Affordance-Aware Planning

David Abel & Gabriel Barth-Maron, James MacGlashan, Stefanie Tellex

Computer Science Department, Brown University

{dabel,gabrielbm,jmacglashan,stefie10}@cs.brown.edu

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 planning in large stochastic state spaces fail to prevent autonomous agents from considering many actions that are obviously irrelevant to a human solving the same task. To reduce the size of the state/action space without sacrificing optimality, we formalize the notion of *affordances* as goal-oriented knowledge added to an Object Oriented Markov Decision Process (OO-MDP). Affordances prune actions based on the current state and the robot's goal, reducing the number of state-action pairs the planner must evaluate in order to synthesize a near optimal policy. Furthermore, we show that an agent can learn affordances through unsupervised experience, and that learned affordances can equal or surpass the performance of those provided by experts. We demonstrate our approach in the state-rich Minecraft domain, showing significant increases in speed and reductions in state-space exploration during planning, with minimal loss in quality of the synthesized policy. Additionally, we employ affordance-aware planning on a Baxter robot, demonstrating it is able to assist a person performing a collaborative cooking task.**

I. Introduction

Robots operating in unstructured, stochastic environments such as a factory floor or a kitchen face a difficult planning problem due to the large state space and inherent uncertainty [4, 14]. Robotic planning tasks are classically formalized as a stochastic sequential decision making problem, modeled as a Markov Decision Process (MDP). In these problems, the agent must find a mapping from states to actions for some subset of the state space that enables the agent to achieve a goal while minimizing costs along the way. However, many robotics tasks are so complex that modeling them as an MDP results in a massive state/action space, which in turn restricts the types of robotics problems that are computationally tractable.

For example, when a robot is manipulating objects in an environment, an object can be placed anywhere in a large set of locations. Depending on the task, most of these locations are irrelevant; for example, when making brownies, the oven and flour are important, while the soy sauce and sauté pan are not. For a different task, such as stir-frying broccoli, a different set of objects and actions are relevant. Unfortunately, the size of the state space increases exponentially with the number of objects, which bounds the placement problems that the robot is able to expediently solve.

To address this state-action space explosion, prior work has explored adding knowledge to the planner, such as options [25] and macroactions [5, 20]. However, while these methods allow the agent to search more deeply in the state space, they add high-level actions to the planner which *increase* the size of the state-action space. The resulting augmented space is even larger, which can have the paradoxical effect of increasing the search time for a good policy [13]. Deterministic forward-search algorithms like hierarchical task networks (HTNs) [19], and temporal logical planning (TLPlan) [2, 3], add knowledge to the planner that greatly increases planning speed, but do not generalize to stochastic domains. Additionally, the knowledge provided to the planner must be given by a domain expert, reducing the agent's autonomy.

To address these issues, we propose augmenting an MDP with a formalization of *affordances*. An affordance [10] specifies which actions an agent should consider in different states of the world in order to satisfy a given goal. By applying affordances to planning, we prune the agent's action set to focus on aspects of the environment that are most relevant to solving its current goal and avoid exploration of irrelevant parts of the state-action space. Affordances are not specific to a particular reward function or state space, and provide the agent with transferable knowledge that is effective in a wide variety of problems. Moreover, our methods enable a single agent to autonomously learn affordances through unsupervised experience, making affordances a concise, transferable, and learnable means of representing useful planning knowledge.

Our experiments demonstrate that affordances provide dramatic speedups for a variety of planning tasks compared to baselines and apply across different state-spaces. We conduct experiments in the game Minecraft, and on a robotic cooking assistant.

II. Technical Approach

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 future rewards (the agent prefers to maximize 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.

A. OO-MDPs

An Object-Oriented Markov Decision Process (OO-MDP) [8] can be used to represent an MDP. Unlike the vectorized state of an MDP, an OO-MDP state is a collection of objects, $O = \{o_1, \ldots, o_o\}$. Each object o_i belongs to a

class, $c_j \in \{c_1, \ldots, c_c\}$. Every class has a set of attributes, $Att(c) = \{c.a_1, \ldots, c.a_a\}$, each of which has a domain, $Dom(c.a)$, of possible values. The collection of attribute values of a given object is termed that object's state, $o.state$. A vectorized MDP state can be equivalently understood as the set of all the object states, $s \in \mathcal{S} = \cup_{i=1}^{o} \{o_i.state\}$, in an OO-MDP.

B. Affordances

Gibson [10] proposed that an affordance is "what [the environment] offers [an] animal, what [the environment] provides or furnishes, either for good or ill". We define an affordance, Δ, as the tuple $\langle p, g, A \rangle$, where:

- p is a predicate on states, $s \longrightarrow \{0, 1\}$ representing the *precondition* for the affordance.
- g is a *goal type*, representing the type of problem the agent is solving.
- A is a distribution on the OO-MDP action space, $\mathcal{A}$, representing the probability that each action is optimal.

The precondition, p, and goal type, g, refer to predicates that are defined in the OO-MDP definition. The precondition specifies when certain affordances are relevant, and the goal allows the agent to focus on different actions depending on what it is trying to accomplish. The distribution A indicates the affordance's belief that each action is optimal, represented as a Bernouli on each action. The weights of these distributions may be specified by a domain expert or learned during training time.

We call an affordance *active*, when its precondition p evaluates to true in the given state and its goal type g is entailed by the goal the agent is currently trying to satisfy.

Our definition of affordances builds on OO-MDPs. Using OO-MDP predicates for affordance preconditions and goal types allows for state space independence, as predicates generalize across state-spaces. **E: I think a sentence explaining/emphasizing this would be good since it's not entirely obvious at a first pass why OO-MDPs give you state-space independence**. **D: I added a note here but it sounds superfluous to me. Let me know what you think** Thus, a planner equipped with affordances can be used in any number of different environments. For instance, the affordances defined for navigation problems can be used in any task regardless of the spatial size of the world, number of objects in the world, and specific goal the agent is trying to satisfy..

C. Affordance-Aware Planning

Affordances restrict the action set of a planner on a state by state basis. We define $\mathcal{A}^o$ to be the optimal action set for a given state s and goal G, and define $\mathcal{A}^\Delta$ to be the action set provided by a knowledge base of affordances, given a state s and goal G. For each state, the planner's available actions are constrained to be $\mathcal{A}^\Delta \subseteq \mathcal{A}$, the action set believed to be optimal by the affordances.

This pruning is informed by the distribution over the optimal action set, given the current state, the type of the goal the agent is trying to satisfy, and a knowledge base K of affordances:

$$\Pr(\mathcal{A}^\Delta = \mathcal{A}^o \mid s, G, K) \tag{1}$$

We may replace K, s, and G with the action distributions associated with the set of *active* affordances, for the given state s under goal G.

$$\Pr(\mathcal{A}^\Delta = \mathcal{A}^o \mid \Delta_1.A, \ldots, \Delta_m.A) \tag{2}$$

We may reinterpret this probability in terms of the probability that each action in the OO-MDP action space is in the optimal action set

$$\prod_{i=1}^{|\mathcal{A}|} \Pr(a_i \in \mathcal{A}^o \mid \Delta_1.A_i, \ldots, \Delta_m.A_i) \tag{3}$$

We abbreviate $\Delta_j.A_i$ to b_{ji}, and $a_i \in \mathcal{A}^o$ to a_i:

$$\prod_{i=1}^{|\mathcal{A}|} \Pr(a_i \mid b_{1i}, \ldots, b_{mi}) \tag{4}$$

Applying Bayes Rule, we get:

$$\prod_{i=1}^{|\mathcal{A}|} \frac{\Pr(b_{1i}, \ldots, b_{mi} \mid a_i) \Pr(a_i)}{\Pr(b_{1i}, \ldots, b_{mi} \mid a_i) \Pr(a_i) + \Pr(b_{1i}, \ldots, b_{mi} \mid \neg a_i) \Pr(\neg a_i)} \tag{5}$$

We assume a uniform prior on each action's optimality and that each affordances action distributions are conditionally independent given an action a_i:

$$\prod_{i=1}^{|\mathcal{A}|} \frac{\prod_{i=1}^{m} \Pr(b_{ji} \mid a_i \in \mathcal{A}^o)}{\prod_{j=1}^{m} \Pr(b_{ji} \mid a_i \in \mathcal{A}^o) + \prod_{j=1}^{m} \Pr(b_{ji} \mid a_i \notin \mathcal{A}^o)} \tag{6}$$

Since each affordance is associated with a distribution over actions, we can compute this posterior directly and sample from it to compute $\mathcal{A}^\Delta$.

Any OO-MDP solver may be made affordance-aware by replacing the OO-MDP's action set $\mathcal{A}$ in each state with the affordance suggested action set $\mathcal{A}^\Delta$. If no actions were considered optimal, then $\mathcal{A}^\Delta$ is defined to be the full OO-MDP action set, $\mathcal{A}$

D. Learning Affordances

Even with expert domain knowledge it is often unclear how to create an optimal knowledge base, and it can be arduous to specify a large number of affordances. We developed an unsupervised learning process that requires only minimal seeding from an expert. The full learning algorithm is shown in Algorithm 1. The goal of the learning algorithm is to learn the affordance knowledge base, $\mathcal{K}$, that maximizes the probability that the affordance action set $\mathcal{A}^\Delta$ is optimal:

$$\mathcal{K} = \underset{K \in \boldsymbol{K}}{\operatorname{argmax}} \Pr(\mathcal{A}^\Delta = \mathcal{A}^o \mid s, G, K) \tag{7}$$

The primary tasks in computing $\mathcal{K}$ are to learn reasonable precondition-goal combinations and the distribution A for each affordance.

To learn an affordance knowledge base, a domain expert must supply a set of relevant domain specific predicates, $\mathcal{P}$, and possible goals the agent will have to solve, $\mathcal{G} \subset \mathcal{P}$. Additionally, a domain expert must provide a means of generating candidate state spaces in which each goal $g \in \mathcal{G}$ may be satisfied (i.e. the function $createTestWorld(g)$ at line 5 in Algorithm 1).

Algorithm 1 $learn(\mathcal{P}, \mathcal{G})$

1: **for** $(p, g) \in \mathcal{P} \times \mathcal{G}$ **do**
2:     $knowledgeBase.add(\Delta(p, g))$
3: **end for**
4: **for** $g \in \mathcal{G}$ **do**
5:     $w_i = createTestWorld(g)$
6:     $\pi_i = planner.solve(w_i, g)$
7:     $updateParameters(knowledgeBase, \pi_i)$
8: **end for**
9: $removeLowInfoAffordances(knowledgeBase)$

To determine good p and g pairs, the algorithm creates one affordance for each combination of $\langle p, g \rangle$, where $p \in \mathcal{P}$ and $g \in \mathcal{G}$, as seen in line 1-3 of Algorithm 1. Affordances whose precondition-goal pairs don't provide useful information are thrown out by the function call on line 9, leaving only those affordances with sound precondition-goal pairs. We chose to remove affordances with little or no α counts at the end of training, or those whose α counts were close to the actual action distribution of the policy, indicating that the affordance contained little information.

To learn the distribution A for each affordance, we synthe-size a policy of m goal-annotated OO-MDPs that have small state spaces, but share similar characteristics to more complex state spaces the agent might expect to see at test time. For example, the agent learns to build bridges over trenches in small state spaces that can be solved exactly (i.e. a state space of several thousand states), but generalizes its knowledge to worlds that are too large to solve with exact algorithms (state spaces of hundreds of thousands of states). With this policy, we know the optimal action in each state and can generalize this optimality to larger state spaces.

We learn A for each affordance according to Algorithm 2. For each optimal policy, for each affordance, α is set to the number of states in which an action was optimal when its affordance's predicate was true and goal was entailed by the present goal. We then inform a Bernouli distribution on each action using these counts.

For experiments, we also introduce a thresholded version of an affordance, in which the action set $\mathcal{A}^\Delta$ is defined to be the actions in the posterior whose probability of being optimal was

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Algorithm 3

1: **for** $state \in \pi.reachableStates()$ **do**
2:     **for** $\Delta \in knowledgeBase$ **do**
3:         **if** $\Delta.p(s) \wedge \Delta.g \models s.g$ **then**
4:             $\Delta.\alpha(\pi.getOptimalAction(s))$++
5:         **end if**
6:     **end for**
7: **end for**

Figure listing the expert affordances

greater than an expert specified parameter. In all experiments, we set this parameter to be 0.01.

III. EXPERIMENTS

We use Minecraft as our planning and evaluation domain. Minecraft is a 3-D blocks game in which the user can place, craft, and destroy blocks of different types. It serves as a model for a variety of complex planning tasks involving assembly, crafting, and construction. Minecraft's physics and action space are expressive enough to allow users to create complex systems, including logic gates and functional scien-tific graphing calculators[1]. Minecraft serves as a model for robotic tasks such as cooking assistance, assembling items in a factory, object retrieval, and complex terrain traversal. As in these tasks, the agent operates in a very large state/action space in an uncertain environment.

For experiments, we introduce a simplified baseline version of the affordance where the action set A associated computed by $\Delta.\delta$ is defined as the set of actions whose probability of being optimal was greater than 1% of the probability mass of the multinomial created over the α counts. This baseline is listed as LT (for learned threshold).

A. Minecraft Tests

We conducted a series of experiments in the Minecraft domain that compared the performance of several planner without affordances to their affordance-aware counterparts. We created a set of expert affordances from our background knowledge of the domain, which are listed in Figure III-A. Additionally, we ran our full learning process and learned affordances for each task. We compared Real Time Dynamic Programming (RTDP) with its expert-affordance-aware and learned-affordance-aware counterparts.

Our experiments consisted of 5 common tasks in Minecraft, including constructing bridges over trenches, smelting gold, tunneling through walls, and digging to find an object. We tested on randomized worlds of varying size and difficulty. The generated test worlds varied in size from tens of thousands of states to hundreds of thousands of states.

The training data consisted of 10 simple state spaces of each map type (50 total), each approximately a 1,000-10,000

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

state world with randomized features that mirrored the agent's actual state space. The same training data was used for each test state space. **D: We'll need to update all this once we actually count state space sizes**

The evaluation metric for each trial was the number of Bellman updates that were executed by each planning algorithm, as well as the CPU time taken to find a plan. RTDP was terminated when the maximum change in the value function was less than 0.01 for fifty consecutive policy rollouts, or the planner failed to converge after 2500 rollouts. We set the reward function to -1 for all transitions, except transitions to states in which the agent was on lava, which returned -10. The goal was set to be terminal. The discount factor was set to $\lambda = 0.99$. For all experiments, movement actions (move, rotate, jump) had a small probability (0.05) of incorrectly applying a different movement action.

B. Learning Rate

Additionally, we conducted experiments in which we varied the number of states visited at training time. As in Table **??**, we randomly generated simple state spaces containing several thousand states containing features that mirrored the agent's state space at test time. We then solved the OO-MDP with knowledge bases learned from 10 to 10000 states. **D: same here**

C. Temporally Extended Actions

Furthermore, we compared our approach to Temporally Extended Actions: macroactions and options. We compared RTDP with expert affordances, expert Macroactions, and expert Options, as well as the combination of affordances, macroactions, and options. We conducted these experiments with the same configurations as our Minecraft experiments. The option policies and macro actions provided were hand coded by domain experts.

D. Robotic Task

Finally, we deployed an affordance-aware planner onto Baxter for use in an assistive cooking task. **D: Need to fill in more details here**

IV. RESULTS

A. Baxter

Fig. 1. Placeholder for baxter results/image

B. Minecraft: Expert vs Learned vs None

D: Should we switch tables to bar charts so we can show error bars?

State Space	Size	RTDP	Learned	Learned Threshold	Expert
Trench	-	-	-	-	-
Mine	-	-	-	-	-
Smelt	-	-	-	-	-
Wall	-	-	-	-	-
Plane	-	-	-	-	-

TABLE I
PLACE HOLDER FOR RTDP BELLMAN/CPU

Planner	CPU	Reward	Bellman
RTDP	-	-	-
ERTDP	-	-	-
LRTDP	-	-	-
LTRTDP	-	-	-

TABLE II
D: THOUGHTS ON THIS STYLE TABLE INSTEAD? THEN WE WOULD JUST REPORT AVERAGES? OR A BAR CHART? ONLY DOWNSIDE IS THAT WE DON'T SPECIFY THE STATE SPACE/SIZE
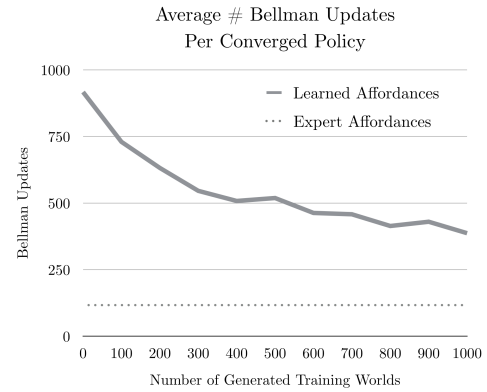
C. Minecraft: Learning rate

Fig. 2. Place holder for learning rate results

D. Temporally Extended Actions

State Space	Size	Options	Macroactions	Affordances	All
Trench	-	-	-	-	-
Mine	-	-	-	-	-
Smelt	-	-	-	-	-
Wall	-	-	-	-	-
Climb	-	-	-	-	-

TABLE III
PLACEHOLDER: TEMPORALLY EXTENDED ACTIONS VS AFFORDANCES

V. RELATED WORK

In this section, we discuss the differences between affordance-aware planning and other forms of knowledge engineering that have been used to accelerate planning. We divide these approaches into those that are built to plan in stochastic domains, and those that are deterministic planners.

A. Stochastic Approaches

1) 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* [12] and *options* [25]. 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.

Although the classic options framework is not generalizable to different state spaces, creating *portable* options is a topic of active research [17, 15, 22, 6, 1, 16].

Given the potential for unhelpful temporally extended actions to negatively impact planning time [13], we believe combing affordances with temporally extended actions may be especially valuable because it will restrict the set of temporally extended actions to those useful for a task. We conducted a set of experiments to investigate this intuition.

2) Action Pruning: Sherstov and Stone [24] 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. The main 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, where as the learned action pruning is on per task level. Further, with lifted goal descriptions, affordances may be attached to subgoal planning for a significant benefit in planning tasks where complete subgoal knowledge is known.

Rosman and Ramamoorthy [23] provide a method for learning action priors over a set of related tasks. Specifically, they compute a Dirichlet distribution over actions by extracting the frequency that each action was optimal in each state for each previously solved task.

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 ϵ-greedy rollout policy; (2) the priors are only utilized for fraction ϵ 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 enables higher-level reasoning such as subgoal planning.

3) Heuristics: Heuristics in MDPs are used to convey information about the value of a given state-action pair with respect to the task being solved and typically take the form of either *value function initialization*, or *reward shaping*. Initializing the value function to an admissible close approximation of the optimal value function has been shown to be effective for LAO* and RTDP [11].

Reward shaping is an alternative approach to providing heuristics. 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, but does not guarantee convergence to an optimal policy unless certain properties of the shaped reward are satisfied [21].

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, whereas affordances are state space 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.

B. Deterministic Approaches

There have been several successful attempts at engineering knowledge to decrease planning time for deterministic planners. These are fundamentally solving a different problem from what we are interested in, but there approaches are interesting to consider. **D: Need to rephrase this with justification for dealing with deterministic planners.**

1) Hierarchical Task Networks: **D: I think we should have a shoutout to Branavan's Learning High Level Plans from Text paper in this section (and include subgoal planning as part of this section**

E: I've been writing traditional as I expect we'll discover some HTNs that grapple with the issues stated below – which we should probably cite Traditional Hierarchical Task Networks (HTNs) employ *task decompositions* to aid in planning. The goal at hand is decomposed into smaller tasks which are in turn decomposed into smaller tasks. This decomposition continues until primitive tasks that are immediately achievable are derived. The current state of the task decomposition, in turn, informs constraints which reduce the space over which the planner searches.

At a high level both HTNs and affordances fulfill the same role: both achieve action pruning by exploiting some form of supplied knowledge. HTNs do so with the use of information regarding both the task decomposition of the goal at hand and the sorts constraints that said decomposition imposes upon the planner. Similarly, affordances require knowledge as to how to extract values for propositional functions of interest by querying the state.

However there are three of essential distinctions between affordances and traditional HTNs. (1) HTNs deal exclusively with deterministic domains as opposed to the stochastic spaces with which affordances grapple. As a result they produce plans and not policies. (2) Moreover, HTNs do not incorporate reward into their planning. Consequently, they lack mathematical guarantees of optimal planning. **E: I think.. We should double check this.** (3) On a qualitative level, the degree of supplied knowledge in HTNs surpasses that of affordances: whereas affordances simply require relevant propositional functions, HTNs require not only constraints for sub-tasks but a hierarchical framework of arbitrary complexity. Thus, despite a superficial similarity between affordances and HTNs wherein both employ supplied knowledge, the two deal

with disparate forms of planning problems; HTN's planning problem is deterministic, reward-agnostic and necessitates a plethora of knowledge while affordances solve a planning problem that is stochastic, reward-aware and requires only relatively basic knowledge about the domain. **E: Need citations for HTNs D: needs to be shorter**

2) Temporal Logic: Bacchus and Kabanza [2, 3] provided planners with domain dependent knowledge in the form of a first-order version of linear temporal logic (LTL), which they used for control of a forward-chaining planner. With this methodology, a STRIPS style planner may be guided through the search space by checking whether candidate plans do not falsify a given knowledge base of LTL formulas, often achieving polynomial time planning in exponential space.

The primary difference between this body of work and affordance-aware planning is that affordances may be learned (increasing autonomy of the agent), while LTL formulas are far too complicated to learn effectively, placing dependence on an expert.

VI. CONCLUSION

D: Conclusion could use some work/rewriting We proposed a novel approach to representing transferable knowledge in terms of *affordances* [10] that allows an agent to efficiently prune actions based on domain knowledge, providing a significant reduction in the number of state-action pairs the agent needs to evaluate in order to act near optimally. We demonstrated the effectiveness of the affordance model by comparing standard planners to their affordance-aware equivalents in a series of challenging planning tasks in the Minecraft domain. Further, we designed a full learning process that allows an agent to autonomously learn useful affordances that may be used across a variety of task types, reward functions, and state-spaces, allowing for convenient extensions to robotic applications.

We compared the effectiveness of augmenting planners with affordances compared to temporally extended actions. The results suggest that affordances, when combined with temporally extended actions, provide substantial reduction in the portion of the state-action space that needs to be explored.

Lastly, we deployed an affordance-aware planner on a robotic task with a massive state space. **D: Need to flesh out once we have more detail**.

In the future, we hope to automatically discover useful state-space-specific-subgoals online - a topic of some active research [18, 7]. This will allow for affordances to plug into high-level subgoal planning, which will reduce the size of the explored state-action space and improve the relevance of the action pruning. Additionally, we hope to decrease the amount of knowledge given to the planner by implementing lowering the expert seed requirements for learning affordances. One plan is to only provide a base of primitive predicates, and to implement Incremental Feature Dependency Discovery [9], allowing our affordance learning algorithm to discover novel preconditions that will further enhance action pruning. **D:**

Maybe put in a note about the forward search sparse sampling algorithm? Or perhaps the Bayesian planner?

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