MDP domains [Puterman, 2014] can be defined in the form of $D = \langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \gamma \rangle$, where $\mathcal{S}$ is a set of states, $\mathcal{A}$ is a set of actions, $\mathcal{T} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$ is a the transition function, $\mathcal{T}(s, a, s') = \Pr(s' | s, a)$ denotes a probability of reaching a future state $s'$ by taking action $a$ in state $s$. $\mathcal{R} : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{R}$ is a reward function. $\mathcal{R}(s, a)$ denotes the reward when the agent takes action $a$ in state $s$. $\gamma$ is the discount factor that expresses the preference towards earlier rewards over later ones.

We consider discrete, finite MDP domains, where agents (robots) interact with the environments at discrete time-steps, $n \in \mathbb{N}$. Given an MDP, one can compute a policy using the following Bellman equations.

$$Q^*(s, a) \leftarrow \mathcal{R}(s, a) + \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s, a, s') V^*(s')$$

$$\pi^* \leftarrow \arg\max_a Q^*(s, a)$$

where $V^*(s)$ denotes the value of state $s$, and $Q^*(s, a)$ denotes the value of state-action pair $(s, a)$. In practice, such Bellman equations can be solved using algorithms, such as value iteration and policy iteration [Puterman, 2014].

3.2 Reinforcement Learning

When world models (transition, reward, or both) are not known, the agent must learn action policies from trial-and-error experiences. Q-learning is a model-free RL algorithm, and its $Q$ function can be updated as below.

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[ r + \gamma \max_{a'} Q(s', a') - Q(s, a) \right]$$

where $r$ is the immediate reward after taking action $a$ in state $s$. This update procedure enables the agent to incrementally learn from every single $(s, a, s', r)$ sample.

Model-based RL algorithms, on the other hand, learn the world model, including $\mathcal{R}(s, a)$ and $\mathcal{T}(s, a, s')$, and then use
planning algorithms to compute the action policy. Dyna-Q [Sutton, 1991] is a model-based RL framework, and includes the two primary components of model-free RL (Q-learning) and probabilistic planning (e.g., value iteration). The real-world interaction experience is used for two purposes in Dyna-Q: world model learning, and action policy learning. Besides, Dyna-Q is able to generate extra (simulation) experience through interacting with the learned world model, which further speeds up the policy learning process. We use declarative action knowledge to prevent the Dyna-Q agent from exploring less-relevant states.

4 Algorithm

In this section, we present Guided Dyna-Q (GDQ), the key contribution of this research, that enables the interplay between a model-based reinforcement learner and an automated planner. Although both of the paradigms have been well developed in AI literature, their development has been largely isolated in the past. GDQ bridges the two fundamentally different paradigms to leverage goal-independent action knowledge for sample-efficient RL.

We use $\Pi(S^A, A^A, M)$ to represent our automated planner, where $S^A$ and $A^A$ are the state and action sets respectively. A task to the automated planner is defined as

$$M = (s_0, s^G)$$

where $s_0, s^G \in S^A$ are the initial state and goal states respectively. For simplification, the goal is defined as a single state, $G$, where

$$\Pi(s, a, s) = \begin{cases} 1 & \text{if } G = s \\ 0 & \text{otherwise} \end{cases}$$

Intuitively, the automated planner can serve as an optimistic planning algorithm [Brafman and Tennenholtz, 2002]. Lines 1-5 are used for initializing the Q-values, as well as the state and action spaces of both the reinforcement learner and the automated planner. $M$ is the provided task. The output is policy $\pi$, which is generated by the agent interacting with the world.

Lines 1-5 are used for initializing the Q-values, as well as the transition and reward functions. The transition function is initialized in a way that all state-action pairs deterministically lead to the initial state. This setting is necessary, because all plans computed by the automated planner start from the initial state. Given task $M = (s_0, s_g)$, our automated planner computes a set of optimistic plans in Line 6. The two for-loops in Lines 7-11 assigns the highest reward, $R_{max}$, to all state-action pairs that appear in the plans from our automated planner. This setting is very similar to the R-MAX algorithm [Brafman and Tennenholtz, 2002]. Lines 13-19 are used for computing an action policy using policy iteration. Finally, the computed policy is returned in Line 20.

It should be noted that the agent has not started interacting with the environment while running OptInit (Algorithm 1). This initialization process enables the agent to prioritize states that are more relevant to the current task in exploring its working environment, which helps the agent to accomplish tasks more efficiently.

4.1 Optimistic Initialization

The plans computed by the automated planner are referred to as optimistic plans, because real-world domain uncertainty is frequently overlooked in building planners. For instance, a robot taking the action of "navigate to room R" sometimes does not result in the robot being in room R due to the possibility of obstacles on the way there. The goal of optimistic initialization (OptInit) is to use the plans computed by the automated planner to initialize Q-values, and prevent the agent from exploring less-relevant states.

Algorithm 1 Optimistic Initialization: OptInit

| Parameter | | |
|---|---|---|
| $\gamma$, $\alpha$, $R_{max}$ | |

**Input:** $S, A, S^A, A^A, M = (s_0, s^G)$

1: for $s \in S, a \in A(s)$ do // Initialize Q-values and $R, T$
2: $Q(s, a) \leftarrow 0$
3: $R(s, a) \leftarrow 0$
4: $T(s, a, s_0) \leftarrow 1.0$
5: end for
6: $\mathcal{H} \leftarrow \Pi(S^A, A^A, M)$ // Compute a set of optimistic plans
7: for $p$ in $\mathcal{H}$ do
8: for $(s, a, s')$ in $p$ do
9: $R(s, a) \leftarrow R_{max}$ // Optimistically update $R$
10: end for
11: end for
12: $\pi \leftarrow$ random policy // Randomly initialize a policy
13: while $\pi \neq \pi'$ do
14: $\pi' \leftarrow \pi$
15: for $s \in S$ do
16: $Q(s, \pi(s)) \leftarrow -R(s, \pi(s)) + \gamma \sum_{s' \in S} T(s, \pi(s), s') Q(s', \pi(s'))$
17: end for
18: $\pi(s) \leftarrow \text{argmax}_a Q(s, a)$
19: end while
20: return $\pi$

The last subsection (Sec. 4.1) presents the process of initializing the Q-function using the optimistic plans generated by our automated planner. Given the initialized value function, the agent is able to compute an initial policy, and use this policy to interact with the real world. In this subsection, we describe how the interaction experience, along with the automated planner, is used to update the value function at runtime. Intuitively, the automated planner can serve as an optimistic
Algorithm 2 Policy Update (POLICYUP)

Input: $S, A, S^A, A^A, M = (s_0, s^G)$, $\pi$, $C$, $R_{sum}$
Parameter: $\gamma$, $\alpha$, $R_{max}$, $m$, $N$
Output: $R(s,a)$, $T(s,a,s')$, $\pi_{new}$

1: Collect the current world state $s$ from the world
2: $a \leftarrow \pi(s)$ // Select an action using policy $\pi$
3: Collect resulting state $s'$ and reward $r$ after taking $a$
4: Update the Q-value using real interaction experience
   $$Q(s,a) \leftarrow Q(s,a) + \alpha [r + \gamma \max_a Q(s',a) - Q(s,a)]$$
5: $C(s,a,s') \leftarrow C(s,a,s') + 1$
6: $R_{sum}(s,a) \leftarrow R_{sum}(s,a) + r$
7: if $\sum_{s'} C(s,a,s') > m$ then
8: $T(s,a,s') \leftarrow C(s,a,s') / \sum_{s'} C(s,a,s')$
9: $R(s,a) \leftarrow R_{sum}(s,a) / \sum_{s'} C(s,a,s')$
10: end if
11: $H \leftarrow \pi(M,s,s^G)$ // Compute a set of plans
12: for $n \in \{1...N\}$ do
13: $p \leftarrow$ randomly selected plan in $H$
14: $s, a, s' \leftarrow$ randomly selected transition in $p$
15: $Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha[R(s,a) + \gamma \max_{a'} Q(s',a')]$
16: end for
17: $\forall s \in S, \forall a \in A, \pi(s) \leftarrow \arg\max_a Q(s,a)$
18: return $R(s,a)$, $T(s,a,s')$, $\pi(s)$

Algorithm 3 Guided Dyna-Q (GDQ)

Input: $S, A, S^A, A^A, M = (s_0, s^G)$, $\pi$, $C$
Output: $\pi$
1: Call Algorithm-1:
   $\pi \leftarrow \text{OPTINIT}(S,A,S^A,A^A,M)$
2: for all $s \in S, \forall a \in A, \forall s' \in S, C(s,a,s') \leftarrow 0$
3: while Current state $s$ is not terminal do
4: Call Algorithm-2:
   $R, T, \pi \leftarrow \text{POLICYUP}(S,A,S^A,A^A,M,\pi,C)$
5: end while
6: return $\pi$

simulator to enable the reinforcement learner to learn from interaction experience in simulation.

Algorithm 2 presents the runtime policy update process. Its input is the same as Algorithm 1, except that it also includes an action policy and a counter function $C$. This policy can be provided by Algorithm 1. Parameter $m$ is a threshold, representing how many times a state-action pair has been selected. Parameter $N$ is used for determining how many state-action pairs are simulated using the automated planner. The output includes not only a policy, but also the reward and transition functions, because our reinforcement learner is model-based.

Lines 1-4 are used for interacting with the real world using the current action policy, $\pi$. Then, $C(s,a,s')$ is increased by one for counting the number of state-action-state triples. If the agent has visited a state-action pair for more than $m$ times (Line 7), the transition and reward functions are updated. Intuitively, $m$ is a parameter that indicates a state-action pair being known or unknown. In Line 11, the automated planner generates a set of plans. Using the generated plans, we randomly select one transition from a randomly-selected plan $p \in H$, and update the Q-value accordingly. This Q-value update process is repeated for $N$ times in Lines 12-16. Finally, the reward function, transition function, and updated policy is returned.

Algorithm 3 integrates the two sub-procedures for optimistic initialization (Algorithm 1) and repeatedly conducting runtime policy update (Algorithm 2), which identifies the main contribution of this research. Informally, Algorithm 1 helps the agent avoid the near-random exploration behaviors through a “warm start” enabled by our automated planner, and Algorithm 2 guides the agent to only try the actions that can potentially lead to the ultimate goal states. Next, we present our experiment setup, and results from comparisons between GDQ and a number of baseline methods selected from the literature.

5 Experiment

Our central hypothesis (Hypothesis-I) is that GDQ performs better than existing reinforcement learning methods (model-based and model-free), and the performance is evaluated based on the cumulative reward in each episode. Our secondary hypothesis (Hypothesis-II) is that GDQ can help the robot avoid visiting less-relevant areas. We have selected a set of baseline methods that are very well-known within the RL community, including Q-learning, Sarsa, Dyna-Q, and RMAX [Sutton and Barto, 2018; Brafman and Tennenholtz, 2002], where the first two are model-free and the other two are model-based.

We have conducted experiments in a mobile robot naviga-
tion domain both in simulation and using a real robot. In each trial (episode), the robot is tasked with navigating from its initial position to a goal position. There are doors connecting rooms and corridors, and there are different costs and success rates in navigation and door opening actions. The robot has four actions of goto, approach, open door, and gothrough for navigational purposes. We used the Building Wide Intelligence codebase for robot navigation [Khandelwal et al., 2017] and automated planning [Zhang et al., 2015].

In order to evaluate our hypothesis that GDQ helps the robot avoid visiting less-relevant areas (Hypothesis-II), we define seven areas in the map, as shown in Figure 2. Some of the areas are directly accessible to each other (e.g., Areas 6 and 7), where the others are connected through doors (e.g., Areas 1 and 2). We have labeled five doors in the map. All doors are automatic, meaning that, to go through a door, the robot must get close to it, and open it before taking the gothrough action. The real robot needs help from people for door opening actions (printing on its screen “Please help me open the door”), which requires different time durations depending on people’s availability. In simulation, each door is associated with a distribution over success rates, and another distribution over action costs. We tried to give realistic distributions to match to the real door’s physical properties (width, location, weight, etc). Informally, $D_1$, $D_3$, and $D_4$ are difficult doors, where $D_1$ is the most difficult. $D_0$, $D_2$, and $D_5$ are relatively easy and $D_2$ is the easiest.

### 5.1 Simulation Experiment

The robot receives a big reward, $R_{\text{max}}$, in successful trials, receives a big penalty, $-R_{\text{max}}$, in failure trials, and receive a small cost, $c$, from all navigation actions. In this experiment, $R_{\text{max}} = 50$, and $c = 1$. Our robot tries a random action in the probability of $\epsilon = 0.1$. The learning rate is $\alpha = 0.1$, and the discount factor is $\gamma = 0.95$. We set a threshold as the maximum number of actions allowed in each episode. Not being able to complete a task within 25 action makes a trial unsuccessful. Each “run” includes 500 episodes in a row, and each data point of our figures is an average over 10 runs.

We have conducted four independent experiments in simulation, where each experiment has a different pair of initial and goal positions. From Task $A$ to Task $D$, their initial and goal positions are $S_1 \rightarrow G_1$, $S_1 \rightarrow G_2$, $S_2 \rightarrow G_1$, and $S_2 \rightarrow G_2$ respectively.

**Cumulative Reward** Figures 3’s (Figures 4’s) top and bottom subfigures respectively present the cumulative rewards collected from the robot conducting Tasks $A$ and $B$ (Tasks $C$ and $D$). We observe that GDQ performed the best in learning rate in comparison to the four baselines, which supports Hypothesis-I.

Looking into Task-$A$ (results shown in the top sub-figure of Figure 3), there are the following valid routes that can lead to the goal position (with different costs and success rates): $[1 \rightarrow 2 \rightarrow 6]$, $[1 \rightarrow 3 \rightarrow 6]$, $[1 \rightarrow 3 \rightarrow 4 \rightarrow 7 \rightarrow 6]$, $[1 \rightarrow 3 \rightarrow 2 \rightarrow 6]$, $[1 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 7 \rightarrow 6]$, where each number corresponds to the index of an area. The shortest routes are $[1 \rightarrow 2 \rightarrow 6]$, and $[1 \rightarrow 3 \rightarrow 6]$. However, the two routes have doors of $D_0$ and $D_2$ on the way. In comparison, the route of $[1 \rightarrow 3 \rightarrow 2 \rightarrow 6]$ provides the best trade-off between traveling distance and door difficulty, and is the best solution. GDQ enabled the robot to convert to this solution earlier than all other baseline methods.

**Exploration** Our secondary hypothesis (Hypothesis-II) is that GDQ can help the robot avoid exploring the irrelevant
states. We manually provide the ground truth relevance information, where $IRR$ maps a task to a set of irrelevant areas, $\{4, 5, 7\} \leftarrow IRR(A)$, $\{5\} \leftarrow IRR(B)$, $\{1, 2, 3, 4\} \leftarrow IRR(C)$, and $\{1, 2, 3, 4, 6\} \leftarrow IRR(D)$.

Table 1 shows the results in evaluating the performances in exploration. The blue color highlights the method that produced the least visits, and we say the robot successfully avoids the area using this method. Consider the first five rows that correspond to Task-A. We see that GDQ enabled the robot to visit Area-4 for as few as only 106 times, which is much lower than the numbers of visits required by the other methods (say Sarsa requires 49362 visits), while still producing the best performance in policy quality. This observation is consistent with our prior knowledge that Areas 4, 5, and 7 are less-relevant to Task-A. In all four tasks, the robot successfully avoided 11 less-relevant areas out of the total 13 areas over the four tasks.

### 5.2 Real Robot Experiment

We have conducted experiments in the real world using a Segway-based mobile robot platform. In the real world, the robot has to ask people to help open doors, where the action cost and success rate are out of our control. We intentionally forbade the robot to enter Area-5, because it is a long corridor, and navigating through that area takes a very long time. The robot’s task is $S2 \rightarrow G1$, which is referred to as Task-X. The following parameters are used in real-world experiment: $R_{\text{max}} = 1000$, $\alpha = 0.5$, $\gamma = 0.95$, and $\epsilon = 0.1$. What is different from simulation is that we use time to measure the cost of navigation, and door-opening actions (instead of a predefined fixed value). A maximum of 10 steps is allowed, i.e., if the robot cannot complete Task-X in 10 steps, the corresponding trial will be deemed unsuccessful. We have conducted a total of 30 trails using the real robot. Due to the very long time required for each trial, we only compared GDQ to one baseline of Dyna-Q.

Figure 5 reports the results collected from the real-robot experiment. The curves have been smoothed using a sliding window over five episodes. Looking at the very left of the two curves, the “jump start” of GDQ shows that Algorithm 1 (optimistic initialization) helped the robot successfully avoid the “random” exploration behaviors in the early phase. Once the robot started interacting with the real world, we can see the cumulative reward of GDQ is consistently higher than Dyna-Q, except for only the 17th episode. After that, GDQ soon found the optimal solution. In comparison, Dyna-Q could not find a meaningful solution within total 30 episodes. We have generated a video (anonimized) for the demonstration of GDQ’s performance in a real world.

### 6 Conclusions

In this paper, we develop Guided Dyna-Q (GDQ) for bridging the gap between model-based RL, and automated planning. The goal is to help the agent (robot) avoid exploring less-relevant states toward speeding up the learning process. GDQ has been demonstrated and evaluated both in simulation and using a real robot conducting navigation tasks in a many-room office environment. We see that, using the widely available action knowledge, GDQ performed significantly better than four popular baseline methods from the literature.

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1. https://www.dropbox.com/s/a8nde17733unxnxUCAI2020
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