Planning with Affordances

Abstract

Current methods for decision-making under uncertainty require exhaustive enumeration of all possible states and actions, leading to exponential run times caused by the well-known "curse of dimensionality." Approaches to address this problem by providing the system with formally encoded knowledge such as options or macro-actions still fail to prevent the system from considering many actions which would be obviously irrelevant to a human solving the same problem. To address this issue, we introduce a novel approach which represents knowledge about the domain in terms of *affordances* [3]. Our affordance formalism and associated planning framework allows 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, showing a significant increase in speed and reduction in state-space exploration compared to subgoal (partial order) planning.

ST: High level things we should add:

- **Runtime of the three algorithms in big O notation.**
- **Results with non-deterministic T.**

1 INTRODUCTION

As robots move out of the lab and into the real world, planning algorithms need to be able to scale to domains of increased noise, size, and complexity. A classic formalization of this issue is the sequential decision making problem, where increases in 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 large [4].

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. Humans provide an excellent existence proof for such planning, as we are capable of searching over an immense number of possible actions when presented with a goal. However prior 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 has the paradoxical effect of increasing search times.

One approach to explaining how humans solve this planning problem is by focusing on problem-specific aspects of the environment which focus the search toward the most relevant and useful parts of the state-action space. This alternative approach aims to *reduce* the size of the state action space, leading to dramatic speedups in planning. Our approach is a formalization of *affordances*, introduces by Gibson [3] as "what [the environment] offers [an] animal, what [the environment] provides or furnishes, either for good or ill."

In this paper we will formalize the notion of an affordance as a piece of planning knowledge provided to an agent operating in a Markov Decision Process (MDP) [5]. We demonstrate that, like an option or macro-action, an affordance provides additional information to the agent, enabling more transferable and efficient planning. However, unlike previous approaches, an affordance enables more significant speedups by reducing the size and branching-factor of the search space, enabling an agent to focus its search on the most

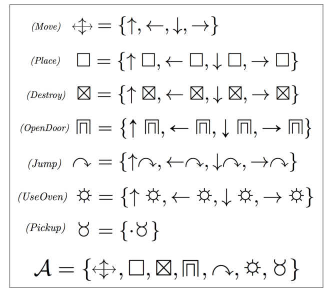
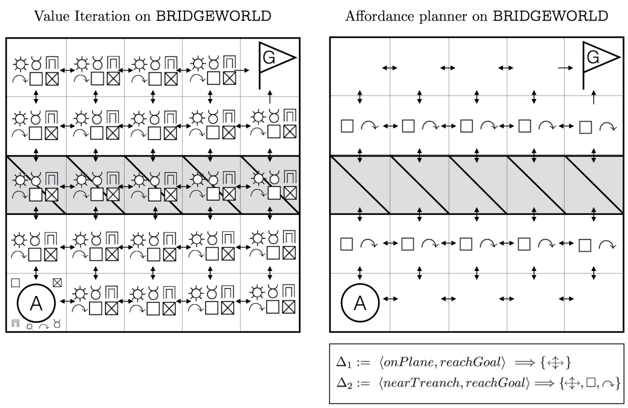


Figure 2: The set of all actions in the Minecraft domain



ST: What about a picture of minecraft, with the agent placing a block in the corner for VI, compared to the agent placing a block in the trench for the affordance planner? To say "VI is thinking about placing blocks in the corner, but affordances don't." I like for the first picture to be intuitive and immediately understandable. So I like the icon idea, but not as the first figure. I think this figure should go with the definition of affordances, showing the state space affordance VI is using vs VI.

Figure 1: 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). This problem was only solvable by the Affordance planner. (see Fig. 2 for a description of the action-symbols)

relevant part of the problem at hand. This approach means that a single set of affordances provides general domain knowledge, becoming relevant just when the agent reasons that it needs to pursue a particular goal. Furthermore, affordances are not specific to a particular reward function or goal, and thus, provide the agent with transferrable knowledge that is effective in a wide variety of problems.

2 BACKGROUND

We define affordances in terms of an Object Oriented Markov Decision Process (OO-MDP) [2] and review competing approaches for adding knowledge to planning.

2.1 OO-MDP

OO-MDPs are an extension of the classic Markov Decision Process (MDP). A finite 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 $s' \in \mathcal{S}$, and $\mathcal{R}(s, a)$ denotes the reward at s when action a is applied, and γ is a discount factor.

ST: Need to define variables and types. Should use the same variables as the OO-MDP paper. The OO-MDP represents the state space S as a collection of objects, o. Each object has a class, c. The state space is represented as a collection of objects, which are instances of the aforementioned classes. Additionally, upon instantiation the attributes of the object's class are given a state (an assignment of values). Finally, the underlying MDP is the union of all the states of its objects [2].

Our motivation for using an OO-MDP instead of an MDP lies in the ability to formulate predicates over classes of objects. As we will see in section 3, this helps us form preconditions and goals that generalize beyond a particular instance of a state space. **ST:**

Need to stay why using an OO-MDP earlier.

As with a classical finite MDP, planning with an OO-MDP involves running value iteration to determine a policy. Reward propagation in value iteration occurs as in a Bellman update:

$$U_{i+1}(s) \leftarrow \mathcal{R}(s) + \gamma \max_{a \in \mathcal{A}(s)} \sum_{s'} \Pr(s' \mid s, a) U_i(s') \quad (1)$$

Where $U_i(s)$ is the *utility* of state s at iteration i, representing the expected reward of being in that state. See Algorithm 3 for the full pseudocode of the algorithm [7].

Algorithm 1 Value-Iteration($\mathcal{A}$, $\mathcal{R}$, $\mathcal{S}$, ϵ, γ)

while $\delta < \epsilon \frac{(1-\gamma)}{\gamma}$ **do**
  $U \leftarrow U'; \delta \leftarrow 0$
  for each state $s \in \mathcal{S}$ **do**
    $U'[s] \leftarrow \mathcal{R}(s) + \gamma \max_{a \in \mathcal{A}(s)} \sum_{s'} \Pr(s' \mid s, a) U[s']$
    if $|U'[s] - U[s]| > \delta$ **then**
      $\delta \leftarrow |U'[s] - U[s]|$
    end if
  end for
end while
return U;

In practice, Value Iteration scales very poorly, either as the state space grows, or the action set grows. This is because the state-action space, depending on the domain, grows exponentially in the number of actions. This problem is ameliorated slightly by introducing the OO-MDP, but it still fails in just about all of the planning scenarios we introduce here because the agent explores all states that result from applying every action in every state.

ST: Need to introduce the bridgeworld problem with more detail. As a running example, we consider the problem of an agent attempting to cross a trench in the game Minecraft, shown in Figure **??**. To solve the problem, the agent must place a block in the trench, forming a bridge, then cross the bridge to reach the goal. However when running an uninformed planning technique such as value iteration, the agent must enumerate all possible states, for example placing a block in the corner and subsequently destroying it. Considering these actions, which would be obviously irrelevant to a human player, results in a combinatoric explosion of the state space (see Equation 3).

2.2 SUBGOALS

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, one must first place a block in the trench to create a bridge before crossing the trench. Branavan et al. [1] 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:

$$SG = \langle x_k, x_l \rangle \quad (2)$$

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.

Algorithm 2 Plan with Knowledge Base of Subgoals

subgoalSequence ← BFS(subgoalKB, goal)
plan = []
curState ← subgoalSequence.pop()
for subgoal ∈ subgoalSequence **do**
  plan += ValueIteration(curState, subgoal)
  curState ← plan.getLastState()
end for
return plan;

In the case of `BRIDGEWORLD`, the agent might consider placing a block somewhere along the trench to be a subgoal. Then, it runs Value Iteration to get from its starting location to the subgoal. Next, it runs Value Iteration 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. 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: posessing wheat is always required to make bread, and it is impossible to construct a world where this precondition is not true.

ST: I don't get granular planning; this seems identical to the first problem.

Problem 2: Efficient Search The last problem with

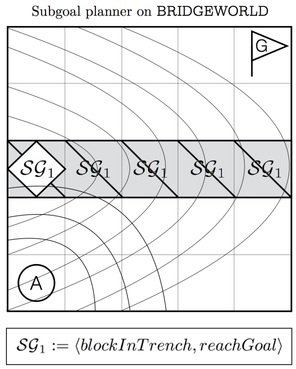


Figure 3: The agent re-explores a large portion of the state space once it finds $\mathcal{SG}_1$. Also note that this subgoal highlights **Problem 1**, in that it would be useless in many other Minecraft state spaces

subgoal planning is that the use of subgoals actually requires that we research a huge portion of the state space. Consider the BRIDGEWORLD example in which the subgoal is to place a block along the trench somewhere - once we plan from the state in which a block has been placed at the trench, Value Iteration will search paths exploring both sides of the trench rather than focusing on the opposite side of the trench toward the goal.

A final, but less significant problem, is that Subgoal planning still requires the use of Value Iteration, which does not scale well - if there is ever a case in which planning between two subgoals is at all complex, then Subgoal planning is out of luck.

2.3 OPTIONS

The options framework proposes incorporating high-level policies to 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.

As Konidaris and Barto point out, the classic options framework is not generalizable, as it does not enable an agent to transfer knowledge from one state space to another. Recently, Konidaris and Barto's [6] expand on the classic options framework and allow for a more portable implementation of options. Still, though, planning with options requires either that we plan in a mixed space of actions *and* options (which blows up the size of the search space), or requires that we plan entirely in the space of options. Additionally, providing an agent with an option policy is a difficult task for a human designer (especially if we want an optimal policy, which we do).

2.4 MACROACTIONS

Running Example

3 AFFORDANCES

We define an affordance, Δ, as a tuple, $\langle p, g \rangle \longrightarrow \alpha$, 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*.

ST: Need to immediately connect the definition with how it will be used in the aglorithm. I would first give a high-level intuition of how they will be used, then say why they will speed up. Then there should be a paragraph explaining affordance-based value iteration which also gives a runtime. Also the predicate functions should connect to OO-MDPs. I think we need OO-MDPs to make this work, because otherwise we couldn't factor the pre and post condition as predicates on states (because where do the predicates come from?) This connection needs to be made explicitly.

The intuition is that in a huge number of planning scenarios, given a goal, the agent should be able to focus on only a subset of its available actions, dramatically reducing the size of the state-action space. Our definition of an affordance parallels the intuition of Gibson [3], in which a human is capable of trimming down their action space by a huge amount when directed toward a particular goal. For instance, consider an agent with the standard Minecraft action set seen in Figure 2. If the agent need only walk across a flat surface to reach the goal, it should not even bother trying to place blocks or destroy blocks. If it needs to dig a ten block hole, then the agent should not consider placing blocks.

The reason that each goal encodes information about the goal relevant to those actions is that it, given perfect subgoal knowledge for a particular planning task, the affordance formalism will find an optimal policy *extremely* quickly. We imagine extensions in which an agent gets stuck and must ask a human partner for help using natural language, and the resulting dialogue could endow the agent with subgoal knowledge. This also allows the agent to prune way unnecessary actions in $\mathcal{A}$ in each specific planning task, making it possible to solve a engage with a large number of planning scenarios that may call for different actions. Furthermore, since actions may be pruned with respect to a given goal, agents may be endowed with huge action sets that enable them solve a variety of problems across variable state-spaces, yet the branching factor of an affordance agent's exploration will be significantly smaller, since actions that are not relevant to the current goal will be pruned. This makes the affordance formalism extremely robust, as well as transferrable relative to subgoal planning and options.

Algorithm 3 Affordance-Value-Iteration($\mathcal{A}$, $\mathcal{R}$, *initState*, *kb*, *goal*, ϵ, γ,)

```
1: Â ← pruneActions(kb, initState, A, goal)
2: Ŝ ← genStates(kb, Â)
3: while δ < ε(1−γ)/γ do
4:     U ← U′; δ ← 0
5:     for each state s ∈ Ŝ do
6:         U′[s] ← R(s) + γ max_{a∈Â(s)} Σ_{s′} Pr(s′ | s, a)U[s′]
7:         if |U′[s] − U[s]| > δ then
8:             δ ← |U′[s] − U[s]|
9:         end if
10:    end for
11: end while
12: return U;
```

The affordance formalism introduced above and expanded on in this paper resolves the weaknesses of these other frameworks by limiting the complexity of the seed knowledge required of the designer, while still providing enough knowledge to limit the search space but also maintain scalability.

4 EXPERIMENTS

ST: To write the experiments section, it's good to say what we are interested in learning first. What are we testing? What is our hypothesis? Then explain the setup, then explain what the results say about the hypothesis. I would make experiments and results one section, with subsections for each experiment + results

We conducted a series of experiments in the Minecraft domain that tested each planning system on 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 to demonstrate the scalability of each system. In Table 5, we provide results on testing the planners across each system. For each data point, we ran the planning system 3 times and took the average result (they rarely deviated beyond $\frac{1}{10}$ of a second).

For the scenarios listed in Table 5, we limited the agent's action set across all planners so that it did not have access to block placement (☐) and block destruction (☒). The reason for excluding these two action types up is that, in Minecraft, the agent has an extraordinary ability to modify the state space via placing and destroying blocks. As a result, if an agent begins placing or destroying blocks in cases where it does not need to, the state-action space will explode exponentially and grow far too fast for (almost) any planner to finish in our lifetime.

Consider that the agent is capable of destroying and placing blocks in a 10x10x2 world; there are on the order of:

$$O\left(\sum_{n=1}^{10\cdot 10\cdot 2}\binom{10\cdot 10\cdot 2}{n}\right) \tag{3}$$

states, which is far too large to explore. We will demonstrate that our affordance model *is* capable of handling these types of actions, and can plan using them as in a bridge building scenario or tunnel digging scenario (among others) while the other planners cannot. In fact, with these actions, none of the other planning systems can solve even the most basic path planning (even on just a flat surface with no obstacles). We explore this ability in the results seen in Table 5

As discussed above, one of the major advantages of using Affordances to plan is that they enable an agent to have a massive action set, making Affordances effectively transfer between domains. We conducted an additional set of experiments on the 15x15 world with no obstacles `15WORLD`. For this round of testing, we varied the number of actions available to the agent (starting from $|\mathcal{A}| = 4$ up to $|\mathcal{A}| = 25$) and ran the planner on `15WORLD` with the same goal (to reach the goal in the corner).

An additional advantage of planning with Affordances is that the problems of block-placement and block-

	Affordances	Subgoals	VI
10WORLD	**0.6s**	1.8s	1.1s
13WORLD	**2.5s**	10.1s	6.0s
15WORLD	**6.7s**	21.6s	11.8s
17WORLD	**16.6s**	45.4s	28.2s
20WORLD	**57.6s**	144.3s	140.5s
JUMPWORLD	**4.3s**	21.1s	10.1s
BREADWORLD	25.5s	**22.8s**	51.6s
DOORWORLD	**16.3s**	25.0s	25.3s
MAZEWORLD	**17.9s**	114.8s	37.6s
HARDWORLD	**34.5s**	215.9s	149.7s

Table 1: Tests on a variety of tasks without block placement and destruction actions

	Affordances	Subgoals	VI
$\|\mathcal{A}\| = 4$	?	?	?
$\|\mathcal{A}\| = 8$	?	?	?
$\|\mathcal{A}\| = 12$	?	?	?
$\|\mathcal{A}\| = 16$	?	?	?
$\|\mathcal{A}\| = 17$	?	?	?
$\|\mathcal{A}\| = 21$	?	DNF	DNF
$\|\mathcal{A}\| = 25$	?	DNF	DNF

Table 2: Plan on the simplest possible task (path planning in a flat plane with no obstacles) with incrementally larger action sets.

destruction illustrated by 3 are overcome. With Affordances, we are able to solve a variety of novel planning problems in the Minecraft domain, such as building a bridge to cross a long trench, or digging a hole through a wall to reach the goal (see Table 5). This is indeed a compelling result, as no other planning system is currently able to avoid falling prey to the state-space explosion mentioned above. Additionally, the malleability of Minecraft that causes this explosion is a reasonable model of the way that an agent in the real world is capable of modifying its surroundings. Thus, we foresee the Affordance planner as being extremely deft at handling real world planning scenarios.

5 RESULTS

As one can see from Table 5, in those cases where $|\mathcal{A}| = 21$ and $|\mathcal{A}| = 25$, the only planning algorithm to actually complete the tasks was the Affordance planner. This is because each of these cases scaled to include block destruction and block placement actions. Thus, any case in which these actions are required to complete the task at hand, only Affordance planning will succeed. This is significant, as Table 5 indicates that the Affordance planner plans more effectively than the other systems, but it can also handle novel problems involving those actions that alter the environment in sever ways. We also include a Bonus round indicating those tasks that only the Affordance planner was able to solve. Finally, since each Affordance is attached to a particular goal, a single knowledge base will scale across state-spaces and task types, causing Affordance planning to be extremely transferrable.

6 CONCLUSION

We proposed a novel approach to representing knowledge in terms of *affordances* [3] that allows an agent to efficiently prune its action space based on domain knowledge. This pruning was shown to significantly reduce the number of state/action pairs the agent needs to evaluate in order to act optimally, and resulted in faster planning than subgoal planning, options, and vanilla value iteration. We demonstrated the efficacy as well as the transferability of the affordance model 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.

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