Affordance-Aware Planning

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***Abstract*—Planning algorithms for non-deterministic domains are often intractable in large state spaces due to the well-known "curse of dimensionality." Existing approaches to address this problem fail to prevent the planner from considering many actions which would be obviously irrelevant to a human solving the same problem. We introduce a novel, state- and reward-general approach to pruning actions while solving an MDP by encoding knowledge about the domain in terms of *affordances* [?]. This pruning significantly reduces the number of state-action pairs the agent needs to evaluate in order to act optimally. We demonstrate our approach in the Minecraft domain, showing significant increase in speed and reduction in state-space exploration compared to the standard versions of these algorithms. Further, we provide a learning framework based on simulation through scaffolding that enables an agent to learn affordances through experience, removing the dependence on the expert. We provide preliminary results indicating that the learning process effectively produces affordances that help solve an MDP faster.**

I. Introduction

As robots move out of the lab and into the real world, planning algorithms need to scale to domains of increased noise, size, and complexity. A classic formalization of this problem is a stochastic sequential decision making problem in which the agent must find a policy (a mapping from states to actions) for some subset of the state space that enables the agent to achieve a goal from some initial state, while minimizing any costs along the way. Increases in planning problem size and complexity directly correspond to an explosion in the state-action space. Current approaches to solving sequential decision making problems in the face of uncertainty cannot tackle these problems as the state-action space becomes too large [?].

To address this state-space explosion, prior work has explored adding knowledge to the planner to solve problems in these massive domains, such as options [?] and macroactions [? ?]. However, these approaches add knowledge in the form of additional high-level actions to the agent, which *increases* the size of the state-action space (while also allowing the agent to search more deeply within the space). The resulting augmented space is even larger, which can have the paradoxical effect of increasing the search time for a good policy. Further, other approaches fall short of learning useful, transferable knowledge, either due to complexity or lack of generalizability (cite? where is this stated? George?).

Instead, we propose a formalization of *affordances* [?] that enables an agent to focus on problem-specific aspects of the environment. Our approach avoids exploration of irrelevant parts of the state-action space, which leads to dramatic speedups in planning.

We formalize the notion of an affordance as a piece of planning knowledge provided to an agent operating in a Markov Decision Process (MDP). Affordances are not specific to a particular reward function or state space, and thus, provide the agent with transferable knowledge that is effective in a wide variety of problems. Because affordances define the *kind* of goals for which actions are useful, affordances also enable high-level reasoning that can be combined with approaches like subgoal planning for even greater performance gains. In Figure **??**, we demonstrate the effectiveness of affordance-aware subgoal planning on a complicated task in the Minecraft domain.[1] We let other standard planners try to solve this task for several hours, but they all failed to converge on a policy (while affordance-aware subgoal planner found a near-optimal policy in less than 5 minutes).

II. Background

We use Minecraft as our planning and evaluation domain. Minecraft is a 3-D blocks world game in which the user can place and destroy blocks of different types. Minecraft's physics and action space is expressive enough to allow very complex worlds to be created by users, such as a functional scientific graphing calculator[2]; simple scenes from a Minecraft world appear in Figure **??**.

Minecraft serves as an effective parallel for the actual world, both in terms of approximating the complexity and scope of planning problems, as well as modeling the uncertainty and noise presented to a real world agent. For instance, robotic agents are prone to uncertainty all throughout their system, including noise in their sensors (cameras, LIDAR, microphones, etc.), odometry, control, and actuation. In order to accurately capture some of the inherent difficulties of planning under uncertainty, the Minecraft agent's actions were modified to have stochastic outcomes. These stochastic outcomes may require important changes in the optimal policy in contrast to deterministic actions, such as keeping the agent's distance from a pit of lava. We chose to give the Minecraft agent perfect sensor data about the Minecraft world, as that is outside the focus of this work.

A. OO-MDPs

We define affordances in terms of propositional functions on states. Our definition builds on the Object-Oriented Markov Decision Process (OO-MDP) [?]. OO-MDPs are an extension of the classic Markov Decision Process (MDP). A classic MDP is a five-tuple: $\langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \gamma \rangle$, where $\mathcal{S}$ is a state-space; $\mathcal{A}$ is the agent's set of actions; $\mathcal{T}$ denotes $\mathcal{T}(s' \mid s, a)$, the transition probability of an agent applying action $a \in \mathcal{A}$ in state $s \in \mathcal{S}$ and arriving in $s' \in \mathcal{S}$; $\mathcal{R}(s, a, s')$ denotes the reward received by the agent for applying action a in state s

[1] Watch at: https://vimeo.com/88689171
[2] https://www.youtube.com/watch?v=wgJfVRhotlQ

and and transitioning to state s'; and $\gamma \in [0, 1)$ is a discount factor that defines how much the agent prefers immediate rewards over distant rewards (the agent more greatly prefers to maximize more immediate rewards as γ decreases).

A classic way to provide a factored representation of an MDP state is to represent each MDP state as a single feature vector. By contrast, an OO-MDP represents the state space as a collection of objects, $O = \{o_1, \ldots, o_o\}$. Each object o_i belongs to a class $c_j \in \{c_1, \ldots, c_c\}$. Every class has a set of attributes $Att(c) = \{c.a_1, \ldots, c.a_a\}$, each of which has a domain $Dom(c.a)$ of possible values. Upon instantiation of an object class, its attributes are given a state $o.state$ (an assignment of values to its attributes). The underlying MDP state is the set of all the object states: $s \in \mathcal{S} = \cup_{i=1}^{o} \{o_i.state\}$.

There are two advantages to using an object-oriented factored state representation instead of a single feature vector. First, different states in the same state space may contain different numbers of objects of varying classes, which is useful in domains like Minecraft in which the agent can dynamically add and remove blocks to the world. Second, MDP states can be defined invariantly to the specific object references. For instance, consider a Minecraft world with two block objects, b_1 and b_2. If the agent picked up and swapped the position of b_1 and b_2, the MDP state before the swap and after the swap would be the same, because the MDP state definition is invariant to which object holds which object state. This object reference invariance results in a smaller state space compared to representations like feature vectors in which changes to value assignments always result in a different state.

III. Hard-Affordances

A. Formalism

B. Experiments

C. Results

IV. Learning-Affordances

A. Extended Formalism

B. Learning Process

C. Experiments

D. Results

V. Conclusion

VI. RSS citations

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```
\cite{kalman1960new} demonstrated...
```

rendered as "[**?**] demonstrated...," or the inconvenient

```
Kalman \cite{kalman1960new}
demonstrated...
```

rendered as "Kalman [**?**] demonstrated...", one can write

```
\citet{kalman1960new} demonstrated...
```

which renders as "**?**] demonstrated..." and is both easy to write and much easier to read.

A. RSS Hyperlinks

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@article{McGeer01041990,
  author = {McGeer, Tad},
  title = {\href{http://ijr.sagepub.com/content/9/2/62.a
  volume = {9},
  number = {2},
  pages = {62-82},
  year = {1990},
  doi = {10.1177/027836499000900206},
  URL = {http://ijr.sagepub.com/content/9/2/62.abstract}
  eprint = {http://ijr.sagepub.com/content/9/2/62.full.p
  journal = {The International Journal of Robotics Resea
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[1] Tad McGeer. Passive Dynamic Walking. *The International Journal of Robotics Research*, 9(2):62–82, 1990.

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Acknowledgments