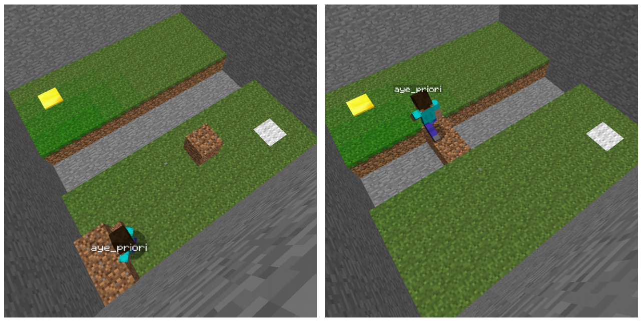
Planning with Affordances

Abstract

Planning algorithms for non-deterministic domains are often intractable in large state and action spaces due to the well-known "curse of dimensionality." Approaches to address this problem by providing the system with formally encoded knowledge still fail to prevent the system from considering many actions which would be obviously irrelevant to a human solving the same problem. To solve this issue, we introduce a novel approach which represents knowledge about the domain in terms of *affordances* [11]. Our affordance formalism and may be coupled with a variety of planning frameworks in what we call "affordance-aware planning", allowing an agent to efficiently prune its action space based on domain knowledge. 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 on several planning and building tasks by solving these tasks with affordance-aware versions of planners from a variety of planning paradigms. We show a significant increase in speed and reduction in state-space exploration compared to the standard versions of these algorithms.

1 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 cannot tackle these problems as the state-action space becomes too large [12].



(a) Planning with VI. (b) Planning with affordances.

Figure 1: Scenes from a Minecraft agent planning using Value Iteration (VI) compared to affordance-aware VI in a bridge building task. VI considers states which would be obviously irrelevant to a human solving the same problem, such as stacking blocks in the corner. Our affordance agent, in contrast, focuses on placing blocks in the trench, which are much more relevant to reaching the goal.

To address this state-space explosion, prior work has explored adding knowledge to the planner to enable it to solve problems in these massive domains. However, previous approaches such as options and macro-actions work by providing 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.

We propose addressing this issue by focusing on problem-specific aspects of the environment which guide the search toward the most relevant and useful parts of the state-action space. This approach aims to *reduce* the size of the explored state action space, leading to dramatic speedups in planning. Our approach is a formalization of *affordances*, introduced by Gibson [11] as "what [the environment] offers [an] animal, what [the environment] provides or furnishes, either for good or ill."

We formalize the notion of an affordance as a piece of planning knowledge provided to an agent operating in a Markov Decision Process (MDP). We explain how affordances can be leveraged by a variety of planning algorithms to prune the action set the agent uses dynamically based on the agent's current goal. We call any planning algorithm that uses affordances to prune the action set an *affordance-aware* planning algorithm. A useful property of affordances is that they are not specific to a particular reward function or goal, and thus, provide the agent with transferable knowledge that is effective in a wide variety of problems.

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 players have constructed complex worlds, including models of a scientific graphing calculator [1]; scenes from a Minecraft world appear in Figure ref-fig:minecraft.

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 an real world agent (e.g. a robot). 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 (and the API through which it is controlled) as well as the planning tasks we experiment on all capture the stochasticity that affect robotics agents. We have chosen to give the Minecraft agent non-noisy sensory data about the Minecraft world, as that is outside the scope of this project. **DG: Not sure how to phrase this bit, but we want to state that sensory noise is not a problem we are catering to**

One of the most significant difficulties of dealing with an agent planning in a noisy world (such as a robot) is that many of its actions can have unintended consequences, often leading to disastrous results. We model these potentially dangerous situations by requiring that the actions in the Minecraft domain be non-deterministic. Furthermore, we add pits of lava to many (but not all) of our experiments, which force the agent to plan conservatively in order to avoid falling in.

[1]https://www.youtube.com/watch?v=wgJfVRhotlQ

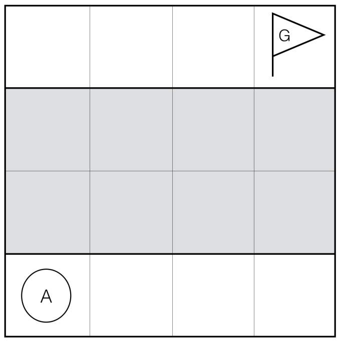


Figure 2: In the above Minecraft planning problem `BRIDGEWORLD`, the agent must place a block in the trench in order to reach the goal (the trench is too wide to jump over).

As a running example, we will consider the problem of an agent attempting to cross a trench in a $4 \times 4 \times 2$ Minecraft world shown in Figure 2. The floor (at $z = 1$) [2] is composed of 8 solid blocks, with horizontal empty trenches at $y = 2$ and $y = 3$. The agent is at the starting location $(1, 1, 2)$ and needs to reach the goal at $(4, 4, 2)$

To solve the problem, the agent must place a block in the trench to form a bridge, then cross the bridge to reach the goal. This task is challenging for planning algorithms to solve because the reachable state space in Minecraft is so large. For example, the number of places an agent can place and destroy blocks alone can result in a combinatorial explosion of the state space. Given an agent capable of placing and destroying blocks in a world with dimensions $w \times l \times h$, there are:

$$O\left(\sum_{n=1}^{w \cdot l \cdot h} \binom{w \cdot l \cdot h}{n}\right) \tag{1}$$

states, which is too large for a standard planner to explore in a reasonable time.

An affordance-aware planner, however, (when equipped with the proper affordances) will only attempt to place a or destroy a block when it is useful. The usefulness of a given action is congruent to how effective that action is at moving the agent closer to the goal (akin to a heuristic). Thus, when the agent is in states that are not considered useful (i.e. the

[2]The z-axis is the height of the Minecraft world. Similarly, the x-axis is its width and the y-axis is its length.

predicate p is false), the agent will not have access to the block placement action. This prevents the agent from trying countless applications of actions that would ultimately not contribute towards reaching the goal.

2 BACKGROUND

We define affordances in terms of propositional functions on states. Our definition builds on the Object-Oriented Markov Decision Process (OO-MDP) [10]. OO-MDPs [10] 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 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. In 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 $Dom(c.a)$. 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 (and then returned to the agent's previous position in the world), 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. Formally, if there exists a bijection between two sets of objects that maps each object in one set to an object in the other set with the same object state, then the two sets of objects define the same MDP state. This object reference invariance results in a smaller state space compared to

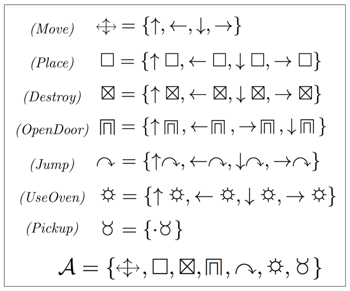


Figure 3: The set of all actions in the Minecraft domain.

representations like feature vectors in which changes to value assignments always result in a different state.

While the OO-MDP state definition is a good fit for the Minecraft domain, our motivation for using an OO-MDP lies in the ability to formulate predicates over classes of objects. That is, the OO-MDP definition also includes a set of predicates $\mathcal{P}$ that operate on the state of objects to provide additional high-level information about the MDP state. For example, in `BRIDGEWORLD`, a `nearTrench(AGENT)` predicate evaluates to true when the singular instance of class `AGENT` is directly adjacent to an empty location at floor level (i.e. the cell beneath the agent in some direction does not contain a block). In the original OO-MDP work, these predicates were used to model and learn an MDP's transition dynamics. In the next section, we use the predicates to define affordances that enable planning algorithms to prune irrelevant actions.

3 AFFORDANCES

In many planning scenarios, not all actions are needed in all states. In fact, many applications of actions in states do not contribute toward solving the planning task, but instead, cause the state-space to grow exponentially, especially true in domains in which the agent's actions can drastically shape the environment, such as in Minecraft. We capture this intuition via an affordance Δ, defined as a tuple, $\langle p, g \rangle \longmapsto \alpha$, where:

α is a subset of the action space, $\mathcal{A}$

p is a predicate on states, $s \longrightarrow \{0, 1\}$ representing the *precondition* for the affordance.

g is a predicate on states, $s \longrightarrow \{0, 1\}$ representing the *postcondition*.

The precondition, p, and goal, g, refer to predicates over an OO-MDP state, where an OO-MDP state is represented as a union of all of the objects' current attribute values: $\cup_{i=1}^{o} o_i.state$. The use of an OO-MDP

here makes predicates more general and robust (e.g. OO-MDP predicates may be relational) across tasks and is one of the reasons that affordance-aware planners may be untethered from specific state spaces, as the predicates of an affordance p and g are as prescribed by an OO-MDP. **JM: This text doesn't quite make sense to me. How are the OO-MDP predicates subsets of the objects? I think what this is trying to say is that p and g can be defined compactly using OO-MDP predicates. However, it's not necessarily true that OO-MDP predicates *completely* describe the MDP. In fact, unless you have explicit position predicates, it won't completely describe the MDP state space.**
I think an example of an affordance in terms of the formal definition needs to be provided here as well. ST: Agree with JM's comment. We need to say how affordances connect to an OO-MDP, but above isn't quite right. DG: Does this version work? Do we need to be more specific?

Algorithm 1 pruneActions(*state*, *KB*)
Complexity: $\mathcal{O}(|KB|)$

```
1: for $\Delta \in KB$ do
2:     if $\Delta.p(state)$ and $\Delta.g == state.goal$ then
3:         $\alpha.update(\Delta.p, \Delta.g)$
4:     end if
5: end for
6: return $\alpha$
```

The primary benefit of encoding goal relative knowledge in each affordance is that actions may be pruned with respect to a given goal. For instance, if the agent is at the trench in `BRIDGEWORLD` and trying to reach the goal then it would not consider destroying any arbitrary block, as that would not further its ability to reach the goal. Instead, we endow the agent with the following affordance: $\Delta_1 = \langle nearWall, reachGoal\rangle\rangle \longmapsto \{\boxtimes\}$, that tells the agent to try destroying blocks when next to a wall (as the wall could inhibit its progress toward reaching the goal). In conjunction with the other affordances provided for this problem[3] Eliminating the "destroy" action avoids exploring every consequent state in which that block has been destroyed. As a result, agents may be endowed with huge action sets that enables them to solve a variety of problems across variable state-spaces, while only exploring a small action set that is relevant to each task. Currently, we provide each agent with sets of affordances that enable the agent to prune away its unnecessary actions optimally. We envision that these affordances may be learned as well.

We propose the notion of an *affordance-aware* planner, which refers to a planning algorithm that prunes the actions set according to affordances. Action set pruning affects different planning algorithms in different ways. In particular, we focus on how action pruning benefits *dynamic programming*, *policy rollout*, and *subgoal* planning paradigms.

3.1 Dynamic Programming

In dynamic programming paradigms, the planning algorithm estimates the optimal *value function* for each state. Formally, the optimal value function (V^*) defines the expected discounted return from following the optimal policy in each state:

$$V^*(s) = \max_{a \in \mathcal{A}(s)} \sum_{s'} \Pr(s' \mid s, a) \left[\mathcal{R}(s, a, s') + \gamma V^*(s')\right]; \tag{2}$$

this equation is known as the Bellman equation [4]. Given the optimal value function, the optimal policy is derived by taking the action that maximizes the values of each state. More specifically, by taking the action with the highest optimal state-action value:

$$Q^*(s, a) = \sum_{s'} \Pr(s' \mid s, a) \left[\mathcal{R}(s, a, s') + \gamma V^*(s')\right]. \tag{3}$$

Dynamic programming planning algorithms (such as Value Iteration [4]) estimate the optimal value function by initializing the value of each state arbitrarily and iteratively updating the value of each state by setting its value to the result of the right-hand-side of the Bellman equation using its current estimate of V instead of V^*. Iteratively updating the value function estimate in this way is guaranteed to converge to the optimal value function.

Using a pruned action set in dynamic programming can accelerate its computation in two ways: (1) by reducing the number of actions over which the max operator in the Bellman equation must iterate and (2) by restricting the state space for which the value function is estimated to the states that are reachable with the pruned action set from the initial state. Note that neither of these computational gains come at the cost of solution optimality as long as the pruned action set contains the actions necessary for an optimal policy from the initial state. In the case of the Bellman equation, the max operator makes the value function indifferent to the effects of actions that are not part of the optimal policy; therefore, the action set can be reduced entirely to the actions in the optimal policy without sacrificing optimality. Similarly, since we are only concerned with finding a good policy to dictate behavior from some initial state, the state space for

[3] $\Delta_2 = \langle onPlane, reachGoal\rangle\rangle \longmapsto \{\updownarrow\leftrightarrow\}$,
$\Delta_3 = \langle nearTrench, reachGoal\rangle \longmapsto \{\square\}$

which the value function is computed can be reduced to that which is reachable using only the optimal actions without sacrificing optimality. **ST: So the stuff about not sacrificing the optimal policy seems right, but I wonder if we can say something more formal about what has to be true about affordances in order for affordance planning to still be optimal.** **DG: Agreed - that would be a compelling bit to include, though I think we're ironing out the details of affordances still (more to come in our next email). So for now I vote we table this until a few days down the line**

3.2 Policy Rollout

In policy rollout planning paradigms, the agent starts with some initial policy and follows it (or rolls out the policy) from an initial/current state to either some maximum time horizon or until a terminal state is reached. Often, these approaches use samples from the policy rollout to improve estimates of the value function and indirectly improve the rollout policy. Examples of planning algorithms in this paradigm include Monte Carlo methods [7, 26] and temporal difference methods [2, 19, 22, 24, 27, 28]. By using a pruned action set, the policy space, and resulting state space explored from the searched policies, is reduced, thereby reducing the number of rollouts necessary to find a good policy. Similar to dynamic programming paradigms, as long as the pruned action set contains actions necessary for the optimal policy, solution optimality will not be sacrificed.

In this work, we will explore how real time dynamic programming (RTDP) [3] benefits from affordances. RTDP is both a dynamic programming algorithm and a policy rollout algorithm. RTDP starts by initializing the value function optimistically. It then follows a greedy rollout policy with respect to its currently estimated value function. After each action selection in the policy rollout, RTDP updates its estimate of the value function for the last state using the Bellman equation. RTDP is guaranteed to converge to the optimal policy from some initial state and has the advantage that it iteratively refocuses its attention to states that are likely to be on the path of the optimal policy.

In affordance-aware RTDP, the action selection of the rollout policy is restricted to the affordance-pruned action set and the Bellman equation is similarly restricted to operating on the affordance-pruned action set.

3.3 Subgoal Planning

Subgoal planning leverages the intuition that certain goals in planning domains may only be brought about if certain preconditions are first satisfied. For instance, in the bridge problem, the agent must first place a block in the trench to create a bridge before crossing the trench. Branavan et al. [6] explore learning subgoals from the Minecraft wiki and applying them in order to plan through a variety of problems in Minecraft.

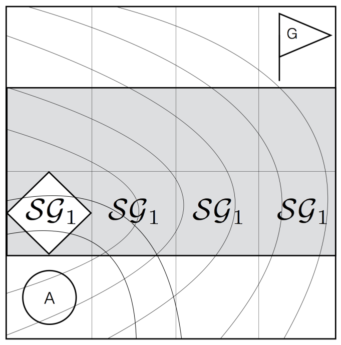
Formally, in subgoal planning, the agent is set of subgoals, where each subgoal is a pair of predicates:

$$SG = \langle x_k, x_l \rangle \tag{4}$$

where x_l is the effect of some action sequence performed on a state in which x_k is true. Thus, subgoal planning requires that we perform high-level planning in subgoal space, and low-level planning to get from subgoal to subgoal. The low-level planner may vary, though Metro-FF and A* are popular choices (depending on domain constraints), as is Value Iteration.

In the case of `BRIDGEWORLD`, the agent might consider placing a block somewhere along the trench to be a subgoal. Then, it runs a low-level planner to get from its starting location to the subgoal. Next, it runs the same low-level planner from the first subgoal to the finish. Subgoals enhance an agent's planning abilities when they propose *necessary* claims about the domain. If the subgoals are *contingent* (i.e. true in some state spaces of the domain but not in others), then they do not limit the search space (and in fact can negatively effect planning). For instance, consider the task in `BRIDGEWORLD`, in which the agent must place a block in the trench that separates the agent from the goal. The subgoal $\langle blockInTrench, reachGoal \rangle$ might be a perfectly useful subgoal in `BRIDGEWORLD`, but an adversary could easily come up with thousands of worlds in which such a subgoal would completely derail the agent's planner. Thus, many subgoals do not scale beyond a particular instance of a state space. In order for subgoals to be useful, they must be necessary claims about the domain, otherwise, one can always come up with a counter world (by definition of necessary). Compare this scenario to the problem of baking bread in Minecraft: possessing grain is always required to make bread, and it is impossible to construct a world where this precondition is not true.

Subgoal planners benefit in many ways by being made affordance-aware. One of the main problems of subgoal planning is that subgoal planners re-explore large portions of the state space, as illustrated by Fig. 4. The affordance-aware version of subgoal planners will tend to avoid this problem by focusing on actions that



$\mathcal{SG}_1 := \langle blockInTrench, reachGoal \rangle$

Figure 4: Subgoal planner in `BRIDGEWORLD`

are likely to direct the agent to the goal. Since subgoals are handcrafted to be preconditions for arriving at the goal, a large portion of the state space should will be pruned away (namely, the portion that is only accessible through actions that do not take you toward the goal). Furthermore, the low-level planners still suffer from all of the standard issues of planning we have discussed above; particularly in the Minecraft domain, planners cannot scale to accommodate that state space sizes that are possible in Minecraft (and thus, the real world). Thus, we may make Subgoal planners affordance-aware by equipping the subsequent low-level planners with affordances in order to plan efficiently from subgoal to subgoal.

4 EXPERIMENTS

We conducted a series of experiments in the Minecraft domain that tested standard planners from each planning paradigm: Value Iteration, RTDP, and Subgoal planning (with RTDP as the low-level planner). These planners were compared with *affordance-aware* versions of each algorithm tasked with the same set of problems. Our experiments consisted of a variety of tasks, ranging from basic path planning, to baking bread, to opening doors and jumping over trenches. We also tested each planner on worlds of varying size and difficulty to demonstrate the scalability and flexibility of each the affordance formalism. The evaluation metric for each trial is the number of state backups that were executed in each iteration of each planning algorithm.

4.1 RESULTS

DG: We will wait until the next iteration of results are complete to iterate on the writing here. The old version was extremely outdated, but we don't feel we are 100% prepared to write the next version

	VI	RTDP	SG	A-VI	A-RTDP	A-S
`4B`	51867	2285	46137	25990	2075	460
`6B`	234090	5994	202461	93840	4105	1547
`8B`	679320	20682	596453	226320	5540	3648
`10B`	1565190	54115	?	?	?	?
`BDOOR`	?	?	?	?	?	?
`BLAVA`	?	?	?	?	?	?

Table 1: Tests on a variety of tasks without block placement and destruction actions **DG: Need to fit this on the page for final**

	VI	RTDP	SG	A-VI	A-RTDP	A-SG
`10W`	1600	1369	2100	1600	1408	2100
`15W`	5850	5920	7770	5850	5819	7770
`20W`	14400	15645	?	?	?	?
`JUMPW`	?	?	?	?	?	?
`DOORW`	?	?	?	?	?	?
`MAZEW`	?	?	?	?	?	?
`HARDW`	?	?	?	?	?	?
`LAVAW`	?	?	?	?	?	?

Table 2: Tests on a variety of tasks without block placement and destruction actions

5 Related Work

In the past, numerous different forms of background knowledge have be used to accelerate planning algorithms. In section 3.3, subgoal planning was discussed and in our experimental results, was compared against affordance-aware planning. In this section, we discuss the differences between affordance-aware planning and other forms of background knowledge that have been used to accelerate planning. Specifically, we discuss heuristics, temporally extended actions, and related action pruning work.

5.1 Heuristics

Heuristics in MDPs are used to convey information about the value of a given state or state-action pair with respect to the task being solved and typically take the form of either *value function initialization*, or *reward shaping*. For planning algorithms that estimate state-value functions, heuristics are often provided by initializing the value function to values that are good approximations of the true value function. For example, initializing the value function to an admissible close approximation of the optimal value function has been shown to be effective for LAO* and RTDP, because it more greatly biases the states explored by the rollout policy to those important to the optimal policy [13]. Planning algorithms that estimate Q-values instead of the state value function may similarly initialize the Q-values to an approximation of the optimal Q-values. For instance, PROST [15] creates a *determinized* version of a stochastic domain (that is, treating each action as if its most likely outcome always occurred), plans a solutions in the determinized domain, and then initializes Q-values to the value of each action in the determinized domain.

Reward shaping is an alternative approach to providing heuristics in which the planning algorithm uses a modified version of the reward function that returns larger rewards for state-action pairs that are expected to be useful. Reward shaping differs from value function initialization in that it may not preserve convergence to an optimal policy unless certain properties of the shaped reward are satisfied [21] that also have the effect of making reward shaping equivalent to value function initialization for a large class of planning/learning algorithms [29].

A critical difference between heuristics and affordances is that heuristics are highly dependent on the task being solved; therefore, different tasks require different heuristics to be provided, whereas affordances are task independent and transferable between tasks. However, if a heuristic can be provided, the combination of heuristics and affordances may even more greatly accelerate planning algorithms than either approach alone.

5.2 Temporally Extended Actions

Temporally extended actions are actions that the agent can select like any other action of the domain, except executing them results in multiple primitive actions being executed in succession. Two common forms of temporally extended actions are *macro-actions*and *options* [27]. Macro-actions are actions that always execute the same sequence of primitive actions. Options are defined with high-level policies that accomplish specific sub tasks. For instance, when an agent is near a door, the agent can engage the 'door-opening-option-policy', which switches from the standard high-level planner to running a policy that is hand crafted to open doors. An option o is defined as follows:

$o = \langle \pi_0, I_0, \beta_0 \rangle$, where:

$$\pi_0 : (s, a) \rightarrow [0, 1]$$

$$I_0 : s \rightarrow \{0, 1\}$$

$$\beta_0 : s \rightarrow [0, 1]$$

Here, π_0 represents the *option policy*, I_0 represents a precondition, under which the option policy may initiate, and β_0 represent the post condition, which determines which states terminate the execution of the option policy.

Although the classic options framework is not generalizable to different state spaces, creating *portable* options is a topic of active research [1, 9, 16, 17, 18, 23].

Although temporally extended actions are typically used because they represent action sequences (or sub policies) that are often useful to solving the current task, they can sometimes have the paradoxical effect of increasing the planning time because they increase the number of actions that must be explored. For example, deterministic planning algorithms that successfully make use of macro-actions often avoid the potential increase in planning time by developing algorithms that restrict the set of macro-actions to a small set that is expected to improve planning time [5, 20] or by limiting the use of macro-actions to certain conditions in the planning algorithms like when the planner reaches heuristic plateaus (areas of the state space in which all child states have the same heuristic value) [8]. Similarly, it has been shown that the inclusion of even a small subset of unhelpful options can negatively impact planning/learning time [14].

Given the potential for unhelpful temporally extended actions to negatively impact planning time, we believe combing affordances with temporally extended actions may be especially valuable, because it will restrict the set of temporally extended actions to those which may actually be useful to a task. In the future, we plan to more directly explore the benefit from combining these approaches.

5.3 Action Pruning

Perhaps the most similar work to ours is Sherstov and Stone's action transfer work [25]. In their work, they considered MDPs with a very large action set and for which the action set of the optimal policy of a source task could be transferred to a new, but similar, target task to reduce the learning time required to find the optimal policy in the target task. Since the actions of the optimal policy of a source task may not include all the actions of the optimal policy in the target task, source task action bias was reduced by randomly perturbing the value function of the source task to produce new synthetic tasks. The action set transferred to the target task was then taken as the union of the actions in the optimal policies for the source task and all the synthetic tasks generated from it.

A critical difference between our affordance-based action set pruning and this action transfer work is that affordances represent knowledge defined independently of any specific task. Therefore, affordances can be defined once and reused in a variety of very different tasks, whereas in the action transfer work, action set pruning must begin anew when the current task is very dissimilar from previously experienced tasks.

JM: Do we want to make any comments about how this work might be useful in future work that learns affordances rather than is given them?

DG: We could, although we really haven't thought much about learning beyond some brief brainstorms. It does seem like the Sherstov/Stone work will be crucial, though, so maybe we could add a small note?

6 CONCLUSION

We proposed a novel approach to representing knowledge in terms of *affordances* [11] that allows an agent to efficiently prune its action space based on domain knowledge. This led to the proposal of affordance-aware planners, which improve on classic planners by providing a significant reduction in the number of state/action pairs the agent needs to evaluate in order to act optimally. We demonstrated the efficacy as well as the portability of the affordance model by comparing standard paradigm planners to their affordance-aware equivalents in a series of planning tasks in the Minecraft domain.

In the future, we hope to learn affordances from experience as opposed to providing them directly to the agent. Additionally, we hope to introduce uncertainty into the action set that is pruned, in order to improve the effectiveness of the pruning. Lastly, we hope to incorporate aid from a human partner through natural language dialogue, in which the agent may ask for help when it is stuck and receive subgoal *hints* from a human companion.

References

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