
From Reals to Logic and Back: Inventing Symbolic Vocabularies, Actions, and Models for Planning from Raw Data

Naman Shah, Jayesh Nagpal, Pulkit Verma, and Siddharth Srivastava
Autonomous Agents and Intelligent Robots Lab,
School of Computing & Augmented Intelligence,
Arizona State University, Tempe, AZ, USA
{shah.naman, nagpal.jayesh, verma.pulkit, siddharths}@asu.edu

Abstract

Hand-crafted, logic-based state and action representations have been widely used to overcome the intractable computational complexity of long-horizon robot planning problems, including task and motion planning problems. However, creating such representations requires experts with strong intuitions and detailed knowledge about the robot and the tasks it may need to accomplish in a given setting. Removing this dependency on human intuition is a highly active research area.

This paper presents the first approach for autonomously learning generalizable, logic-based relational representations for abstract states and actions starting from unannotated high-dimensional, real-valued robot trajectories. The learned representations constitute auto-invented PDDL-like domain models. Empirical results in deterministic settings show that powerful abstract representations can be learned from just a handful of robot trajectories; the learned relational representations include but go beyond classical, intuitive notions of high-level actions; and that the learned models allow planning algorithms to scale to tasks that were previously beyond the scope of planning without hand-crafted abstractions.

1 Introduction

Abstract, symbolic domain models in PDDL-like languages have emerged as powerful tools for enabling safe and reliable autonomy, especially in complex robot planning tasks that feature long horizons [Srivastava et al., 2014, Garrett et al., 2021]. However, such representations require domain experts to create a relational vocabulary (e.g., “on(x,y)”, “clear(x)”, etc.) for expressing the state of the environment, and high-level actions such as “pickup” and “place”, together with their descriptions in terms of the predicate vocabulary. These processes rely on the intuition of the domain expert. Consequently, most symbolic representations in robot planning have been limited to these hand-crafted actions and capture a limited set of humanoid capabilities. For instance, there are no non-trivial high-level PDDL actions for a trailer truck to use while autonomously parking itself. This severely limits the scope and scalability of robot planning in long-horizon tasks.

We take the view that if symbolic, logic-based representations can be learned autonomously with no human annotation of training data, they can enable more generalizable forms of autonomous and scalable robot planning. This paper shows for the first time that it is indeed possible to do so.

We present the first approach for learning symbolic predicates and actions from continuous demonstrations and no a priori labeling. These auto-generated predicates and actions turn out to include predicates with semantics close to the classically hand-crafted predicates (e.g. “on(x,y)”) and actions (e.g., “pickup(x)”), but they also go beyond and include new, robot, and task-specific relations and actions that vastly increase the generalizability of planning. More precisely, our approach takes

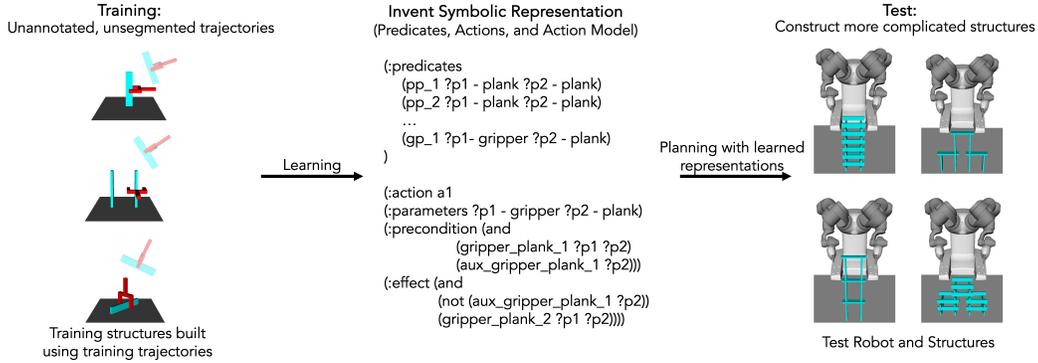


Figure 1: Our overall approach. We start with a set of demonstrations on relatively simple tasks using a simple robot and learn a symbolic model in the form of a set of predicates and high-level actions. This symbolic model can be used with any off-the-shelf planner for solving unseen complex long-horizon planning problems with other similar robots.

as input a small set of demonstrations in the form of time-indexed real-valued trajectories of the configuration of the robot and the objects in the environment. It uses these real-valued trajectories to invent a vocabulary in predicate logic and a set of high-level actions together with models in terms of the invented logical vocabulary. Empirical evaluations in deterministic, fully observable settings show that these representations generalize beyond the training tasks to problems with significantly greater numbers of objects and significantly longer horizons.

While prior work indicates that predicate vocabularies can be learned when high-level actions or options are available as inputs [Konidaris et al., 2018], and that high-level actions can be learned when a predicate vocabulary is available with demonstrations [Verma et al., 2022, Silver et al., 2022], this is the first known approach that requires neither predicate vocabularies nor high-level skills or options to be included or labeled in the input. Furthermore, this approach is complementary to research on integrated task and motion planning as it provides a general paradigm for learning domain models that are used as inputs in that direction of work. A greater discussion is presented in Sec. 5.

Intuitively, our approach consists of two phases. In the first phase, our approach for few-shot learning uses demonstrations to invent a relational vocabulary and symbolic actions, which are expressed in PDDL. Next, we use the learned PDDL model with an off-the-shelf planner to solve new and unseen complex long-horizon planning problems while continually inventing new symbolic predicates and actions for achieving them. Fig. 1 presents some examples of the scale of demonstrations used, an action in the learned domain, and some examples of the new test tasks that can be solved using this approach.

Our central contribution is the first approach for inventing a relational predicate vocabulary by learning to predict salient sets of real-valued relative poses between objects that tend to be frequently encountered while solving tasks. We formalize this notion of saliency as *relational critical regions*. This allows us to discover generalizable high-level actions as transitions to and from relational critical regions. Our additional key contributions are approaches for (i) learning a relational predicate vocabulary along with an interpretation function for each learned predicate in a continuous configuration space (ii) learning high-level actions that the robot can perform, along with their definitions



Figure 2: Our approach with a physical robot. Top: a few training demonstrations for learning an initial model for our approach. Bottom: robot solving an unseen test problem that is significantly more complex than training tasks.

in a PDDL-like relational representation, and (iii) continual planning and learning of new predicates and actions facilitated using off-the-shelf planners.

We present an extensive evaluation of our approach with various robots carrying out tasks in deterministic simulated and real-world settings. These empirical results show that the learned abstractions can be efficiently used with off-the-shelf planners for solving robot planning problems that are significantly more complex than those used in the demonstrations provided, with significantly greater horizons, branching factors, and more objects that need to be manipulated to reach the goal.

2 Preliminaries

We formalize our approach using standard terminology from first order logic and robot planning literature. A universe of our planning problem consists of various objects and robots. Each object in the environment is defined as a rigid body that has a 3D geometry and a collision property. A 6D pose represents position and orientation relative to a fixed frame of reference. A “world” frame serves as a default frame of reference for every object in the environment. We call the pose in the world frame the absolute pose of the object and refer to it as P_o^W for an object o . We also refer to the set of all absolute poses of object o as \mathcal{X}_o^W .

A robot is a special object. It is defined as a kinematic chain of links and joints that connect two links. The root link of the robot is referred to as a base link. The link that interacts with other objects in the environment is known as an end-effector, e.g., a gripper. For the scope of this paper, we say two robots are *similar* if the geometries of their end-effectors are similar. A configuration x of the robot specifies values for each joint of the robot. The set of all possible configurations is known as a configuration space [LaValle, 2006]. Given the pose of the base link and the configuration of the robot, a forward kinematic function can be used to compute the pose for every link of the robot. Therefore, we define the state of a robot as a tuple $\langle P_{base}, x \rangle$ where P_{base} is the pose of the base link of the robot and x is a configuration of the robot. We abuse the notation and define \mathcal{X}_r as a set of all states for a robot r .

We assume a fully observable setting. Given an environment with a set of objects $\mathcal{O} = \{o_1, \dots, o_n, r_1, \dots, r_m\}$, the state-space of the environment \mathcal{X} is defined as $\mathcal{X} = \mathcal{X}_{r_i} \times \mathcal{X}_{o_j}$ for every robot $r_i \in \mathcal{O}$ and every object $o_j \in \mathcal{O}$. Given a collision function c , the state-space \mathcal{X} can be partitioned as $\mathcal{X} = \mathcal{X}_{free} \cup \mathcal{X}_{obs}$ where \mathcal{X}_{free} defines the set of collision-free states and \mathcal{X}_{obs} defines the set of states with collisions.

Our approach extensively uses *relative poses*. Every object in the environment also defines a frame of reference. A relative pose defines the pose of an object in the reference frame of another object. Basis transformations from linear algebra can be used to compute relative transformations of objects w.r.t to other objects in the environment. This is explained in detail in appendix A. We refer to the pose of an object o_1 relative to an object o_2 as $P_{o_1}^{o_2}$. Let $\tilde{\mathcal{X}}_{o_1}^{o_2}$ define a relative state-space for the pair of objects o_1 and o_2 , i.e., the set of all poses of the object o_1 in the relative frame of the object o_2 . and $\tilde{\mathcal{X}}$ define the set of relative state spaces such that $\tilde{\mathcal{X}} = \{\tilde{\mathcal{X}}_{o_j}^{o_i} | o_i, o_j \in \mathcal{O} \wedge o_i \neq o_j\}$. Lastly, we define a transformation function $\xi : \mathcal{X} \rightarrow \tilde{\mathcal{X}}$ that computes the relative state for each absolute state of the environment.

Primitive actions (low-level actions) enable a robot to change its state, i.e., the configuration of the robot and/or the pose of the base link. This allows robots to move around in the environment and manipulate different objects in the environment. Formally, a primitive action a defines a deterministic function $a : x \mapsto x'$. Here, $x \in \mathcal{X}$ and $x' \in \mathcal{X}$ are environment states such that applying an action a in an environment state x results in an environment state x' .

Now, we define a domain for a robot planning problem.

Definition 1 A *robot planning domain* is defined as a tuple $\langle \mathcal{O}, \mathcal{T}, \mathcal{X}, \mathcal{A} \rangle$ where \mathcal{O} is a set of objects, \mathcal{T} is a set of object types, \mathcal{X} is a state space, and \mathcal{A} is an uncountably infinite set of primitive deterministic actions.

Similarly, a robot planning problem can be defined as follows.

Definition 2 A *robot planning problem* is defined as a tuple $\langle x_i, \mathcal{X}_g \rangle$ where $x_i \in \mathcal{X}_{free}$ is an initial state and $\mathcal{X}_g \subseteq \mathcal{X}_{free}$ is a set of goal states.

A solution to a planning problem is a sequence of primitive actions a_0, \dots, a_n such that $a_n(\dots(a_0(x_i))) \in \mathcal{X}_g$.

Typically, a motion planner can be used to compute such solutions. However, continuous action spaces and an infinite branching factor make it infeasible for primitive actions to be used for long-horizon robot planning problems.

Symbolic abstractions Symbolic abstractions convert a continuous robot planning problem to a symbolic PDDL [McDermott et al., 1998] problem. We define an abstract symbolic PDDL model for a continuous robot planning domain D as a tuple $\mathcal{M} = \langle \mathcal{T}, \mathcal{P}, \bar{\mathcal{A}} \rangle$. \mathcal{T} is a set of types for objects in the universe. \mathcal{P} is a set of symbolic predicates. Each predicate $p \in \mathcal{P}$ is parameterized by typed parameters and represents a relation between these objects. Each predicate $p \in \mathcal{P}$ can be grounded using the objects in the universe of the model. We refer to a predicate as p and a grounded predicate as p' . Each grounded predicate p' defines a Boolean classifier that evaluates true in a low-level state x (denoted as $p'_x = 1$) if the corresponding relation holds true between the objects used to ground the predicate in the state x . We also define an abstraction function $\alpha : x \mapsto s'$ that evaluates every grounded predicate in a low-level state $x \in \mathcal{X}$ and returns an abstract grounded state $s' \in 2^{\mathcal{P}'}$. Here, the symbolic grounded state s' is defined as a set of grounded predicates that are true in the low-level state x . We refer to the symbolic grounded state as s' and to the symbolic lifted state as s ($s \in 2^{\mathcal{P}}$).

$\bar{\mathcal{A}}$ defines the set of symbolic lifted actions defined using the set of lifted predicates \mathcal{P} . Each abstract action $\bar{a} \in \bar{\mathcal{A}}$ is parameterized with typed symbolic parameters. Each action \bar{a} is defined as a tuple $\langle pre_{\bar{a}}, eff_{\bar{a}} \rangle$. Here, $pre_{\bar{a}}$ is a conjunctive formula of parameterized predicates from the set of predicates \mathcal{P} . $eff_{\bar{a}}$ is the effect of the action \bar{a} . It is defined as a tuple $eff_{\bar{a}} = \langle add_{\bar{a}}, del_{\bar{a}} \rangle$ where $add_{\bar{a}}$ is a set of predicates that are added to the state and $del_{\bar{a}}$ is a set of predicates that are removed from the state when the action \bar{a} is executed. Similarly to the predicates, an action \bar{a} can be grounded using the objects yielding a grounded action \bar{a}' . This also generates grounded precondition $pre_{\bar{a}'}$ and grounded effect $eff_{\bar{a}'}$. A grounded action \bar{a}' is applicable in a state s if and only if $pre_{\bar{a}'} \models s$. Formally, every deterministic grounded action $\bar{a}' \in \bar{\mathcal{A}}'$ defines a function $\bar{a}' : s_i \mapsto s_j$ that maps each symbolic state s_i to the resulting state s_j .

Our objective in this paper is to automatically invent symbolic abstractions for robot planning problems in PDDL-like representations. A symbolic robot planning problem is defined as a tuple $\langle \bar{\mathcal{O}}, s'_i, S'_g \rangle$. Here, $\bar{\mathcal{O}}$ is a set of symbolic references (mainly names) for the objects in the environment, and s'_i is an initial grounded state and $S'_g \subseteq \mathcal{S}'$ is the set of grounded goal states. A solution to a symbolic planning problem is a sequence of grounded symbolic actions $\bar{a}'_0, \dots, \bar{a}'_n$ such that $\bar{a}'_n(\dots(\bar{a}'_0(s_i))) \in S'_g$. A planner such as FF [Hoffmann, 2001] or FD [Helmert, 2006] can be used to compute such a solution.

Symbolic plans cannot be executed by a robot. It needs to be converted to a sequence of primitive actions that a robot can execute. Task and motion planning approaches use abstract symbolic models along with *pose generators* for computing a sequence of primitive actions for planning problems. A pose generator defines an inverse abstraction function. Let γ_p be a pose generator for a lifted symbolic predicate $p \in \mathcal{P}$. For a grounded predicate p' , a pose generator $\gamma_{p'} = \{x | x \in \mathcal{X} \wedge p'_x = 1\}$. A pose generator for a grounded state s' is defined as $\bigcap_{p' \in s'} \gamma_{p'}$.

Critical regions We use the concept of *critical regions* for automatically inventing a predicate vocabulary. Molina et al. [2020] and Shah and Srivastava [2022] propose the concept of a critical region in the configuration space of a robot for learning propositional symbolic abstractions. Critical regions generalize the concepts of hubs or access points and bottlenecks or pinch points in a single concept. Earlier work defines critical regions in a goal-agnostic manner, however, in this work we consider goal-conditioned critical regions. Intuitively, as the name suggests, goal-conditioned critical regions learn critical regions for a specific training problem. In this work, we learn goal-conditioned critical regions for each training task and combine them in order to compute the set of critical regions. Given a robot with a configuration space \mathcal{X} , goal-conditioned regions are defined as follows.

Definition 3 Given a set of solutions for a robot planning problem T , the measure of criticality of a Lebesgue-measurable open set $\rho \subseteq \mathcal{X}$, $\mu(\rho)$, is defined as $\lim_{s_n \rightarrow +r} \frac{f(r)}{v(s_n)}$ where $f(r)$ is a fraction of observed motion plans solving the task T that pass through s_n , $v(s_n)$ is the measure of s_n under a

Algorithm 1: LAMP: Learning Abstract Model for Planning

Input: A set of demonstrations \mathcal{D}_{train} for training tasks T_{train} , a set of objects \mathcal{O} , a set of types of objects \mathcal{T}
Output: PDDL Domain \mathcal{M}

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/* Prepare data */
1 Use  $\xi$  to compute trajectories with relative poses of each object
/* Invent predicates */
2 Compute sets of relative critical regions  $\Psi$  for each pair of object types  $\tau_i, \tau_j \in \mathcal{T}$ 
 $\mathcal{R} \leftarrow \text{discover\_relations}(\Psi, \mathcal{O}, \mathcal{T})$ 
4  $\tilde{\mathcal{R}} \leftarrow \text{discover\_auxiliary\_relations}(\mathcal{R})$ ;
5  $\mathcal{P} \leftarrow \text{generate\_predicate\_vocabulary}(\mathcal{R}, \Psi)$ 
/* Invent actions */
6  $\tilde{\mathcal{A}} \leftarrow \text{invent\_actions}(\mathcal{D}, \mathcal{P})$ ;
7  $\mathcal{M} \leftarrow \text{generate\_PDDL}(\mathcal{T}, \mathcal{O}, \mathcal{R}, \tilde{\mathcal{A}})$ ;
8 return  $\mathcal{M}$ ;

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reference density (usually uniform), and \rightarrow^+ denotes the limit from above along any sequence $\{s_n\}$ of sets containing ρ ($\rho \subseteq s_n, \forall n$).

3 Our approach

This work’s central idea is to learn state and action abstractions that can be transferred to settings with different robots and goals. In this context, different goals are characterized by different numbers and configurations of the objects. We formally define the abstraction learning problem as follows.

Definition 4 Let T_{train} be a set of training problems and \mathcal{D}_{train} be a set of demonstrations that successfully solve the training problems. We define the **abstraction learning problem** as learning 1) a predicate vocabulary \mathcal{P} , 2) a set of high-level actions $\tilde{\mathcal{A}}$, and 3) a set of generators Γ for each learned predicate.

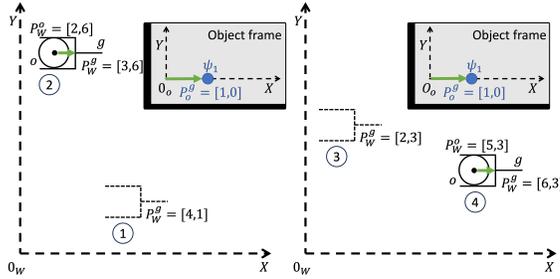


Figure 3: An example of relational critical regions. The gripper g is tasked to grasp the object o . Stages 1 and 3 show an initial configuration of the gripper g and stages 2 and 4 show the final configuration. The inset figures show the pose of the gripper for stages 2 and 4 in the relative reference frame of the object and the blue region shows the identified relative critical region.

3.1 Inventing Predicates

We now discuss our approach for automatically discovering a predicate vocabulary only using the set of training demonstrations \mathcal{D}_{train} for solving the set of training problems T_{train} .

Def. 3 define critical regions in the configuration space of a robot. However, these critical regions fail to capture relationships between different objects in the environment. E.g., consider a simple task of grasping an object in a 2D setting with a gripper shown in Fig. 3. Here, every problem instance would have a different initial state and hence a different pose of the object o . This would require a

The core contribution of this paper is the first known approach for simultaneously inventing a predicate vocabulary and abstract actions that solve unseen test problems T_{test} with similar robots and types of objects but significantly varying goals. We now present our approach -- *Learning Abstract Model for Planning (LAMP)* -- that automatically learns these abstractions in a continual fashion and represents them as a PDDL domain. The next section (Sec. 3.1) presents our approach for automatically inventing a predicate vocabulary and generators and then we present our approach for inventing symbolic actions (Sec. 3.2). Lastly, Sec. 3.3 presents a method for using the learned abstractions for planning for novel test problems and continually updating the abstractions.

different configuration of the gripper in order to grasp the object for every problem, and therefore the critical regions in the configuration space of the robot (as defined by Shah and Srivastava [2022]) would fail to identify any useful abstractions.

3.1.1 Relational Critical Regions

In this work, we propose the concept of *relational critical regions* (RCR) that overcome shortcomings of critical regions. Relational critical regions extend the notion of critical regions to the relative spaces between two objects in order to capture salient relationships between objects that only exist in these spaces. E.g., in Fig. 3, the absolute poses of the gripper g and object o do not have a specific relationship, however, the relative poses of the object and the gripper display a “holding” relationship. The inset images in Fig 3 show the “holding” relation between the object and the gripper and its corresponding relational critical region (blue regions in the inset images). Given a pair of objects o_1 and o_2 and the relative state space $\mathcal{X}_{o_2}^{o_1}$, relational critical regions can be defined similarly to critical regions (Def. 3) by considering the relative spaces between two objects ($\mathcal{X}_{o_2}^{o_1}$) instead of the configuration space of the robot (\mathcal{X}_r). Formally, a criticality threshold v , relational critical regions can be defined as follows.

Definition 5 Let T be a robot planning problem and \mathcal{D}_T be a set of solution trajectories for the planning problem T . Let $o_1, o_2 \in \mathcal{O}$ be a pair of objects and let $\mathcal{X}_{o_2}^{o_1}$ define the relative state space for object o_2 in the relative reference frame of object o_1 . The measure of criticality of a Lebesgue-measurable open set $\rho \subseteq \mathcal{X}_{o_2}^{o_1}$, $\mu(\rho)$, is defined as $\lim_{s_n \rightarrow +\rho} \frac{f(s_n)}{v(s_n)}$ where $f(\rho)$ is a fraction of observed solution trajectories solving for the planning problem T that contains a relative pose $P_{o_2}^{o_1}$ such that $P_{o_2}^{o_1} \in \rho$, $v(s_n)$ is the measure of s_n under a reference density (usually uniform), and \rightarrow^+ denotes the limit from above along any sequence $\{s_n\}$ of sets containing ρ ($\rho \subseteq s_n, \forall n$).

Now, we describe our approach for learning a set of relational critical regions.

Learning relational critical regions Alg. 1 describes our approach for learning symbolic abstractions. We start with the set of demonstrations \mathcal{D}_{train} that solves the set of training problems T_{train} . Recall the function ξ defined in Sec. 2. Our approach uses the function ξ to convert training demonstrations \mathcal{D}_{train} containing absolute poses of the objects and robot to relative demonstrations in relative state space $\tilde{\mathcal{X}}$ (line 1) and use these trajectories to identify relational critical regions (Def. 5).

Our approach assumes that objects of similar types interact similarly. E.g., the relational critical region between the object o and the gripper g generalizes to every similar object and gripper in the environment. Therefore, Alg. 1 accumulates demonstrations for similar types of objects and then identifies critical regions between two types of objects. Alg. 1 first identifies task-specific relational critical regions and then combines them in order to construct the complete set of relational critical regions. Let Ψ be this set of automatically identified relational critical regions.

Once a set of relational critical regions Ψ is constructed, our approach uses Gaussian parameters to parameterize the hypotheses space of the relational critical regions. Formally, let $\Psi_{ij} \subset \Psi$ be a set of relational critical regions between the pair of object types τ_i and τ_j . Given a pre-defined threshold ϵ , our approach uses Gaussian mixture model (GMM) to estimate Gaussian parameters μ_ψ and Σ_ψ for every relational critical region $\psi \in \Psi_{ij}$ such that support for every pose $P \in \psi$ is greater than epsilon, i.e., for every pose $P \in \psi$, for every relational critical region $\psi \in \Psi_{ij}$, support for every pose $P \in \psi$ is $Pr(P|\mathcal{N}(\mu_\psi, \Sigma_\psi)) > \epsilon$.

Now, we describe our approach for inventing relations using the learned relational critical regions.

3.1.2 Representing Invented Critical Regions as Relations

We use the identified relational critical regions to define a set of relations between objects in the environment. Let τ_i, τ_j be a pair of object types from the set of types \mathcal{T} and let $\Psi_{ij} = \{\psi_1, \dots, \psi_n\} \subset \Psi$ be the set of critical regions for the type of objects τ_i and τ_j . For each pair of object types $\tau_i, \tau_j \in \mathcal{T}$, we define a parameterized functional relation $r_{ij} : \mathcal{O}_{\tau_i} \times \mathcal{O}_{\tau_j} \times \Psi_{ij} \rightarrow \{T, F\}$. Given a pair of low-level objects o_i and o_j of object types τ_i and τ_j respectively and a relation critical region $\psi_k \in \Psi_{ij}$, a grounded relation $r_{ij}(o_i, o_j, \psi_k)$ is true in a low-level state $x \in \mathcal{X}$ if $P_{o_j}^{o_i} \in \psi_k$. Additionally, we define a relation such that for a given pair of objects o_i and o_j

Algorithm 2: Inventing Symbolic Actions

Input: Set of demonstrations \mathcal{D}_{train} , learned predicates \mathcal{P} **Output:** Set of lifted actions $\bar{\mathcal{A}}$

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1  $\bar{\mathcal{D}}'_{train} \leftarrow \text{get\_abstract\_demonstrations}(\mathcal{D}_{train}, \mathcal{P});$ 
2  $\bar{\mathcal{D}}_{train} \leftarrow \text{lift\_demonstrations}(\bar{\mathcal{D}}'_{train});$ 
3  $\text{changed\_predicates} \leftarrow [];$ 
4 foreach  $d^k \in \mathcal{D}$  do
5   foreach consecutive state  $s_i, s_j \in d^k$  do
6      $+C_{ij}^k \leftarrow s_j \setminus s_i; -C_{ij}^k \leftarrow s_i \setminus s_j;$ 
7      $C_{ij}^k \leftarrow \langle +C_{ij}^k, -C_{ij}^k \rangle;$ 
8      $\text{changed\_predicates.add}(C_{ij}^k);$ 
9  $\mathcal{C} \leftarrow \text{create\_clusters}(\bar{\mathcal{D}}_{train}, \text{changed\_predicates});$ 
10  $\bar{\mathcal{A}} \leftarrow [];$ 
11 foreach  $(S_i \rightarrow S_j), C \in \mathcal{C}$  do
12    $\text{eff} \leftarrow \langle \text{add} = +C, \text{del} = -C \rangle;$ 
13    $\text{pre} \leftarrow \bigcap_{s \in S_i} s;$ 
14    $\text{pre} \leftarrow \text{prune\_precondition}(\text{pre});$ 
15    $\text{param} \leftarrow \text{extract\_params}(S_i \rightarrow S_j);$ 
16    $\bar{\mathcal{A}}.add(\text{create\_action}(\text{param}, \text{pre}, \text{eff}));$ 
17 return  $\bar{\mathcal{A}}$ 
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$r_{ij}(o_i, o_j, \psi_0) \implies [\forall \psi_k \in \Psi_{ij}, \neg r_{ij}(o_i, o_j, \psi_k)]$. E.g., Fig. 3 shows low-level states where the relation $r_{og}(o, g, \psi_0)$ is true for configurations 1 and 3 and the relation $r_{og}(o, g, \psi_1)$ is true for configurations 2 and 3. Let R be the set of all relations between each pair of types of objects.

We define an auxiliary relation for each relation $r \in \mathcal{R}$ using a key geometrical property of the relational critical regions. Intuitively, this relation captures the number of objects that a relational critical region can occupy. Auxiliary relations are defined using the free volume of the critical region and the volume of the objects that are supposed to occupy the region. Formally, let $\psi_k \in \Psi_{ij}$ define a relational critical region for object types τ_i and τ_j . Let $\rho(\psi_k)$ (or $\rho(o_i)$) define the total volume of the region ψ_k (or object o_i) and let $\rho_{free}(\psi_k)$ define the free volume of the region ψ_k given a current state $x \in \mathcal{X}$. For every relation $r_{ij} \in \mathcal{R}$, we define an auxiliary relation $\tilde{r}_{ij} : \mathcal{O}_{\tau_i} \times \Psi_k \rightarrow \{0, 1\}$ such that given a pair of objects o_i and o_j of object types τ_i and τ_j and a relational critical region $\psi_k \in \Psi_{ij}$, $\tilde{r}_{ij}(o_i, \psi_k) \implies \rho_{free}(\psi_k) > \rho(o_j)$. Let $\tilde{\mathcal{R}}$ be the set of these auxiliary relations.

A critical advantage of inventing relations in such a bottom-up fashion is that the pose generators (Sec. 2) do not have to be explicitly defined. Instead, automatically learned relational critical regions also serve as learned pose generators. This is explained in detail in Sec. 3.3.

Generating predicate vocabulary Relations invented by our approaches can be easily translated into PDDL representation (or any other representation). For a given pair of object types $\tau_i, \tau_j \in \mathcal{T}$, let $\Psi_{ij} \subset \Psi$ be the set of critical regions. For each relational critical region $\psi_k \in \Psi_{ij}$, each relation r_{ij} can be translated into a binary predicate ($\mathbf{p}_{ij}^{\psi_k} ?y_i ?y_j$) where $?y_i$ is a typed parameter of type τ_i and $?y_j$ is a typed parameter of type τ_j . Similarly, each auxiliary predicate \tilde{r}_{ij} can be translated to a unary predicate ($\mathbf{p}_{ij}^{\psi_k} ?y_i$) where $?y_i$ is a typed parameter of type τ_i . Let \mathcal{P} be a set of predicates for all relations (line 5).

Now, we describe our approach for inventing high-level actions using the identified predicates.

3.2 Inventing Symbolic Actions

In this work, we aim to learn relational actions that can be used efficiently for transfer and generalization. To achieve this, our approach invents high-level lifted actions, each of which corresponds to at least one change in the abstract state represented using the predicates discovered earlier (Sec. 3.1). Alg. 2 explains our approach for inventing high-level actions. This corresponds to line 6 in Alg. 1.

3.2.1 Identifying High-Level Actions

The first step in inventing high-level actions is to first identify these actions. In order to identify high-level actions, we first abstract every training demonstration in $d = \langle x_0, x_1, \dots, x_n \rangle$, where $d \in \mathcal{D}_{train}$, to an abstract demonstration $\langle s'_0, s'_1, \dots, s'_n \rangle$ using the invented predicates \mathcal{P} such that $s'_i \in 2^{\mathcal{P}}$ (line 1) and then to a lifted demonstration $\langle s_0, s_1, \dots, s_n \rangle$ such that $s_i \in 2^{\mathcal{P}}$ (line 2). Given the set of abstract demonstrations \mathcal{D}_{train} , line 7 computes a set of changed predicates C for each transition in every lifted demonstration in $\bar{\mathcal{D}}_{train}$. Precisely, for a demonstration $d^k \in \bar{\mathcal{D}}_{train}$ and a pair of consecutive lifted states $s_i, s_j \in d^k$, let $+C_{ij}^k = s_j \setminus s_i$ and $-C_{ij}^k = s_i \setminus s_j$ and let C_{ij}^k be $\langle +C_{ij}^k, -C_{ij}^k \rangle$. Line 9 uses these sets of changed predicates and cluster transitions such that each cluster has all the transitions corresponding to the same set of changed predicates. Let \mathcal{C} denote these clusters where each cluster $c = \langle S_i \rightarrow S_j, C_{ij} \rangle$ is a tuple of the set of transitions $(S_i \rightarrow S_j)$ that has the similar changed predicates C_{ij} . Each cluster $c_i \in \mathcal{C}$ induces a high-level action $\bar{a}_i \in \bar{\mathcal{A}}$. This approach is similar to Verma et al. [2022] and Silver et al. [2022]. However, they use grounded states to identify actions while our approach uses lifted predicates (lines 10-15). Next, we discuss our approach for learning effects, preconditions, and parameters for each invented action and explain it in detail in appendix B.

3.2.2 Learning Symbolic Action Model

Once a set of high-level actions $\bar{\mathcal{A}}$ is identified, we use associative learning in order to learn a symbolic model for each automatically identified action $\bar{a} \in \bar{\mathcal{A}}$. A symbolic model for an action is represented in terms of its symbolic effects, symbolic preconditions, and action parameters. Our approach also learns the symbolic model for each high-level action using the set of training demonstrations \mathcal{D}_{train} as follows.

Learning effects In our setting, effect of an action \bar{a} is represented as $eff_{\bar{a}} = \langle add_{\bar{a}}, del_{\bar{a}} \rangle$ (Sec. 2). Each cluster $c_i \in \mathcal{C}$ is generated by clustering transitions in $\bar{\mathcal{D}}$ over the sets of changed predicates. These changed predicates correspond to added and removed predicates as an effect of executing the action induced by the cluster. Therefore, for an action \bar{a}_i induced by the cluster c_i with a set of changed predicates $C_i = \langle +C_i, -C_i \rangle$, $add_{\bar{a}_i} = +C_i$ and $del_{\bar{a}_i} = -C_i$ (line 12).

Learning preconditions To learn the precondition of an action, we take the intersection of all states where the action is applicable. Given a possible set of predicates, this approach generates a maximal precondition that is conservative yet sound [Wang, 1994, Stern and Juba, 2017]. To do this, given an action $\bar{a} \in \bar{\mathcal{A}}$ corresponding to a cluster $c = \langle S_i \rightarrow S_j, C_{ij} \rangle$, $pre_{\bar{a}} = \bigcap_{s \in S_i} s$ (line 13).

Each action can have spurious preconditions corresponding to static relations that do not change on applying the action but are still true in all the pre-states $s \in S_i$. Therefore, we remove predicates (line 14) from the learned precondition that (i) are not parameterized by any of the objects that are changed by the action, and (ii) are not changed at any point in any of the demonstrations. This removes any predicate from the precondition that is spurious with respect to the data.

Learning action parameters Once the precondition and effect of an action are learned, the final step is to learn the parameters of the action, that can be replaced with objects in order to ground the action. In this step, the predicates in precondition and effect are processed in order. These predicates are processed in alphanumeric order and each of their parameters is added to the action's parameter list, if not added already. This process leads to an ordered list of parameters of the action, which can be grounded with compatible objects (line 15).

Now, we describe our approach for using the learned abstractions with any off-the-shelf task and motion planner while continually learning new relations and actions.

3.3 Planning with Learned Abstractions and Continual Learning

This section discusses our approach for using the symbolic model learned using Alg. 3 for solving new unseen long-horizon planning problems. Planning (Alg. 3) starts with the learned symbolic model $\mathcal{M} = \langle \mathcal{T}, \mathcal{P}, \bar{\mathcal{A}} \rangle$, a set of learned generators Γ , a motion planner MP, an initial state $x_i \in \mathcal{X}_{free}$, and a set of goal states $\mathcal{X}_g \subseteq \mathcal{X}_{free}$. Line 1 uses the set of learned predicates \mathcal{P} to compute the symbolic initial state s_i .

Algorithm 3: Planning with Learned Model

Input: Test environment E_{test} , an initial state $x_i \in \mathcal{X}_{free}$, a goal state $x_g \in \mathcal{X}_{free}$, learned symbolic model \mathcal{M} , a motion planner MP, a set of generators Γ , k , training demonstrations D_{train}

Output: A plan of primitive actions π , updated model \mathcal{M}

```
1  $s_i \leftarrow \text{get\_abstract\_state}(x_i)$ ;  
2  $G \leftarrow \text{create\_relation\_graph}(x_g, \mathcal{P})$ ;  
3  $\text{update\_model} \leftarrow \text{False}$ ;  
4  $\pi \leftarrow []$ ;  
5  $R_{missing} \leftarrow \{\}$ ;  
6 while solution not found or G has no edges do  
7    $s_g \leftarrow \text{create\_symbolic\_goal}(G)$ ;  
8    $\bar{\Pi} \leftarrow \text{compute\_k\_symbolic\_plans}(\mathcal{M}, \mathcal{O}, s_i, s_g, k)$ ;  
9   if  $\bar{\Pi} = \emptyset$  then  
10     $p \leftarrow \text{relax the relation graph } G$ ;  
11     $\mathcal{P}_{missing}.\text{add}(p)$ ;  
12     $\text{update\_model} \leftarrow \text{True}$ ;  
13    continue;  
14   foreach  $\bar{\pi} \in \bar{\Pi}$  do  
15     foreach  $\bar{a} \in \bar{\pi}$  do  
16        $a \leftarrow \text{refine\_action}(\bar{a}, \Gamma)$ ;  
17       if refinement fails then  
18          $\text{update\_model} \leftarrow \text{True}$ ;  
19         identify missing relation  $p_{missing}$  in G;  
20          $\mathcal{P}_{missing}.\text{add}(p_{missing})$ ;  
21         goto to next symbolic plan;  
22        $\pi.\text{append}(a)$ ;  
23   if  $\text{update\_model}$  then  
24      $\mathcal{P}_{new} \leftarrow \mathcal{P} \cup \mathcal{P}_{missing}$ ;  
25     generate a trajectory  $\mathcal{D}_\pi$  using  $\pi$ ;  
26      $\mathcal{M} \leftarrow \text{learn\_actions}(\mathcal{D} \cup \{\mathcal{D}_\pi\}, \mathcal{P}_{new})$ ;  
27   return  $\pi, \mathcal{M}$   
28 return failure,  $\mathcal{M}$ 
```

After computing the abstract initial state, line 2 utilizes the set of goal states \mathcal{X}_g and the learned predicate vocabulary \mathcal{P} to create a relation graph G corresponding to the specified goal states. A relation graph is a directed graph with objects in the environment as nodes and predicates between objects as edges. Given the relation graph, lines 7 and 8 generate a PDDL goal and use a top- k -planner to compute a set of distinct high-level plans $\bar{\Pi}$. Once high-level plans are generated, any off-the-shelf task and motion planner can be used to refine one of these plans and generate a sequence of primitive actions π .

Learning pose generators Typically, a task and motion planner requires pose generators to be provided as input. However, due to the fact that Alg. 1 invents predicates in a bottom-up manner using relational critical regions, the relational critical regions can serve as sampling-based pose generators for the learned predicates. Given a predicate $(p_{ij}^{\psi_x} ?y_i ?y_j)$ defined using a relation between object types τ_i and τ_j with a relational critical regions $\psi_k \in \Psi_{ij}$, a pose generator Γ_r can be implemented as a sampler that samples a relative pose P from the distribution $\mathcal{N}(\mu_{\psi_k}, \Sigma_{\psi_k})$. A pose P is a valid sample iff $Pr(P|\mathcal{N}(\mu_{\psi_k}, \Sigma_{\psi_k})) > \epsilon$. Here each pose generator defines a relative pose. The grounded generator for a given low-level state $x \in \mathcal{X}$. It can be computed using concepts of basis transformations outlined in Appendix A.

Updating abstractions Our approach relies on associative learning from passively collected data to invent symbolic predicates and actions, and to learn the action models. Therefore, it is possible that learned abstractions can be incorrect. Our approach uses continual learning for continuously updating the set of predicates, the set of actions, and the action model.

One potential issue arises if the invented actions are insufficient to achieve the goal, leading the top-k-planner to fail in computing any high-level plan (see line 9). In this case, Alg. 3 relaxes the relation graph G by removing an edge from the relation graph at random. It uses the relaxed relation graph to generate a new goal and compute high-level solutions for it. Every time Alg. 3 relaxes the relation graph G by removing an edge from the graph, it stores the corresponding predicate in the set of missing predicates $\mathcal{P}_{missing}$ (line 11). These predicates are used to update the symbolic model. This process is repeated until at least one high-level plan is found or the relation graph G does not have any edges.

Inaccurate action model or insufficient predicate vocabulary can also cause task and motion planning failures leading to unrefineable high-level plans. If refinement for an action fails, line 19 uses an arbitrary computational geometry package to extract a missing relation ($p_{missing}$) from the goal x_g . The computational geometry package is used to evaluate the contact points of the objects involved in the failed action in order to identify a potential relation that was not captured in the training data. Alg. 3 then moves to refining the next high-level plan from the set of high-level plans $\bar{\Pi}$ (line 21).

Finally, if Alg. 3 had failed to find high-level plans without relaxing the relation graph or computing refinement for an action, we update the symbolic model \mathcal{M} using the predicates in the set of missing predicates $\mathcal{P}_{missing}$. Let \mathcal{D}_π be the trajectory induced by the solution π . In order to update the model, Alg. 3 simply re-invents the actions and re-learns the actions models using predicates $\mathcal{P} \cup \mathcal{P}_{missing}$ and training demonstrations $\mathcal{D}_{train} \cup \{\mathcal{D}_\pi\}$.

We now present a thorough evaluation of our approach in various settings with different robots.

4 Empirical Evaluation

We present the salient aspects of our implementation, setup, and observations here. Our empirical evaluation is designed to answer the following key questions: 1) Are the learned abstractions sound and generalizable to unseen complex planning problems?; 2) Are the learned abstractions transferrable to different similar robots?; and 3) How close the learned abstractions are to human intuition?

Results across various different environments show that the presented approach learns powerful abstractions that are effective in solving new unseen problems that are far more complex than the demonstrations used to learn these abstractions. We now present our evaluation framework and results in detail.

Evaluation framework We evaluate our approach as follows. Given an environment E , we use a set of training demonstrations for learning a symbolic model $\mathcal{M}_E = \langle \mathcal{T}, \mathcal{P}, \bar{\mathcal{A}} \rangle$ if the model is not already learned. Once a symbolic model is learned, we evaluate the model using a set of test problems where each problem is defined as a pair $\langle \mathcal{O}, x_i, \mathcal{X}_g \rangle$ where \mathcal{O} is the set of objects, x_i is an initial state and \mathcal{X}_g is a set of goal states such that each test problem can have a different number of objects, different initial poses of the objects, and/or different target poses of the object.

We measure the generalizability of our domain by evaluating the success rate of solving unseen test problems using the learned model. We consider a test successful when Alg. 3 successfully computes a sequence of low-level action using the learned symbolic model. In a subset of test environments (detailed later), we use different robots to learn the symbolic model and evaluate it in order to test the transferability of the learned abstract model. This allows us to use simpler robots at the time of training to generate demonstrations. Lastly, we also evaluate the semantic interpretation of the learned model by carrying out a manual analysis of learned predicates and actions. We now discuss the test environments and robots used to evaluate our approach.

Test environments and robots We evaluate our approach in the following different environments.

- (i) *Building Keva structures (Keva)*: The first environment uses a robot and Keva planks to construct 3D structures. The robot can pick and place the planks to construct these 3D structures. Building these complex structures requires long-horizon planning with a large number of objects and actions that achieve various configurations of the planks. Appendix C shows the structures used to learn the model and evaluate our approach. We use two different robots to learn and evaluate the abstractions in this environment showing the transferability of the

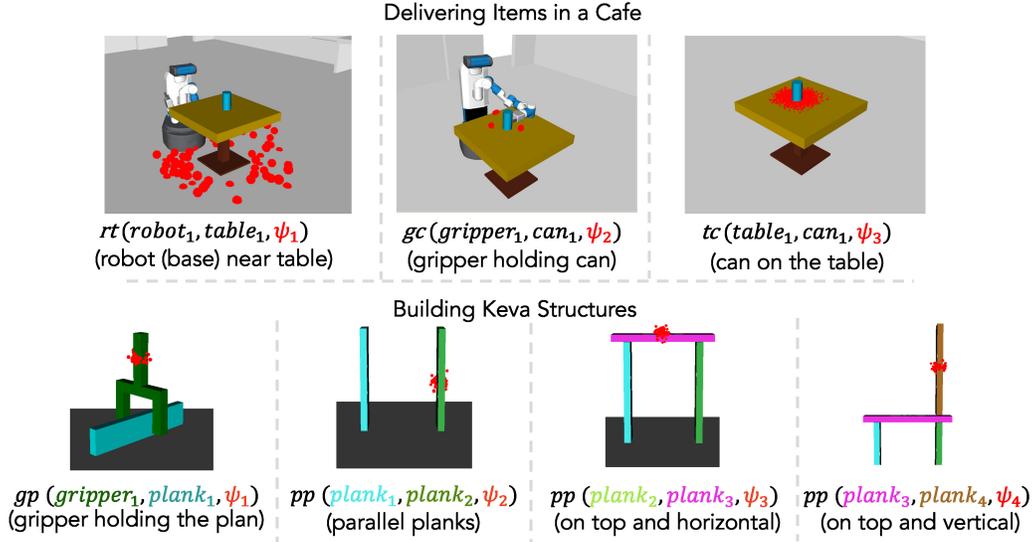


Figure 4: Different relations invented by our approach and their corresponding critical regions. Each image shows one binary predicate and its semantic interpretation. The red dots show sampled possible poses for the object in the relational critical region.

learned abstractions. We use a simple disembodied gripper to learn symbolic abstractions and use the ABB YuMi robot with a 7-DOF arm in test tasks to evaluate the learned abstractions.

- (ii) *Delivering items in a cafe (CafeWorld)*: A fetch robot is tasked to deliver items to different tables. The fetch robot is a mobile manipulator with an omnidirectional base and an 8-DOF arm. We use this environment to show the effectiveness of our learned abstractions in mobile manipulation tasks where different actions involve moving the robot base or its arm.
- (iii) *Packing cans in a box (Packing)*: This is a popular task and motion planning test environment where a robot is tasked to pack multiple objects in a small box. We use a disembodied gripper for this environment that works as a suspended robot in a factory picking objects from the top.

Baseline selection This is the first known approach that automatically invents symbolic predicate vocabularies, symbolic actions, and models for high-level planning directly from raw demonstrations. Therefore, there are no suitable baselines that inputs the same information and generates the same output. Nevertheless, we compare our approach with Code-as-policies (CoP) [Liang et al., 2023]. CoP takes input the high-level actions that the robot can execute and Python code snippets to execute these actions and uses a pre-trained LLM to compute a high-level plan. We also compare our approach with oracle abstractions generated by an expert used with an off-the-shelf task and motion planner [Srivastava et al., 2014]. We set a timeout of 3600 seconds for our approach and baselines to compute high-level plans and refine them into a sequence of primitive actions.

We now discuss the analysis of the results on our test setup.

4.1 Analysis of Results

Can we automatically learn meaningful abstractions? The core contribution of this paper is autonomously learning symbolic abstractions for robot planning problems. However, for these abstractions to be useful, they need to be meaningful. Therefore, we carefully examine the invented predicates as well as high-level actions.

Notably, our approach autonomously invented meaningful relations despite the absence of annotations or labels in the training demonstrations, demonstrating its capability to derive semantic interpretations automatically. This does not only make abstractions invented by our approach effective, but also makes them interpretable. Fig.4 illustrates a subset of invented relations by our

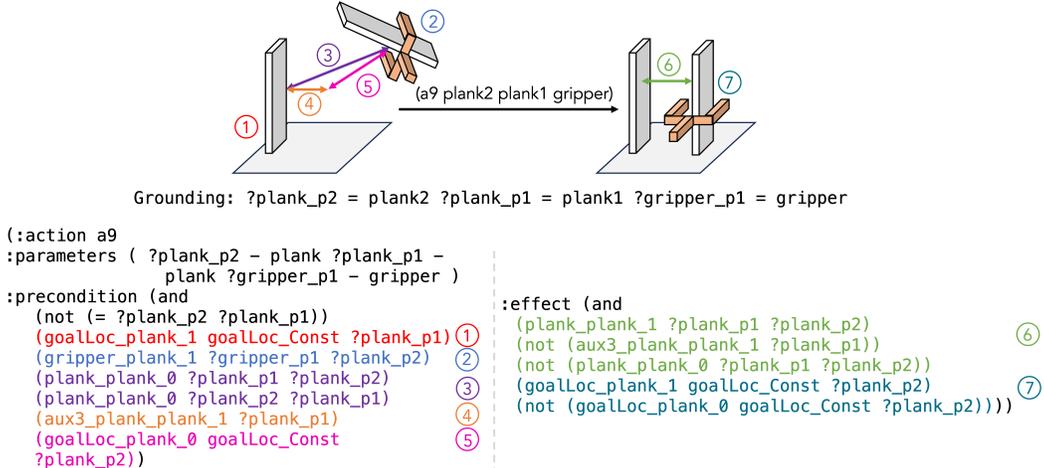


Figure 5: An automatically invented high-level action by our approach. The top figure shows the states before and after executing the high-level action. The bottom part shows the automatically learned precondition and effect of the high-level action.

approach. These predicates include predicates invented in the initial model using training demonstrations shown in Fig. 1 as well as All these predicates are invented while solving the set of test problems with an initial model constructed using training demonstrations shown in Fig. 1. Red regions depict approximations of the learned relational critical regions for corresponding objects using sampled poses. It can be seen from Fig. 4 that our approach autonomously capture crucial relations between objects in terms of the invented predicates. E.g., our approach automatically invents predicates that represent robot near the table and gripper at the grasp pose of the object in the mobile manipulation domain CafeWorld, and it invents relations between different planks such as parallel, on top vertically, and on top horizontally in the Keva domain.

Our approach also learns meaningful and human interpretable actions. E.g., fig. 4 shows one of the automatically invented high-level actions. One a careful examination, we can say that it corresponds to a high-level action that places a plank parallel to an already placed plank. More specifically, when grounded with the objects in the figure, the grounded action (a9 plank2 plank1 gripper) is placing plank2 parallel to plank1 using the gripper. Fig. 4 also shows preconditions and effects for the automatically invented “place parallel” action. The learned preconditions include: (i) plank1 should have been placed, (ii) gripper should be holding plank2, (iii) plank1 and plank2 should not be parallel, (iv) no plank should be parallel to plank1, and (v) plank2 should not be already placed. Similarly, the effects include relations corresponding to (i) plank1 and plank2 are parallel and (ii) plank2 is placed. This highlights ability of our approach to learn effective, yet, intuitive high-level actions. We provide full auto-generated PDDL domains for all test domain in appendix D.

Domain	$ \mathcal{D}_{train} $	$ \mathcal{O}_{train} $	$ \mathcal{O}_{test} $	$ \mathcal{P} $	$ \bar{\mathcal{A}} $	Used $ \mathcal{P} $	Used $ \bar{\mathcal{A}} $	Success rate	Avg. plan length	Avg. planning time (seconds)	Avg. refinement time (seconds)
CafeWorld	500	1	3-8	22	12	21	11	1.0	74	0.17	658.23
Keva	50	1-2	3-24	24	12	17	8	1.0	50	1.92	92.89
Packing	50	1	2-4	8	5	8	5	0.96	20	0.11	476.82

Table 1: Detailed statistics about the empirical evaluation and invented abstractions. The success rate is an average of 50 independent test tasks with 5 random seeds.

How scalable are the learned abstractions? Table 1 presents key observations for our empirical evaluation. It reports the number of training trajectories ($|\mathcal{D}_{train}|$), number of objects in the training demonstrations ($|\mathcal{O}_{train}|$), and number of objects in the test tasks ($|\mathcal{O}_{test}|$), number of invented predicates ($|\mathcal{P}|$) and actions ($|\mathcal{A}|$), number of predicates and actions that were used in one of the test problems, number of objects in the training demonstrations ($|\mathcal{O}_{train}|$), and number of objects in the test tasks, success rate averaged over 50 randomly generated test tasks, and average plan length in test tasks. We also report average times (in seconds) needed to compute high-level plan using off-the-shelf planner task planner [Speck et al., 2020] and times taken by an off-the-shelf task and motion planner [Srivastava et al., 2014] to refine a high-level plan.

It is evident from table 1 that our approach is able to invent effective abstractions from a few of demonstrations that generalize to significantly difficult test problems with significantly high number of objects as well as large branching factor and long horizons. E.g., our approach was able to automatically invent abstractions using only 50 demonstrations (including $\sim 50\%$ random demonstrations that do not achieve the goal) that included not more than 2 planks and a gripper and use it to compute successful solutions for test tasks than contained up to 24 planks, highlighting scalability of the invented abstractions.

Domain	$ \mathcal{D}_{train} $	Solver						
		LAMP (our approach)					Code as Policies	TAMP
		20%	40%	60%	80%	100%		
<i>CafeWorld</i>	500	0.00 \pm 0.00	0.98 \pm 0.04	0.98 \pm 0.04	0.98 \pm 0.04	1.00 \pm 0.00	0.00 \pm 0.00	1.0 \pm 0.0
<i>Keva</i>	50	0.00 \pm 0.00	0.92 \pm 0.00	0.95 \pm 0.04	0.95 \pm 0.04	1.00 \pm 0.00	0.00 \pm 0.00	1.0 \pm 0.0
<i>Packing</i>	50	0.10 \pm 0.11	0.92 \pm 0.04	0.96 \pm 0.05	0.92 \pm 0.08	0.90 \pm 0.13	0.00 \pm 0.00	0.95 \pm 0.07

Table 2: Ablation study of our approach with decreased training demonstrations and comparison with baseline approaches. Success rate for our approach and baselines averaged over 10 different unseen test tasks and 5 random executions. The percentages represent the fraction of training demonstrations used for learning the initial state and action abstractions.

How does our approach compare against the baselines? In Table 2, we present the percentage of successfully solved test tasks using abstractions learned by our method, alongside the performance of two recent approaches that use expert-crafted abstractions as discussed above. These values are averaged across 10 diverse test tasks and through 5 random executions of our approach. Notably, the test tasks are more demanding than the training tasks, each involving at least three times the number of objects compared to any task in the training set used for learning initial symbolic abstractions. Executions of solutions computed by LAMP (our approach) for various test tasks are provided in Appendix C. We can see from Table 2 that our approach significantly outperformed CoP and performed as good as the TAMP oracle. CoP used human-crafted high-level actions as well as needed manual effort to resolve syntactical errors in the output code. Yet, it failed to solve a single task from the set of test tasks across every domain.

Are the invented abstractions robust to variation in the training data? Table 2 also illustrates the number of training demonstrations utilized for different evaluations of our approach, emphasizing the scalability and generalizability of our method even with limited data. With a modest number of training demonstrations, our approach outperformed the baselines in complex problems. It successfully tackled most tasks with abstractions learned in a few-shot manner. Specifically, our approach achieved a 100% success rate in tasks involving building structures with Keva planks and packing cans in a box, needing only 50 trajectories. This underscores the data-efficiency of our approach and its ability to generalize effectively from a small number of demonstrations. Despite the non-trivial nature of learning abstractions for a mobile manipulation problem, our method efficiently solved 100% of these tasks in a cafe setting. However, for more intricate trajectories, such as grasping cans from different sides while positioning the robot on various sides of the table, it required a relatively higher number of trajectories (500). These training demonstrations, as noted above, also include $\sim 50\%$ randomly demonstrations that do not achieve the goal.

Are the invented abstractions transferrable to a different robot? Our approach invents abstractions in portable fashion. The invented abstractions can also be transferred between different robots. In order to evaluate transferrability of the invented abstractions, we use different robots to learn the abstractions and evaluate them. For the tasks involving building structures with Keva planks, we use disembodied gripper as a robot in the training demonstrations. Fig. 1 and Fig. 4 show the disembodied gripper used to learn the abstractions. However, all the test tasks were solved using an ABB YuMi robot with a constrained 7-DOF arm, shown in Fig. 1. This underscores our approach’s ability to invent abstractions that can be transferred between robots with different kinematic constraints but similar geometries.

5 Related Work

The presented approach directly relates to various concepts in task and motion planning, model learning, and abstraction learning. However, to the best of our knowledge, this is the first work that automatically invents generalizable symbolic predicates and high-level actions simultaneously using a set of low-level trajectories.

Task and motion planning approaches [Srivastava et al., 2014, Dantam et al., 2018, Garrett et al., 2020, Shah et al., 2020] develop approaches for autonomously solving long-horizon robot planning problems. These approaches are complementary to the presented approach as they focus on using provided abstractions for efficiently solving the robot planning problems. Shah and Srivastava [2022, 2024] learn state and action abstractions for long-horizon motion planning problems. An orthogonal research direction [Mishra et al., 2023, Cheng et al., 2023, Fang et al., 2023] learns implicit abstractions (low-level generators or high-level skills) for task and motion planning in the form of generative models. However, these approaches do not learn generalizable relational representations as well as complex high-level relations and actions which is the focus of our work.

Several approaches invent symbolic vocabularies given a set of high-level actions (or skills) [Konidaris et al., 2014, Ugur and Piater, 2015, Konidaris et al., 2015, Andersen and Konidaris, 2017, Konidaris et al., 2018, Bonet and Geffner, 2019, James et al., 2020]. Ahmetoglu et al. [2022], Asai et al. [2022], Liang and Boularias [2023] learn symbolic predicates in the form of latent spaces of deep neural networks and use them for high-level symbolic planning. However, these approaches assume high-level actions to be provided as input. On the other hand, the approach presented in this paper automatically learns high-level actions along with symbolic predicates.

Numerous approaches [Yang et al., 2007, Cresswell et al., 2009, Zhuo and Kambhampati, 2013, Aineto et al., 2019, Verma et al., 2021] have focused on learning preconditions and effects for high-level actions, i.e., action model. A few approaches [Čertický, 2014, Lamanna et al., 2021] have also focused on continually learning action models while collecting experience in the environment. Bryce et al. [2016] and Nayyar et al. [2022] focus on updating a known model using inconsistent observations. However, these approaches require a set of symbolic predicates and/or high-level action signatures as input whereas our approach automatically invents these predicates and actions. Several approaches [Silver et al., 2021, Verma et al., 2022, Chitnis et al., 2022, Silver et al., 2022, Kumar et al., 2023, Silver et al., 2023] have been able to automatically invent high-level actions that are induced by state abstraction akin to the presented approach. However, unlike our approach, these approaches do not automatically learn symbolic predicates and/or low-level samplers and require them as input.

LLMs for robot planning Recent years have also seen significantly increased interest in using foundational models such as LLM (large language model), VLM (visual language model), and transformers for robot planning and control owing to their success in other fields such as NLP, text generation, and vision. Several approaches [Brohan et al., 2022, Goyal et al., 2023, Shridhar et al., 2023, Vuong et al., 2023] use transformer architecture for learning reactive policies for short-horizon robot control problems. Problems tackled by these approaches are analogous to individual actions learned by our approach.

Several directions of research explore the use of LLMs for utilize LLMs as high-level planners to generate sequences comprising of high-level, expert crafted actions [Yu et al., 2023, Liang et al., 2023, Huang et al., 2022, Rana et al., 2023, Lin et al., 2023, Huang et al., 2023b, Ahn et al., 2023]. These methods make progress on the problem of near-natural language communication with robots

and are complementary to the proposed work. However, there is a strong evidence against the soundness of LLMs as planners. Valmeekam et al. [2023] show that LLMs are only $\sim 36\%$ accurate as planners even in simple block stacking settings not involving more than 5 object.

On the other hand, approaches that utilize LLMs to translate user requirements to formal specifications [Yu et al., 2023, Ding et al., 2023, Liu et al., 2023b,a, Kwon et al., 2023, Huang et al., 2023a] are complimentary to our approach. These approaches input a set of symbolic predicates and use LLMs for automatically generating symbolic goals from natural language specifications. These goals can be further used by existing planners.

6 Conclusion

This paper presents the first known approach for using continuous low-level demonstration to invent symbolic state and action abstractions that generalize to different robots and unseen problem settings. Thorough evaluation in simulated and real-world settings shows that the learned abstractions are efficient and sound, as well as generate comprehensible abstractions. In the future, we aim to utilize these automatically learned abstractions to allow non-experts to operate robots. Currently, we assume a deterministic setting. However, most real-world scenarios require handling stochasticity. Therefore, we aim to remove this assumption and learn abstractions for stochastic settings in the future. Our approach relies on associative learning with passively collected data for learning action models, which is prone to making errors. We also aim to use active learning in order to learn accurate models and provide guarantees on learned action models.

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A Relative Poses

Let o be an object in the environment and g be a gripper. P_o^W represents the pose of the object o in the world reference frame. Similarly, P_g^W represents the pose of the gripper g in the world reference frame. These poses are also called absolute poses of the object o and gripper g .

Relative poses are defined between a pair of objects. Relative pose of an object defines a pose for the objects in the reference frame defined by another object. E.g., relative pose of object o w.r.t. to gripper g defines the pose of the object relative to the gripper.

Concepts from the basis transformations from linear algebra can be used to compute these relative poses. In this case, we can re-write the equation for the absolute pose of the object o as following,

$$P_o^W = P_g^W P_o^g$$

Using this, we can derive the following equation for the relative pose of the object o in the reference frame of the gripper g that only uses absolute poses of the objects as follows.

$$P_o^g = P_g^g P_o^W$$

$$P_o^g = (P_g^W)^{-1} P_o^W$$

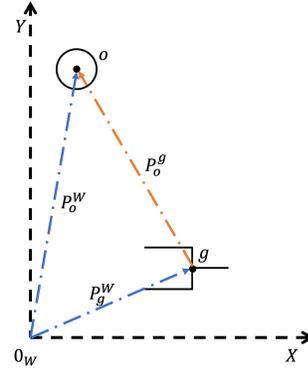


Figure 6: An illustration for computing relative poses

B Example of Learning Actions

Let the set of predicates invented in Sec. 3.1 be the following:

- (table-can0 ?table ?can): Can is not on the table.
- (table-can1 ?table ?can): Can is on the table.
- (can-gripper1 ?can ?gripper): Gripper is at grasp pose (not holding/grasping yet).
- (can-gripper2 ?can ?gripper): Gripper has grasped the object.
- (base-gripper0 ?base ?gripper): Robot's base link and robot's gripper link does not have any relation.
- (base-gripper1 ?base ?gripper): Robot's arm is tucked so there is a specific relative pose between the robot's base link and the robot's gripper link.
- (base-table1 ?base ?table): Robot's base link is located in a way such that the robot's arm can reach objects on the table.

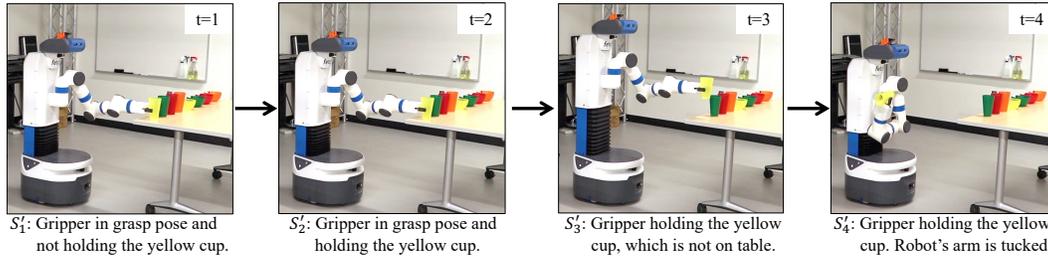


Figure 7: Trajectory $T_1 = \langle S'_1, S'_2, S'_3, S'_4 \rangle$ corresponding to the process of picking up a yellow cup from the table. The state description below each image explains that image in English. These state descriptions are added here for ease of understanding only.

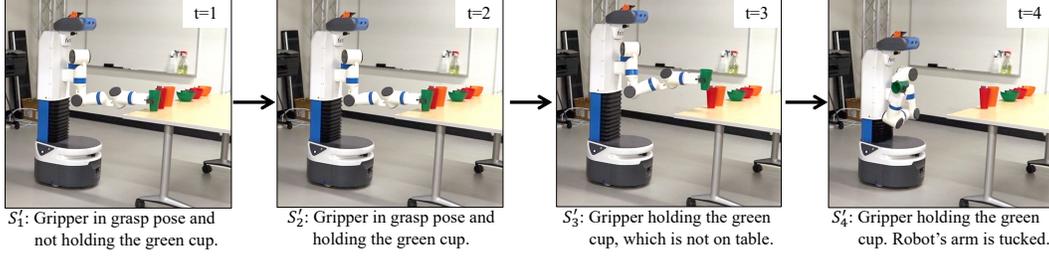


Figure 8: Trajectory $T_2 = \langle S'_1, S'_2, S'_3, S'_4 \rangle$ corresponding to the process of picking up a green cup from the table. The state description below each image explains that image in English. These state descriptions are added here for ease of understanding only.

Now, consider the two trajectories T_1 and T_2 as shown in Fig. 7 and Fig. 8, respectively. Here T_1 corresponds to the Fetch robot picking a yellow cup, and T_2 corresponds to the robot picking up a green cup (kept at a different location on the table compared to that of the yellow cup). Here these two trajectories are expressed in terms of grounded objects. These are converted to a lifted form using line 2 of Alg. 2 in terms of the predicates shown earlier. For T_1 and T_2 both, the lifted states will be:

- $S_1 : \{(table-can1 \ ?table \ ?can), (can-gripper1 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$.
- $S_2 : \{(table-can1 \ ?table \ ?can), (can-gripper2 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$.
- $S_3 : \{(table-can0 \ ?table \ ?can), (can-gripper2 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$.
- $S_4 : \{(table-can0 \ ?table \ ?can), (can-gripper2 \ ?can \ ?gripper), (base-gripper1 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$.

Note that we only show partial states here for brevity. The actual states will also have predicates like $(table-can1 \ ?table \ ?can2)$, $(table-can1 \ ?table \ ?can3)$, $(table-can1 \ ?table \ ?can4)$, $(table-can1 \ ?table \ ?bowl1)$, $(table-can1 \ ?table \ ?bowl2)$, $(table-can1 \ ?table \ ?bowl3)$, etc. corresponding to other objects kept on the table.

Learning effects Alg. 2 creates the following three clusters (lines 4-9) based on these states.

- $C_{12} = \langle {}^+C_{12} = \{(can-gripper2 \ ?can \ ?gripper)\}, {}^-C_{12} = \{(can-gripper1 \ ?can \ ?gripper)\}\rangle$.
- $C_{23} = \langle {}^+C_{23} = \{(table-can0 \ ?table \ ?can)\}, {}^-C_{23} = \{(table-can1 \ ?table \ ?can)\}\rangle$.
- $C_{34} = \langle {}^+C_{34} = \{(base-gripper1 \ ?base \ ?gripper)\}, {}^-C_{34} = \{(base-gripper0 \ ?base \ ?gripper)\}\rangle$.

Learning preconditions Learning preconditions involve taking intersection of states in which all the actions in the same cluster were executed. Here S_1 to S_3 mentioned below will remain the same for the three clusters. For e.g., precondition of $C_{12} = \{(table-can1 \ ?table \ ?can), (can-gripper1 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$. Alg. 2 will prune out $(base-table1 \ ?base \ ?table)$ from the precondition as (i) it is unchanged between S_1 and S_2 , and (ii) none of its parameters ($?base$ and $?table$) are part of any other predicate that is changed. Using this, the precondition for each action will be:

- $pre(C_{12}) = \{(table-can1 \ ?table \ ?can), (can-gripper1 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper)\}$.
- $pre(C_{23}) = \{(table-can1 \ ?table \ ?can), (can-gripper2 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$.
- $pre(C_{34}) = \{(table-can0 \ ?table \ ?can), (can-gripper2 \ ?can \ ?gripper), (base-gripper0 \ ?base \ ?gripper), (base-table1 \ ?base \ ?table)\}$.

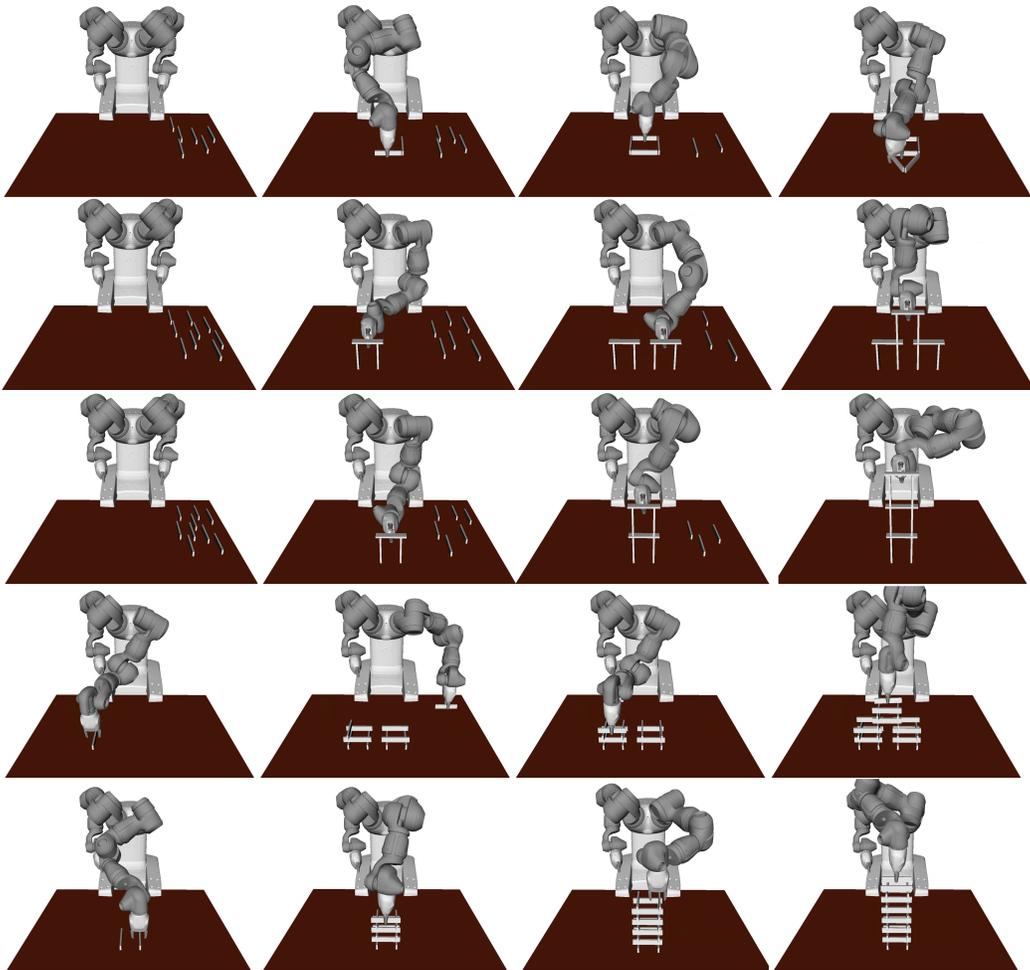
Learning parameters Learning parameters from an action’s precondition and effect is straightforward. All the unique parameters in predicates in the precondition and effect are added to the parameter list of an action representing a cluster. Using this notion, the parameters for the three clusters will be the following:

- $param(C_{12}) = (?table \ ?can \ ?gripper \ ?base)$.
- $param(C_{23}) = (?table \ ?can \ ?gripper \ ?base)$.
- $param(C_{34}) = (?table \ ?can \ ?gripper \ ?base)$.

C Test Environments

We show snippets of some of our different simulated and real-world experiments.

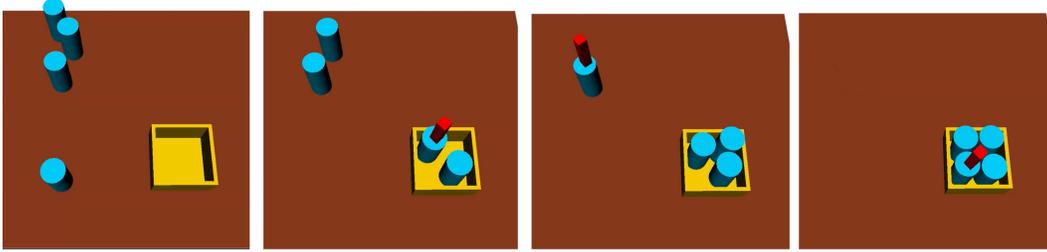
i) Building structures with Keva planks using a total of 20 random training demonstrations.



ii) Delivering items in a cafe



iii) Packing cans in a box



D Learned PDDL Domains

D.1 Domain: Keva

```

(define (domain Keva)
  (:requirements :strips :typing :equality :conditional-effects
    :existential-preconditions :universal-preconditions)
  (:types
    goalLoc
    plank
    gripper
  )

  (:constants
    goalLoc_Const - goalLoc
  )

  (:predicates
    (gripper_plank_0 ?x - gripper ?y - plank)
    (gripper_plank_1 ?x - gripper ?y - plank)
    (gripper_plank_2 ?x - gripper ?y - plank)
    (gripper_plank_3 ?x - gripper ?y - plank)
    (gripper_plank_4 ?x - gripper ?y - plank)
    (plank_plank_0 ?x - plank ?y - plank)
    (plank_plank_1 ?x - plank ?y - plank)
    (goalLoc_plank_0 ?x - goalLoc ?y - plank)
    (goalLoc_plank_1 ?x - goalLoc ?y - plank)
    (aux3_gripper_plank_0 ?x - gripper)
    (aux3_gripper_plank_1 ?x - gripper)
    (aux3_plank_plank_1 ?x - plank)
    (aux3_gripper_plank_2 ?x - gripper)
    (aux3_gripper_plank_3 ?x - gripper)
    (aux3_gripper_plank_4 ?x - gripper)
  )

  (:action a1
  :parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
  :precondition (and
    (gripper_plank_2 ?gripper_p1 ?plank_p1)
    (aux3_gripper_plank_1 ?gripper_p1)
    (aux3_gripper_plank_3 ?gripper_p1)
    (aux3_gripper_plank_4 ?gripper_p1)
  )
  :effect (and
    (gripper_plank_1 ?gripper_p1 ?plank_p1)
    (not (gripper_plank_0 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
  )
  )

```

```

        (not (gripper_plank_2 ?gripper_p1 ?plank_p1))
        (aux3_gripper_plank_2 ?gripper_p1)
        (not (aux3_gripper_plank_1 ?gripper_p1))
    )
)

(:action a2
:parameters ( ?gripper_extra_p1 - gripper ?plank_p1 - plank )
:precondition (and
    (gripper_plank_1 ?gripper_extra_p1 ?plank_p1)
    (goalLoc_plank_0 goalLoc_Const ?plank_p1)
)
:effect (and
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (not (goalLoc_plank_0 goalLoc_Const ?plank_p1))
)
)

(:action a3
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
    (gripper_plank_0 ?gripper_p1 ?plank_p1)
    (aux3_gripper_plank_1 ?gripper_p1)
    (aux3_gripper_plank_2 ?gripper_p1)
    (aux3_gripper_plank_3 ?gripper_p1)
    (aux3_gripper_plank_4 ?gripper_p1)
)
:effect (and
    (gripper_plank_2 ?gripper_p1 ?plank_p1)
    (not (gripper_plank_0 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
    (aux3_gripper_plank_0 ?gripper_p1)
    (not (aux3_gripper_plank_2 ?gripper_p1))
)
)

(:action a4
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (gripper_plank_2 ?gripper_p1 ?plank_p1)
    (aux3_gripper_plank_0 ?gripper_p1)
    (aux3_gripper_plank_1 ?gripper_p1)
    (aux3_gripper_plank_3 ?gripper_p1)
    (aux3_gripper_plank_4 ?gripper_p1)
)
:effect (and
    (gripper_plank_0 ?gripper_p1 ?plank_p1)
    (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_2 ?gripper_p1 ?plank_p1))
    (aux3_gripper_plank_2 ?gripper_p1)
    (not (aux3_gripper_plank_0 ?gripper_p1))
)
)
)

```

```

(:action a5
:parameters ( ?plank_p2 - plank ?plank_p1 - plank ?
              gripper_p1 - gripper )
:precondition (and
  (not (= ?plank_p2 ?plank_p1))
  (plank_plank_0 ?plank_p2 ?plank_p1)
  (gripper_plank_4 ?gripper_p1 ?plank_p1)
  (gripper_plank_2 ?gripper_p1 ?plank_p2)
  (plank_plank_1 ?plank_p1 ?plank_p2)
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (aux3_gripper_plank_0 ?gripper_p1)
  (aux3_gripper_plank_1 ?gripper_p1)
  (aux3_gripper_plank_3 ?gripper_p1)
)
:effect (and
  (gripper_plank_0 ?gripper_p1 ?plank_p1)
  (gripper_plank_0 ?gripper_p1 ?plank_p2)
  (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_2 ?gripper_p1 ?plank_p2))
  (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_2 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_4 ?gripper_p1 ?plank_p2))
  (not (gripper_plank_1 ?gripper_p1 ?plank_p2))
  (not (gripper_plank_3 ?gripper_p1 ?plank_p2))
  (aux3_gripper_plank_2 ?gripper_p1)
  (aux3_gripper_plank_4 ?gripper_p1)
  (not (aux3_gripper_plank_0 ?gripper_p1))
)
)

(:action a6
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (gripper_plank_2 ?gripper_p1 ?plank_p1)
  (aux3_gripper_plank_1 ?gripper_p1)
  (aux3_gripper_plank_3 ?gripper_p1)
  (aux3_gripper_plank_4 ?gripper_p1)
)
:effect (and
  (gripper_plank_0 ?gripper_p1 ?plank_p1)
  (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_2 ?gripper_p1 ?plank_p1))
  (aux3_gripper_plank_2 ?gripper_p1)
)
)

(:action a7
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
  (gripper_plank_1 ?gripper_p1 ?plank_p1)
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (aux3_gripper_plank_2 ?gripper_p1)
  (aux3_gripper_plank_3 ?gripper_p1)
)
)

```

```

:effect (and
  (gripper_plank_2 ?gripper_p1 ?plank_p1)
  (not (gripper_plank_0 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
  (aux3_gripper_plank_1 ?gripper_p1)
  (not (aux3_gripper_plank_2 ?gripper_p1))
)
)

(:action a8
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
  (gripper_plank_0 ?gripper_p1 ?plank_p1)
  (aux3_gripper_plank_1 ?gripper_p1)
  (aux3_gripper_plank_2 ?gripper_p1)
  (aux3_gripper_plank_3 ?gripper_p1)
  (aux3_gripper_plank_4 ?gripper_p1)
)
:effect (and
  (gripper_plank_2 ?gripper_p1 ?plank_p1)
  (not (gripper_plank_0 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_4 ?gripper_p1 ?plank_p1))
  (not (aux3_gripper_plank_2 ?gripper_p1))
)
)

(:action a9
:parameters ( ?plank_p2 - plank ?plank_p1 - plank
              ?gripper_p1 - gripper )
:precondition (and
  (not (= ?plank_p2 ?plank_p1))
  (plank_plank_0 ?plank_p1 ?plank_p2)
  (plank_plank_0 ?plank_p2 ?plank_p1)
  (gripper_plank_0 ?gripper_p1 ?plank_p1)
  (goalLoc_plank_0 goalLoc_Const ?plank_p2)
  (gripper_plank_1 ?gripper_p1 ?plank_p2)
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (aux3_gripper_plank_2 ?gripper_p1)
  (aux3_gripper_plank_3 ?gripper_p1)
  (aux3_plank_plank_1 ?plank_p2)
  (aux3_plank_plank_1 ?plank_p1)
  (aux3_gripper_plank_4 ?gripper_p1)
)
:effect (and
  (gripper_plank_4 ?gripper_p1 ?plank_p1)
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_1 ?plank_p1 ?plank_p2)
  (not (gripper_plank_3 ?gripper_p1 ?plank_p1))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (gripper_plank_0 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
  (not (gripper_plank_2 ?gripper_p1 ?plank_p1))
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (aux3_gripper_plank_0 ?gripper_p1)
  (not (aux3_gripper_plank_4 ?gripper_p1))
)
)

```

```

    (not (aux3_plank_plank_1 ?plank_p1))
  )
)
)

```

D.2 Domain: CafeWorld

```

(define (domain CafeWorld)
  (:requirements :strips :typing :equality :conditional-effects
    :existential-preconditions :universal-preconditions)
  (:types
    goalLoc
    freight
    can
    gripper
    surface
  )

  (:constants
    goalLoc_Const - goalLoc
  )

  (:predicates
    (gripper_can_0 ?x - gripper ?y - can)
    (gripper_can_1 ?x - gripper ?y - can)
    (gripper_can_2 ?x - gripper ?y - can)
    (freight_surface_0 ?x - freight ?y - surface)
    (freight_surface_1 ?x - freight ?y - surface)
    (freight_gripper_0 ?x - freight ?y - gripper)
    (freight_gripper_1 ?x - freight ?y - gripper)
    (freight_can_0 ?x - freight ?y - can)
    (freight_can_1 ?x - freight ?y - can)
    (can_surface_0 ?x - can ?y - surface)
    (can_surface_1 ?x - can ?y - surface)
    (aux3_can_surface_1 ?x - can)
    (aux3_freight_can_1 ?x - freight)
    (aux3_freight_surface_1 ?x - freight)
    (aux3_freight_surface_0 ?x - freight)
    (aux3_can_surface_0 ?x - can)
    (aux3_gripper_can_2 ?x - gripper)
    (aux3_freight_gripper_1 ?x - freight)
    (aux3_gripper_can_1 ?x - gripper)
    (aux3_gripper_can_0 ?x - gripper)
    (aux3_freight_gripper_0 ?x - freight)
    (aux3_freight_can_0 ?x - freight)
  )

  (:action a1
  :parameters ( ?can_p1 - can ?freight_p1 - freight ?
    surface_extra_p1 - surface ?gripper_p1 - gripper )
  :precondition (and
    (can_surface_1 ?can_p1 ?surface_extra_p1)
    (gripper_can_0 ?gripper_p1 ?can_p1)
    (freight_can_0 ?freight_p1 ?can_p1)
    (freight_surface_1 ?freight_p1 ?surface_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (aux3_gripper_can_2 ?gripper_p1)
    (aux3_gripper_can_1 ?gripper_p1)
  )
  )
)

```

```

:effect (and
  (gripper_can_1 ?gripper_p1 ?can_p1)
  (not (gripper_can_0 ?gripper_p1 ?can_p1))
  (not (gripper_can_2 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_0 ?gripper_p1)
  (not (aux3_gripper_can_1 ?gripper_p1))
)
)

(:action a2
:parameters ( ?gripper_extra_p1 - gripper ?can_p1 - can
  ?freight_extra_p1 - freight ?surface_p1 - surface )
:precondition (and
  (freight_surface_1 ?freight_extra_p1 ?surface_p1)
  (gripper_can_2 ?gripper_extra_p1 ?can_p1)
  (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
  (can_surface_1 ?can_p1 ?surface_p1)
)
:effect (and
  (can_surface_0 ?can_p1 ?surface_p1)
  (not (can_surface_1 ?can_p1 ?surface_p1))
  (aux3_can_surface_1 ?can_p1)
)
)

(:action a3
:parameters ( ?gripper_p1 - gripper ?surface_p1 - surface
  ?freight_p1 - freight )
:precondition (and
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
  (freight_surface_0 ?freight_p1 ?surface_p1)
  (aux3_freight_surface_1 ?freight_p1)
)
:effect (and
  (freight_surface_1 ?freight_p1 ?surface_p1)
  (not (freight_surface_0 ?freight_p1 ?surface_p1))
  (not (aux3_freight_surface_1 ?freight_p1))
)
)

(:action a4
:parameters ( ?surface_extra_p2 - surface
  ?gripper_p1 - gripper ?surface_p1 - surface
  ?freight_p1 - freight )
:precondition (and
  (not (= ?surface_extra_p2 ?surface_p1))
  (freight_surface_1 ?freight_p1 ?surface_p1)
  (freight_surface_0 ?freight_p1 ?surface_extra_p2)
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
)
:effect (and
  (freight_surface_0 ?freight_p1 ?surface_p1)
  (not (freight_surface_1 ?freight_p1 ?surface_p1))
  (aux3_freight_surface_1 ?freight_p1)
)
)

```

```

(:action a5
:parameters ( ?gripper_extra_p1 - gripper ?can_p1 - can
              ?freight_extra_p1 - freight ?surface_p1 - surface )
:precondition (and
  (freight_surface_1 ?freight_extra_p1 ?surface_p1)
  (gripper_can_2 ?gripper_extra_p1 ?can_p1)
  (can_surface_0 ?can_p1 ?surface_p1)
  (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
  (aux3_can_surface_1 ?can_p1)
)
:effect (and
  (can_surface_1 ?can_p1 ?surface_p1)
  (not (can_surface_0 ?can_p1 ?surface_p1))
  (not (aux3_can_surface_1 ?can_p1))
)
)

(:action a6
:parameters ( ?can_p1 - can ?freight_p1 - freight
              ?surface_extra_p1 - surface ?gripper_p1 - gripper )
:precondition (and
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (freight_can_1 ?freight_p1 ?can_p1)
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (aux3_freight_can_0 ?freight_p1)
  (aux3_freight_gripper_0 ?freight_p1)
)
:effect (and
  (freight_can_0 ?freight_p1 ?can_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (not (freight_gripper_1 ?freight_p1 ?gripper_p1))
  (not (freight_can_1 ?freight_p1 ?can_p1))
  (aux3_freight_can_1 ?freight_p1)
  (aux3_freight_gripper_1 ?freight_p1)
  (not (aux3_freight_can_0 ?freight_p1))
  (not (aux3_freight_gripper_0 ?freight_p1))
)
)

(:action a7
:parameters ( ?can_p1 - can ?gripper_p1 - gripper
              ?surface_extra_p1 - surface ?freight_p1 - freight )
:precondition (and
  (can_surface_1 ?can_p1 ?surface_extra_p1)
  (freight_can_0 ?freight_p1 ?can_p1)
  (gripper_can_1 ?gripper_p1 ?can_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (aux3_gripper_can_0 ?gripper_p1)
  (aux3_gripper_can_2 ?gripper_p1)
)
:effect (and
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (not (gripper_can_0 ?gripper_p1 ?can_p1))
  (not (gripper_can_1 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_1 ?gripper_p1)
  (not (aux3_gripper_can_2 ?gripper_p1))
)
)

```

```

)
)

(:action a8
:parameters ( ?can_p1 - can ?gripper_p1 - gripper
              ?surface_extra_p1 - surface ?freight_p1 - freight )
:precondition (and
  (freight_can_0 ?freight_p1 ?can_p1)
  (gripper_can_1 ?gripper_p1 ?can_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (aux3_gripper_can_0 ?gripper_p1)
  (aux3_gripper_can_2 ?gripper_p1)
)
:effect (and
  (gripper_can_0 ?gripper_p1 ?can_p1)
  (not (gripper_can_2 ?gripper_p1 ?can_p1))
  (not (gripper_can_1 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_1 ?gripper_p1)
  (not (aux3_gripper_can_0 ?gripper_p1))
)
)

(:action a9
:parameters ( ?can_p1 - can ?gripper_p1 - gripper
              ?surface_extra_p1 - surface ?freight_p1 - freight )
:precondition (and
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (freight_can_0 ?freight_p1 ?can_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (aux3_gripper_can_0 ?gripper_p1)
  (aux3_gripper_can_1 ?gripper_p1)
)
:effect (and
  (gripper_can_1 ?gripper_p1 ?can_p1)
  (not (gripper_can_0 ?gripper_p1 ?can_p1))
  (not (gripper_can_2 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_2 ?gripper_p1)
  (not (aux3_gripper_can_1 ?gripper_p1))
)
)

(:action a10
:parameters ( ?gripper_p1 - gripper ?surface_extra_p1 - surface
              ?freight_p1 - freight )
:precondition (and
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (aux3_freight_gripper_1 ?freight_p1)
)
:effect (and
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
  (not (freight_gripper_0 ?freight_p1 ?gripper_p1))
  (aux3_freight_gripper_0 ?freight_p1)
  (not (aux3_freight_gripper_1 ?freight_p1))
)
)
)

```

```

(:action a11
:parameters ( ?gripper_p1 - gripper ?surface_extra_p1 - surface
              ?freight_p1 - freight )
:precondition (and
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (aux3_freight_gripper_0 ?freight_p1)
)
:effect (and
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (not (freight_gripper_1 ?freight_p1 ?gripper_p1))
  (aux3_freight_gripper_1 ?freight_p1)
  (not (aux3_freight_gripper_0 ?freight_p1))
)
)

(:action a12
:parameters ( ?can_p1 - can ?freight_p1 - freight
              ?surface_extra_p1 - surface ?gripper_p1 - gripper )
:precondition (and
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (can_surface_0 ?can_p1 ?surface_extra_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (freight_can_0 ?freight_p1 ?can_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (aux3_freight_can_1 ?freight_p1)
  (aux3_freight_gripper_1 ?freight_p1)
)
:effect (and
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
  (freight_can_1 ?freight_p1 ?can_p1)
  (not (freight_can_0 ?freight_p1 ?can_p1))
  (not (freight_gripper_0 ?freight_p1 ?gripper_p1))
  (aux3_freight_can_0 ?freight_p1)
  (aux3_freight_gripper_0 ?freight_p1)
  (not (aux3_freight_can_1 ?freight_p1))
  (not (aux3_freight_gripper_1 ?freight_p1))
)
)
)
)

```

D.3 Domain: Packing

```

(define (domain Packing)
(:requirements :strips :typing :equality :conditional-effects
              :existential-preconditions :universal-preconditions)
(:types
  can
  gripper
  surface
)

(:predicates
  (gripper_can_0 ?x - gripper ?y - can)
  (gripper_can_1 ?x - gripper ?y - can)
  (gripper_can_2 ?x - gripper ?y - can)
  (can_surface_0 ?x - can ?y - surface)
  (can_surface_1 ?x - can ?y - surface)
)

```

```

    (aux3_gripper_can_1 ?x - gripper)
    (aux3_gripper_can_2 ?x - gripper)
    (aux3_gripper_can_0 ?x - gripper)
  )

(:action a1
:parameters ( ?can_p1 - can ?gripper_p1 - gripper )
:precondition (and
  (gripper_can_0 ?gripper_p1 ?can_p1)
  (aux3_gripper_can_2 ?gripper_p1)
  (aux3_gripper_can_1 ?gripper_p1)
)
:effect (and
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (not (gripper_can_0 ?gripper_p1 ?can_p1))
  (not (gripper_can_1 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_0 ?gripper_p1)
  (not (aux3_gripper_can_2 ?gripper_p1))
)
)

(:action a2
:parameters ( ?can_p1 - can ?surface_extra_p1 - surface
  ?gripper_p1 - gripper )
:precondition (and
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (can_surface_1 ?can_p1 ?surface_extra_p1)
  (aux3_gripper_can_0 ?gripper_p1)
  (aux3_gripper_can_1 ?gripper_p1)
)
:effect (and
  (gripper_can_0 ?gripper_p1 ?can_p1)
  (not (gripper_can_2 ?gripper_p1 ?can_p1))
  (not (gripper_can_1 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_2 ?gripper_p1)
  (not (aux3_gripper_can_0 ?gripper_p1))
)
)

(:action a3
:parameters ( ?can_p1 - can ?gripper_p1 - gripper )
:precondition (and
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (aux3_gripper_can_0 ?gripper_p1)
  (aux3_gripper_can_1 ?gripper_p1)
)
:effect (and
  (gripper_can_1 ?gripper_p1 ?can_p1)
  (not (gripper_can_0 ?gripper_p1 ?can_p1))
  (not (gripper_can_2 ?gripper_p1 ?can_p1))
  (aux3_gripper_can_2 ?gripper_p1)
  (not (aux3_gripper_can_1 ?gripper_p1))
)
)

(:action a4
:parameters ( ?can_p1 - can ?surface_extra_p1 - surface
  ?gripper_p1 - gripper )
:precondition (and

```

```

    (can_surface_1 ?can_p1 ?surface_extra_p1)
    (gripper_can_1 ?gripper_p1 ?can_p1)
    (aux3_gripper_can_0 ?gripper_p1)
    (aux3_gripper_can_2 ?gripper_p1)
  )
  :effect (and
    (gripper_can_2 ?gripper_p1 ?can_p1)
    (not (gripper_can_0 ?gripper_p1 ?can_p1))
    (not (gripper_can_1 ?gripper_p1 ?can_p1))
    (aux3_gripper_can_1 ?gripper_p1)
    (not (aux3_gripper_can_2 ?gripper_p1))
  )
)

(:action a5
:parameters ( ?can_p1 - can ?gripper_extra_p1 - gripper
  ?surface_p1 - surface )
:precondition (and
  (can_surface_0 ?can_p1 ?surface_p1)
  (gripper_can_1 ?gripper_extra_p1 ?can_p1)
)
:effect (and
  (can_surface_1 ?can_p1 ?surface_p1)
  (not (can_surface_0 ?can_p1 ?surface_p1))
)
)
)
)

```