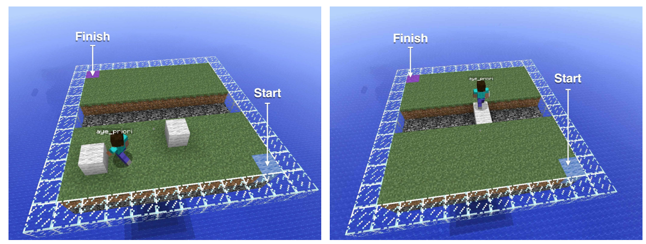
# Affordance-Aware Planning


## 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 system 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 limiting the branching factor in large domains by encoding knowledge about the domain in terms of *affordances* [12]. Our affordance formalism can be coupled with a variety of planning frameworks to create "affordance-aware planning," allowing an agent to efficiently prune its action space based on domain knowledge and its current subgoal. 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.


## 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 in the face of uncertainty cannot tackle these problems as the state-action space becomes too large [15].




(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. We were forced to cut off VI after several hours due to the large nature of the Minecraft state space, while the Affordance-Aware VI converged to a policy in under a minute.

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 [39] and macroactions [5, 29]. 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.

Instead, we propose a formalism that enables an agent to focus on problem-specific aspects of the environment, guiding the search toward the most relevant and useful parts of the state-action space. This approach reduces the size of the explored state action space, leading to dramatic speedups in planning. Our approach is a formalization of *affordances*, introduced by Gibson [12] 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. 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 3, we demonstrate the effectiveness of affordance-aware subgoal planning on a complicated task in the Minecraft domain - a video is provided of the agent achieving this task [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).

## 2 Minecraft Domain

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 [2]; scenes from a Minecraft world appear in Figure 1.

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.

Although we made the actions of the Minecraft domain stochastic, we have chosen to give the Minecraft agent non-noisy sensory data about the Minecraft world, as vision is assumed to be outside the scope of this project.

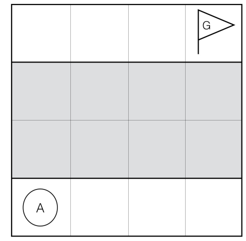



Figure 2: `BRIDGEWORLD`

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; a schematic appears in Figure 2. The floor (at $z = 1$)[3] 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 locations an agent can place and destroy blocks alone can result in a combinatorial explosion of the state space. An affordance-aware planner, however, (when equipped with the proper affordances) will only consider placing or destroying a block when that action moves the agent closer to its goal. Thus, when the agent is in state in which block placement is not considered useful, the agent will not have access to the block placement action (and will not be able to explore the states that result in applying the block placement action in its current state). As a result, the agent dramatically prunes its effective action space.

## 3 BACKGROUND

### 3.1 Affordances

The term "Affordance" was introduced by Gibson [12]. At a high-level, an affordance may be thought of as the action-possibilities that an environment presents to an agent. More specifically, Gibson proposed that an affordance be thought of as "what [the environment] offers [an] animal, what [the environment] provides or furnishes, either for good or ill" [12]. He added that an affordance may not be thought of as a physical property of the environment itself, as an affordance must be defined with respect to the capabilities and

[1]Watch at: https://vimeo.com/88689171

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

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

features of a specific animal in addition to the environment. There have been many attempts at properly grounding affordances in a variety of academic disciplines [14, 17, 19, 24, 25]. Even amongst the psychological literature there is no clear consensus on what to make of an affordance [31]. The result is a landscape of academic work that spans from psychological and cognitive science literature, to HCI and design, to Robotics and Planning, that is largely inconsistent about what is meant by the term *affordance*. Our aim in this paper is to provide a simple, yet general definition of an affordance in terms of knowledge added to an MDP which enables dramatic speedups in planning times, depending on the agent's goal. Specifically, we define an affordance in terms of the agent's current goal; depending on the needs of the agent, it may only perceive certain affordances. For instance, a rock may serve as a fantastic paper-weight to an agent seeking to weigh down a stack of papers. If the agent's goal changes and is instead looking for a means of propping a door open, then the agent may also perceive that the rock will serve as an adequate doorstop.

### 3.2 OO-MDP

We define affordances in terms of propositional functions on states. Our definition builds on the Object-Oriented Markov Decision Process (OO-MDP) [11]. 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 $s$ 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 $\gamma$ 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 $Dom(c.a)$. 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. 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 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.

## 4 AFFORDANCES

We define an affordance $\Delta$, as a tuple, $\langle p, g \rangle \longmapsto \alpha$, where:

> $\alpha$ a subset of the action space, $\mathcal{A}$, representing the relevant *action-possibilities* of the environment.
>
> $p$ is a predicate on states, $s \longrightarrow \{0, 1\}$ representing the *precondition* for the affordance.
>
> $g$ is an ungrounded predicate on states, $g$, representing a *lifted goal description*.

The precondition, $p$ refers to a predicate 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 tasks (e.g. OO-MDP predicates may be relational) and is one of the reasons that affordance-aware planners may be untethered from specific state spaces, as the predicate of $p$ benefit from the richness of the predicates of an OO-MDP. Further, the lifted goal description, $g$, describes the type of task being solved. In Minecraft, this can range from reaching a particular coordinate (*reachGoal*), to constructing an object of a certain type (e.g. smelting gold, building a pickaxe).

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

```
for Δ ∈ KB do
    if Δ.p(state) and Δ.g == state.goal then
        α.update(Δ.p, Δ.g)
    end if
end for
return α
```

The pseudocode for how an affordance-aware agent prunes its actions may be seen in Algorithm 1. For instance, if the agent is at the trench in `BRIDGEWORLD` and is faced with a *reachGoal* task, then the agent would not consider placing a block in any arbitrary location, as that would not further its ability to reach the goal. Instead, we provide[4] the agent with the following affordance:

$$\Delta_1 = \langle nearTrench, reachGoal \rangle \longmapsto \{\Box\}$$

which tells the agent to try placing blocks when next to a trench (as the trench could inhibit its progress toward reaching the goal). So, in any *reachGoal*, the action-possibilities of placing a block are only included in $\alpha$ when the predicate $nearTrench$ is true for the agent. For most *reachGoal* tasks, we also provide the following affordances:

$$\Delta_2 = \langle onPlane, reachGoal \rangle \longmapsto \{\updownarrow\leftrightarrow\}$$

$$\Delta_3 = \langle nearWall, reachGoal \rangle \longmapsto \{\boxtimes\}$$

These two eliminate the possibility of applying the "destroy" action in every state, and emphasize that planes afford movement, but not much else. As a result, the planner avoids exploring every consequent state in which that block has been destroyed, enabling an affordance-aware planner in *reachGoal* task types to handle large state spaces.

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

[4]Currently, we provide a planning agent with annotated affordances. However, our next step is to pursue learning affordances directly

### 4.1 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:

$$V^*(s) = \max_{a \in \mathcal{A}(s)} \sum_{s'} \Pr(s' \mid s, a) \left[\mathcal{R}(s, a, s') + \gamma V^*(s')\right]; \tag{1}$$

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; that is, by taking the action with the highest optimal state-action value:

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

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 which the value function is computed can be reduced to that which is reachable using only the optimal actions without sacrificing optimality.

### 4.2 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, 37] and temporal difference methods [2, 27, 32, 35, 39, 40]. 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. **ST: Need a sentence about why RTDP vs other methods reviewed above.**

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.

### 4.3 Subgoal Planning

Subgoal planning is based on 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 given a set of subgoals, where each subgoal is a pair of predicates:

$$SG = \langle x_k, x_l \rangle \tag{3}$$

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 Metric-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.

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. The affordance-aware version of subgoal planners will tend to avoid this problem by focusing on actions that are likely to direct the agent to 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. We make subgoal planners affordance-aware by equipping the subsequent low-level planners with affordances in order to plan efficiently from subgoal to subgoal. What makes affordances especially useful to subgoal planning is that as long as the subgoals are defined using OO-MDP predicates, each subgoal may activate a different set of affordances, thereby even more greatly focusing the search.

## 5 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. We selected the affordances provided from our background knowledge of the domain. The agent was given a single knowledge base of 15 affordances for all of the tasks. 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 the affordance formalism. The evaluation metric for each trial was the number of state backups that were executed in each iteration of each planning algorithm. Value Iteration was terminated when the maximum change in the value function was less than 0.01. RTDP terminated when the maximum change in the value function was less than 0.01 for five consecutive policy rollouts. In subgoal planning, the high-level subgoal plan was solved using breadth-first

| | VI | RTDP | SG | A-VI | A-RTDP | A-SG |
|---|---|---|---|---|---|---|
| 4BRIDGE | 71604 | 836 | 1373 | **100** | 152 | 141 |
| 6BRIDGE | 413559 | 4561 | 28185 | **366** | 392 | 547 |
| 8BRIDGE | 1439883 | 18833. | 15583 | 904 | **788** | 1001 |
| DOORB | 861084 | 12207 | 6368 | 4368 | 1945 | **1381** |
| LAVAB | 413559 | 4425. | 25792 | 366 | 993 | **597** |
| TUNNEL | 203796 | 26624 | 5404 | **105** | 145 | 182 |
| BREAD | 16406 | 7738 | 7412 | 962 | 809 | **578** |

Table 1: The number of state backups performed by each algorithm for a variety of tasks requiring block placement and destruction. Affordances dramatically improve performance.

| | VI | RTDP | SG | A-VI | A-RTDP | A-SG |
|---|---|---|---|---|---|---|
| 10WORLD | **800** | 1205 | 1263 | **800** | 985 | 960 |
| 15WORLD | 3150 | 3939 | 3328 | 3150 | 3089 | **2331** |
| 20WORLD | 7200 | 10719 | 8738 | 7200 | 8004 | **6099** |
| DOOR | 6315 | 5646 | 4104 | 6315 | 4059 | **2886** |
| JUMP | 2940 | 4313 | 4262 | 2940 | 3548 | **2922** |
| MAZE | 4266 | 5648 | **1949** | 4266 | 2864 | 3073 |
| LAVA | 800 | 1328 | 1003 | 800 | 861 | **772** |

Table 2: The number of state backups performed by each algorithm for a variety of tasks without block placement and destruction actions. Here affordances have a diminished effect.

search; which only took a small fraction of the time compared to the total low-level planning and therefore is not reported.

The reward function was defined as uniformly $-1$, with lava states set to $-200$ reward (where lava states were non-terminal). The goal was set to be terminal, and also initialized with a reward of $-1$. This was done in order to allow for an optimistic RTDP value initialization. The discount factor was set to $\lambda = 0.99$ with a minimum $\delta$ required for convergence of 0.01. For all experiments, the agent was given stochastic actions. Specifically, actions associated with a direction (e.g. movement, block placement, jumping, etc.), had a small probability (0.1) of being applied in the reverse direction.

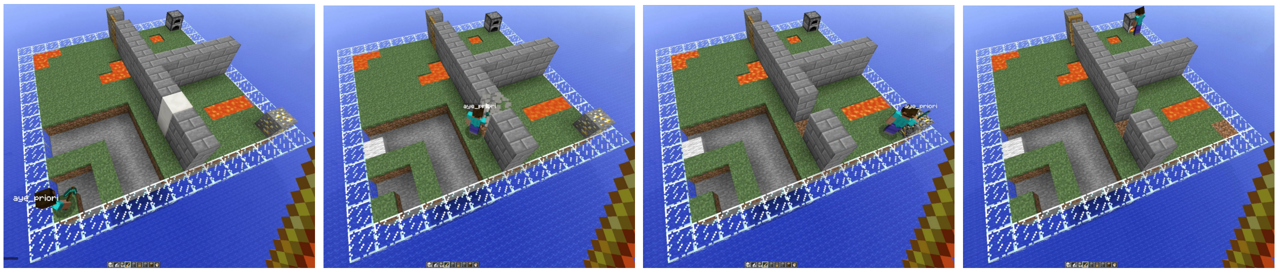
### 5.1 RESULTS

Table 1 shows the results of running the standard planners and their affordance aware counterparts on a set of tasks that require the use of block placement and/or destruction. The affordance aware planners significantly outperformed their unaugmented counterparts in all of these experiments. They proved especially effective when paired with subgoals, as can be seen by the results of the affordance aware subgoal planner, demonstrating that affordances are particularly useful if subgoal knowledge is known. Subgoals combined with affordances allow different types of pruning to occur depending on what the agent is trying to accomplish at each stage. In other words, when the agent is trying to find grain, it will focus on grain finding actions; when it is trying to bake bread, it focuses on bread baking actions. Additionally, affordance aware VI and affordance aware RTDP outperform their unaugmented versions. This result demonstrates that affordances prune away many useless action in these block building, block destruction, and bread baking types of tasks.

Table 2 shows the results of running the standard planners and their affordance-aware counterparts on tasks that do *not* require the use of block placement and destruction. In these cases, the affordance awareness did not improve any of the planners from their baseline versions. Affordances are only beneficial when they allow an agent to prune actions which could combinatorially alter the state space. In each of these worlds, the agent only needed to move itself through the environment, rather than alter the environment.

These results highlight where affordances highlights the fact that affordance aware planers are not always the right way to fix planning scalability issues. The lifted goal description $g$ of each affordance must be defined with a task type (e.g. a predicate that defines the goal) in mind. Additionally, affordances (if defined optimally) only prune away actions that are useless in achieving the goal, but fail to prune away actions whose importance is not easily inferred. For instance, in BRIDGEWORLD, when the agent is up against a trench, it will still explore the space in which it places blocks multiple blocks in the trench, despite the fact that the agent may have already constructed a bridge that affords passage to the goal (i.e. not useful applications of the place action). In future work, we would like to change the precondition $p$ to a set of features that represent the salient portions of the agent's current state and output a distribution over the agent's action set. This would allow an affordance aware planner to *prioritize* and rank actions in each state, which would lead to pruning much larger portions of the state-space.

As can be seen by Table 2, the critical factor in determining if affordances will benefit a planning scenario is whether or not the desired domain provides the agent with actions that can dramatically affect the state space. If the action set is relatively small and the actions don't significantly impact the shape of the state-space with each application, then affordances are not likely to help. For example, consider the classic reinforcement learning problem of balancing an inverted pendulum - in this task, the agent must choose between moving the base of an inverted pendulum $left$ and *right* and attempt to balance the pendulum in equilibrium. For tasks like this equipping a planner with affordances would have little to no impact. However, in cases where actions can affect the state-space



(a) Start (b) Destroy Wall (c) Collect Ore (d) Smelt Ore

Figure 3: The affordance-aware subgoal planner solving an ore-smelting task with a variety of obstacles. This task was only achievable by an affordance-aware planner.

dramatically (i.e. result in combinatoric explosions of the state space), making a planner affordance-aware can dramatically benefit planning, as indicated by the results in Table 1.

One of the most compelling results is the scope of task that affordance-aware planners are capable of solving. With an affordance-aware Subgoal planner (i.e. using an affordance aware RTDP as the low level planner), a Minecraft agent was able to traverse a complicated obstacle course[5], as seen in Figure 3. In this task, the agent had to smelt gold, but in order to do so, it had to jump over a trench, build a bridge over another trench, chop down a wall, mine a block of gold, open a door, avoid lava, and finally smelt the gold ore in a furnace. We have included a video of this task being executed as part of our supplementary materials. Here, the agent was capable of completing several different types of tasks (subgoals) with a single action space and affordance knowledge base.

## 6 Related Work

In the past, numerous different forms of background knowledge have been used to accelerate planning algorithms. In section 4.3, 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. Additionally, we elaborate on other recent attempts of employing Gibson's notion of an affordance to the problems of computer science and robotics.

[5]A full video of the agent solving this task may be found at: https://vimeo.com/88689171

### 6.1 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 [16]. 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 [20] creates a *determinized* version of a stochastic domain (that is, treating each action as if its most likely outcome always occurred), plans a solution 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 [30] that also have the effect of making reward shaping equivalent to value function initialization for a large class of planning/learning algorithms [43].

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

### 6.2 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* [39]. 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, $\pi_0$ represents the *option policy*, $I_0$ represents a precondition, under which the option policy may initiate, and $\beta_0$ 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, 21, 22, 23, 33].

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, 29] 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 successor 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 [18].

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.

### 6.3 Action Pruning

Work that prunes the action space is the most similar to our affordance-aware planning. Sherstov and Stone [36] 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 prune away actions on a state by state basis. Therefore, affordance aware planners are significantly more flexible as they move throughout a state space, as certain actions are useful for a given planning task in general, but not in specific subspaces of the statespace. Further, with lifted goal descriptions, affordances may be attached to Subgoal planning for a huge benefit in planning tasks where complete subgoal knowledge is known (or may be inferred).

Rosman and Ramamoorthy [34] provide a method for learning action priors over a set of related tasks. Specifically, a Dirichlet distribution over actions was computed by extracting the frequency that each action was optimal in each state for each previously solved task. On a novel task learned with Q-learning, a variant of an $\epsilon$-greedy policy was followed in which the agent selcted a random action according to the Dirichlet distribution and $\epsilon$ fraction of the time, and the action with the max Q-value the rest of the time. To avoid dependence on a specific state space, the a Dirichlet distribution was created for each observation-action pair (where the observations were task independent) instead of each state-action pair.

There are a few limitations of the actions priors work that affordance-aware planning does not possess: (1) the action priors can only be used with planning/learning algorithms that work well with an $\epsilon$-greedy rollout policy; (2) the priors are only utilized for fraction $\epsilon$ of the time steps, which is typically quite small; and (3) as variance in tasks explored increases, the priors will become more uniform. In contrast, affordance-aware planning can be used in a wide range of planning algorithms, benefits from the pruned action set in every time step, and the affordance defined lifted goal-description and enables higher-level reasoning such as subgoal planning. However, in the future, the action set each affordance defines could be learned using a similar approach.

### 6.4 Affordances

[38] performed work in formalizing affordances through the Linear Dynamic Event Calculus (LDEC). This work was aimed at linking events and objects in the context of language and prelinguistic cognitive apparatuses, and is partially related to the Frame Problem and symbolic planning. [24] developed an inference algorithm that enables a robotic agent to anticipate a human partner's actions based on the robots perceived affordances. Additionally, [26] performed work in predicting object affordances by treating humans as a latent variable in a given scene. [13] proposed the Affordance-Based-Concept, which targeted using the perception of affordances as a means of determining the set of possible interactions an agent may engage with in a given context. This was then applied toward situated-language understanding and language-generating agents. Lastly, many have used affordances as a paradigm for solving table top grasping problems [10, 28, 41, 42]

## 7 CONCLUSION

We proposed a novel approach to representing knowledge in terms of *affordances* [12] 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 challenging planning tasks in the Minecraft domain.

In the future, we hope to introduce a more robust inference procedure for pruning actions such that the agent not only prunes away *useless* actions, but also prioritizes between *great* actions, and *mediocre* ones. Additionally, each affordance knowledge base must be designed by hand for planning agents - our immediate next step will be to apply learning techniques to learn affordances directly. Further, we foresee extensions in natural language processing and information extraction, in which affordances may be inferred via text or from dialogue with a human partner. This promises extensions in which a robotic agent receives aid from a human partner through natural language dialogue; the agent may ask for help when it is stuck and receive affordance or subgoal *hints* from a human companion. Lastly, we consider applications to a variety of other planning strategies, including A* for use in a robotic-cooking companion, as well as enhancing POMDPs with affordances, directed at applications to robotic care-giver companions.

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