

Learning Symbolic World Model Representations for Long-Horizon Robot Planning

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Abstract—Humans efficiently generalize from limited demonstrations, but robots still struggle to transfer learned knowledge to complex, unseen tasks with longer horizons and increased complexity. We propose the first known method enabling robots to autonomously invent relational concepts directly from small sets of unannotated, unsegmented demonstrations. The learned symbolic concepts are grounded into logic-based world models, facilitating efficient zero-shot generalization to significantly more complex tasks. Empirical results demonstrate that our approach achieves performance comparable to hand-crafted models, successfully scaling execution horizons and handling up to 18 times more objects than seen in training, providing the first autonomous framework for learning transferable symbolic abstractions from raw robot trajectories.

I. INTRODUCTION

The ability to learn from simple examples or demonstrations and generalizing it to solve more complex problems (a hallmark of learning in humans) is a challenging robot learning problem. For instance, all the concepts necessary for clearing a table cluttered with cups are present in one robot trajectory that picks up and places a cup (with no annotations or segmentation). It should therefore be possible to clear a table scattered with cups, given a handful of demonstrations for picking and placing a single cup. Yet, this problem remains a difficult generalization task in robotics — in large part due to the lack of methods for autonomously inventing *inventing generalizable, abstract concepts and world models* that can be transferred to more complex settings. Recent advances in robot learning address complementary problems of learning tasks with short horizons (e.g., picking up an object or closing a door) [23] and of learning to imitate demonstrations in scenarios with minimal differences from training tasks [18, 8, 65, 6].

a) Core contribution: This paper presents the first approach for learning to invent abstract logic-based concepts and world models from raw demonstrations in the form of kinematic trajectories of the robot without any human annotation, segmenting, or guidance about primitive controllers, actions, or concepts. Fig. 1 shows an overview of our approach. The input is a small set of raw training trajectories over kinematic states from simple tasks. Its output is a set of auto-invented logical concepts with concrete semantic definitions, a set of high-level actions with auto-generated pose-generators for refinement, and a logic-based world model. No human annotation is required in the entire process. Extensive empirical analysis in a range of mobile manipulation settings in simulation and

in the real world show that the learned concepts enable the robot to solve tasks it has never encountered before, with up to 18x generalization in the number of objects that need to be manipulated, novel goal configurations and significantly larger horizons.

Typically, logic-based concepts are hand-crafted by human experts [49, 20]. However, this requires extensive domain engineering efforts limiting the applicability of autonomous robots to tasks envisaged prior to deployment. Other related work shows that unary predicates and actions can be learned for motion planning [47, 48] but not for mobile manipulation. Foundation models have been used for composing high-level robot skills provided as Python APIs [37], for translating natural language instructions to logic-based formulas [40], and for planning [16, 2]. However, they still rely on expert-provided knowledge about high-level robot actions and means of executing these actions. Recent work indicates that logical concepts are learnable given a priori knowledge of high-level robot skills or actions [32], and that more complex concepts can be learned from an input set of concepts [52, 53]. However, the problem of learning logical concepts and actions without prior knowledge of either kind has remained understudied at best. We show for the first time that it is possible to solve this problem, and learn symbolic world models that support complex reasoning for solving significantly larger tasks than the ones that are encountered in training demonstrations. Detailed comparison with other related work is presented in Appendix D .

II. PROBLEM SETTING

We represent the set of possible configurations as \mathcal{X} , where each state $x \in \mathcal{X}$ specifies 6-dimensional poses (positions and orientations) of objects in the environment, links of the robot, and the set of objects attached to the robot. The set of *Primitive actions* (\mathcal{A}) represents actions that induce minor changes in the robot pose that are small enough for a native robot controller to execute. Such actions are typically executed in under a second and affect pose changes of at most a few millimeters. However, there are uncountably infinite primitive actions, many of which transform the configuration space (such as closing the gripper around an object to obtain a stable grasp); tasks of interest in this paper comprise of composing tens of thousands of such actions. This makes naïve decision making or planning focused on optimizing over all possible sequences of primitive actions

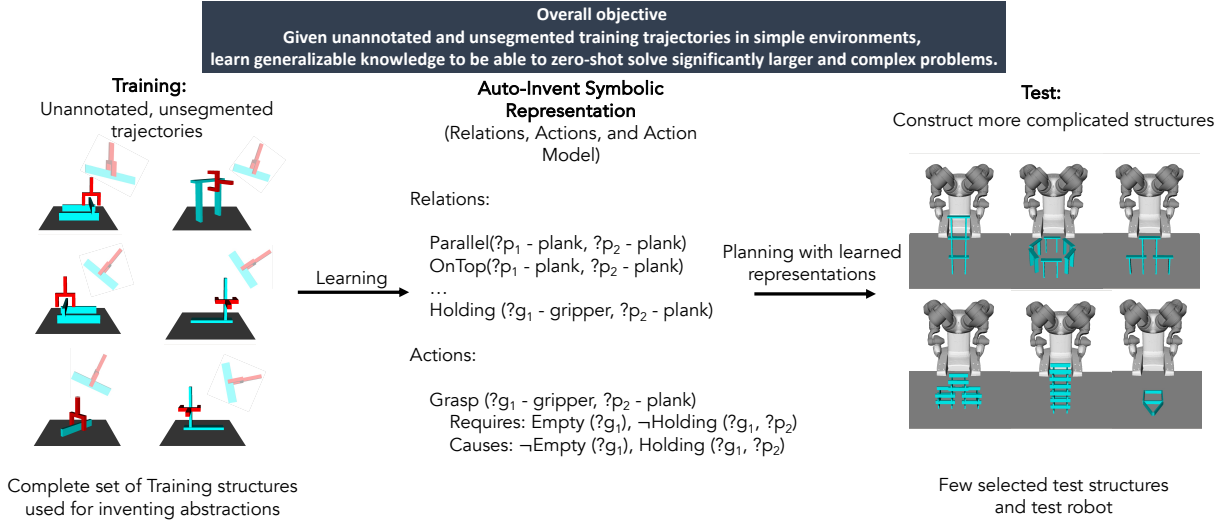


Fig. 1. Example of transfer achieved in this paper. (a) shows the complete set of training tasks for one of our experiment domains; (b) shows the automatically invented symbolic concepts and world models by our approach; (c) shows some of the test tasks zero-shot solved using the learned model despite significantly greater numbers and complexity.

infeasible. Formally, this planning problem can be expressed as an optimization of a utility function over the space of all possible policies as follows:

$$\arg \max_{\pi} \{J(\pi, x_0, H)\}$$

such that $\pi : \mathcal{X} \rightarrow \mathcal{A}$; J is a utility function

Here, we use a satisficing formulation for J that assigns a positive utility to policies meeting a goal condition \mathcal{G} within H time steps. However, the same method is valid for optimization models where J accounts for action costs. Solving this optimization problem in a deterministic setting would yield a motion plan i.e., a sequence of primitive actions starting from x_0 and reaching a state that fulfills the goal condition \mathcal{G} .

a) Abstract World Models: Since solving the planning problem at the level of detail of primitive actions is intractable even for simple tasks, the conventional approach is to use hand-crafted abstract logical concepts and create abstract world models for solving multiple tasks in a domain. These concepts include state abstractions in terms of relationships such as “On(obj, table)” and temporal abstractions or conceptual, high-level actions such as “pickup(obj)” and “place(obj, loc)”. Thus world models consist of three components: a *logical concept vocabulary* \mathcal{V} with semantics (functions determining when each predicate is true), a set of *high-level actions* $\bar{\mathcal{A}}$, and *action interpreters*, or methods for translating high-level actions into a robot’s primitive actions. Each high-level action in $\bar{\mathcal{A}}$ is defined using a precondition (a logical formula over \mathcal{V} describing when the action can be executed) and an effect (a logical formula over \mathcal{V} describing the effects of the action). Each high-level action needs action interpreters that “refine” it into motion plans that can be executed by the robot. Such world models represent knowledge about the world while abstracting away the specifics of robot and object poses, which

may change with changes in goals and problem situations. This yields significant generalizability, as the conceptual relations and actions are task agnostic.

The use of abstract concepts changes the formal planning problem to an optimization over abstract policies defined as follows:

$$\arg \max_{[\pi]} \{J(\pi, [x_0], H) \text{ such that } [x_0] = \alpha(x_0) \text{ and}$$

$$[\pi] : \alpha(\mathcal{X}) \rightarrow \beta(\mathcal{A}) \text{ and } \alpha, \beta \text{ satisfy } \kappa\}$$

Here, α and β are hand-coded state and action abstractions respectively that satisfy refinability constraints κ often crafted by expert roboticists based on their experience with the expected tasks and domains of deployment [10, 28, 54, 15, 49]. However, this formulation introduces dependency on hand-crafted knowledge, and it can result in incorrect solutions because it is difficult to design α and β that satisfy refinability. A detailed description of environment setup is presented in App. E.

b) Critical Regions: Our approach builds on the notion of *critical regions* [43, 47], which generalize the concepts of hubs and bottlenecks 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. 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 1: 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 reference density (usually uniform), and \rightarrow^+ denotes the limit from above along any sequence $\{s_n\}$ of sets containing ρ ($\rho \subseteq s_n, \forall n$).

III. OUR APPROACH

The objective of this work is to enable robots to create well-founded conceptual world models by inventing abstract concepts. It turns out that by including the abstraction as a parameter in the optimization objective, the agent can learn to perform better as it no longer depends on human-crafted abstractions. Formally, this changes the problem to:

$$\arg \max_{\pi, \alpha, \beta} \{J(\pi, x_0, H) \text{ such that} \\ \pi : \alpha(\mathcal{X}) \rightarrow \beta(\mathcal{A}) \text{ and } \alpha, \beta \text{ satisfy } \kappa\}$$

where the abstractions become a part of the parameters to be optimized.

Our approach -- *Learning Abstract Models for Planning (LAMP)* -- automatically learns these abstractions from kinematic demonstrations and represents them in the planning domain definition language (PDDL [41]). LAMP consists of the following steps (Alg. 1, App. A): (i) learn to predict a more general, relational form of critical regions called *relational critical regions* that characterize salient regions in the relative state spaces among objects (Sec. III-A), (ii) invent a symbolic relational vocabulary based on predicted relational critical regions (Sec. III-B), and (iii) invent high-level actions and learn symbolic world models (Sec. III-C). The resulting knowledge, i.e. a symbolic world model, is then used to zero-shot solve new tasks. We now present these components in detail.

A. Learning Proto-Relations

We postulate that high-level robot actions currently crafted by experts are effectively transitions to and from certain salient regions within the environment and that such regions can be automatically discerned. E.g., Fig. 2, illustrates a task where the gripper needs to pick up the can. The area from which the can can be grasped constitutes a salient region. Classically hand-crafted “Pick” and “Place” actions transition the gripper into and out of this salient region respectively. Thus, if we can automatically identify such salient regions, such high-level actions can also be invented autonomously, subsequently enabling autonomous formulations of generalizable concepts for long-horizon problems.

a) Relational Critical Regions: We start formalize the notion of salient regions as *relational critical regions (RCRs)*. Critical regions (CRs, Sec. II) help identify these regions in the robot’s configuration space [35]. However, for long-horizon reasoning involving multiple objects, salient regions occur not in the robot’s absolute configuration space but in the space of relative poses among objects. E.g., in Fig 2(a) the grasping poses for the can constitute a relational critical region (shaded red), regardless of the can’s location. We thus generalize critical regions to define *relational critical regions*. Intuitively,

a relational critical region for object x w.r.t. object y is a region in the set of poses of x relative to y that has a high density of solutions for a given distribution of tasks. Formally, we define relational critical regions as follows.

Definition 2: 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 set of relative poses for object o_2 in the frame of o_1 . The measure of the criticality of a Lebesgue-measurable open set $\rho \subseteq \mathcal{X}_{o_2}^{o_1}$, $\mu(\rho)$, is defined as $\lim_{s_n \rightarrow \rho} \frac{f(\rho)}{v(s_n)}$ 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 ($\rho \subseteq s_n, \forall n$). A region $\rho \subseteq \mathcal{X}_{o_2}^{o_1}$ is a *relational critical region (RCR)* iff $\mu(\rho)$ is greater than a predefined threshold v .

LAMP receives as input, demonstrations for simple tasks in the form of kinematic-state trajectories, and converts them to trajectories of relative poses between pairs of objects. Using Def. 2 over these trajectories, it identifies RCRs Ψ for each such pair. Next, LAMP trains multivariate Gaussian mixture models to learn generative predictors for each RCR as follows. Let $\Psi_{ij} \subset \Psi$ represent RCRs for object types τ_i and τ_j . With a threshold ϵ , the Gaussian mixture model (GMM) estimates Gaussian parameters μ_ψ and Σ_ψ for every region $\psi \in \Psi_{ij}$ ensuring support for each pose $P \in \psi$ exceeds predefined threshold ϵ . A relative pose $p_{o_1}^{o_2}$ is classified in the relational critical region ψ (denoted by $p_{o_1}^{o_2} \in \psi$) iff $\psi(p_{o_1}^{o_2}) = 1$, i.e., support for the relative pose $p_{o_1}^{o_2}$ under the Gaussian parameters μ_ψ and Σ_ψ is greater than ϵ . Our implementation uses `label` from the `OpenCV` python package¹ to extract connected components in a region, utilizing that number as components for the multivariate mixture model in the `scikit-learn` package². Once learned, these predictors are used to zero-shot predict relational critical regions for new unseen environments using the object configurations and occupancy matrix of the environment.

We now discuss our approach for learning symbolic relational vocabulary from the predicted RCRs.

B. Inventing Semantically Well-Founded Concepts for Logic

Relational critical regions represent salient regions in the environment. However, they are insufficient for generalizable long-horizon reasoning; high-level reasoning requires abstract actions, and a relational vocabulary for expressing the pre- and post-conditions of these actions. Therefore, for each relational critical region predicted by the learned multivariate Gaussian predictors between a pair of objects, LAMP’s *Relation Inventor* (Alg. 2, App. B) invents a unique binary relation between the corresponding object types. E.g., the RCR shown in Fig. 2(a) constitutes the extent of a newly invented relation (a concept equivalent to `Holding(Gripper, Can)`), and

¹<https://github.com/opencv/opencv-python>

²<https://scikit-learn.org/1.5/modules/mixture.html>

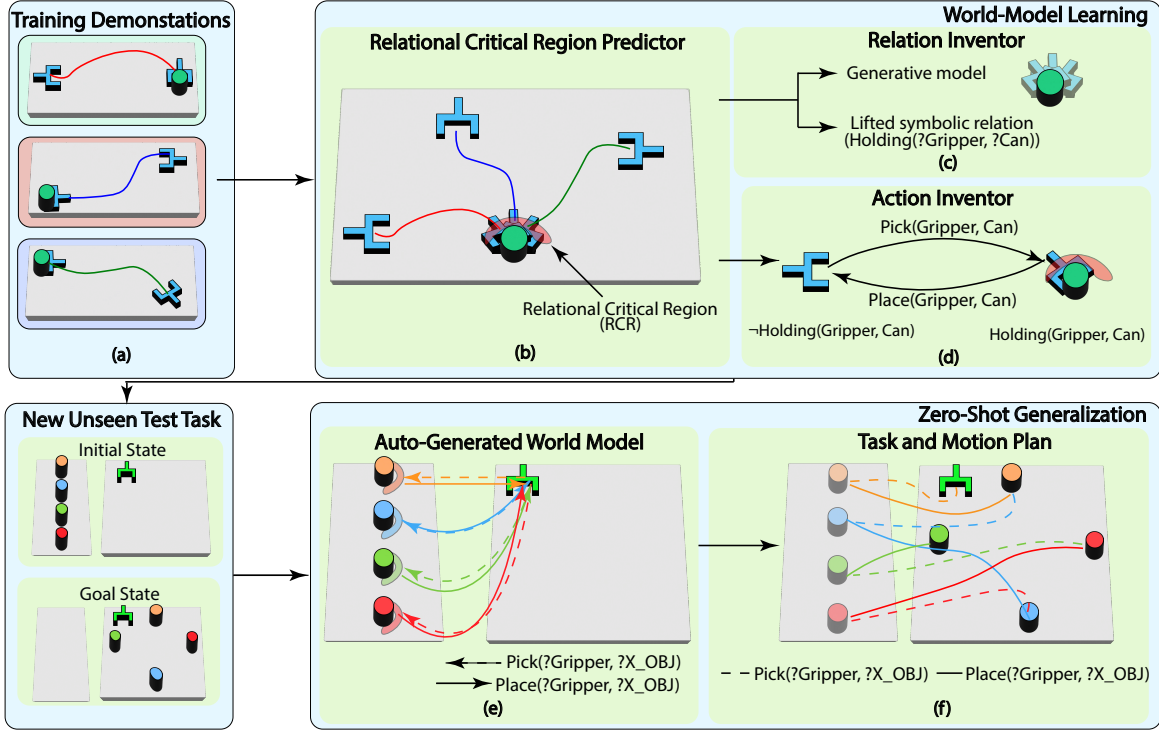


Fig. 2. Overview of LAMP. LAMP receives as input a set of unlabeled and unsegmented training demonstrations (a), from which it learns relational critical region predictors (b). Each of these generative predictors defines a unique relation between a pair of objects (c). These relations define abstract states, and learned actions represent transitions between abstract states (d). Given a new task with potentially greater objects and new obstructions, new relational critical regions and relations are predicted to formulate the abstract state space and goal state, and the learned actions are used to synthesize robot behaviors that achieve the goal (f).

it is true when the gripper is in the shaded red region around the can.

Formally, let \mathcal{O}_{τ_i} and \mathcal{O}_{τ_j} be the set of objects of type τ_i and τ_j , respectively, and let Ψ_{ij} be a set of RCR predictors between \mathcal{O}_{τ_i} and \mathcal{O}_{τ_j} . The Relation Inventor defines a unique binary relation $R_{ij}^k : \mathcal{O}_{\tau_i} \times \mathcal{O}_{\tau_j} \rightarrow \{true, false\}$ for each relation region predictor $\psi^k \in \Psi_{ij}$ such that $R_{ij}^k(o_i, o_j) = true$ iff for the relative pose $p_{o_i}^{o_j}$, $\psi^k(p_{o_i}^{o_j}) = 1$. Here, $p_{o_i}^{o_j}$ is the pose of the object o_i relative to the o_j .

Next, the Relation Inventor (RI) defines two additional sets of Boolean relations. First, given the sets of objects \mathcal{O}_{τ_i} and \mathcal{O}_{τ_j} , it defines a relation $R'_{ij} : \mathcal{O}_{\tau_i} \times \mathcal{O}_{\tau_j} \rightarrow \{true, false\}$ such that $R'_{ij}(o_i, o_j) \implies \forall k [\neg R_{ij}^k(o_i, o_j)]$. Second, it defines a relation for each relational critical region predictor for representing the if the predicted critical regions can occupy multiple objects or not. Intuitively, this models the free volume in the predicted region. E.g., the relational critical region between a gripper and a can (Fig. 2) can be only occupied by a single can but the relational critical region for a table and a can (Fig. 3) can be occupied by multiple cans. Formally, given the sets of objects \mathcal{O}_{τ_i} and \mathcal{O}_{τ_j} , a set of relational regions predictors Ψ_{ij} , the RI defines a Boolean relation for each relational region predictor $\psi^k \in \Psi_{ij}$, $R_{ij}^{free_k} : \mathcal{O}_{\tau_i} \rightarrow \{true, false\}$ such that it is true iff for $o_i \in \mathcal{O}_{\tau_i}$ and $o_j \in \mathcal{O}_{\tau_j}$, $\rho_{free}(\psi^k, o_i) > \rho(o_j)$. Here, $\rho_{free}(\psi^k)$ is the free volume of the predicted region ψ^k and $\rho(o_j)$ is the volume of the object o_j .

Given a new task T and its set of objects \mathcal{O}_T , LAMP uses

the automatically learned relational region predictors to predict the RCRs for objects and generate the relational vocabulary \mathcal{V}_T for the new task.

We now discuss our approach for autonomously inventing symbolic actions and world models.

C. Learning High-Level Actions and Logical World Models from Raw Data

The last step in the overall LAMP algorithm is to synthesize generalizable and transferrable actions, models, and action interpreters. Recall that we hypothesized that high-level actions are transitions to and from relational critical regions. E.g., the transitions in and out from the relational critical region in Fig. 2 induce high-level actions `Pickup(Gripper, Object)` and `Place(Gripper, Object)` respectively. Therefore, LAMP's *Action Inventor* (Alg. 3, App. C) use the predicted relational critical regions in training tasks to invent robot high-level actions. However, using the exhaustive enumeration of the set of predicted regions may lead to a large number of actions, most of which may be infeasible to realize. Instead, the Action Inventor (AI) creates high-level robot actions that facilitate transitions between abstract states in the input training demonstrations for forming the relational concept vocabulary, ensuring that all created actions are executable by the robot.

The Action Inventor (AI) invents high-level actions as transitions between abstract states in the training demon-

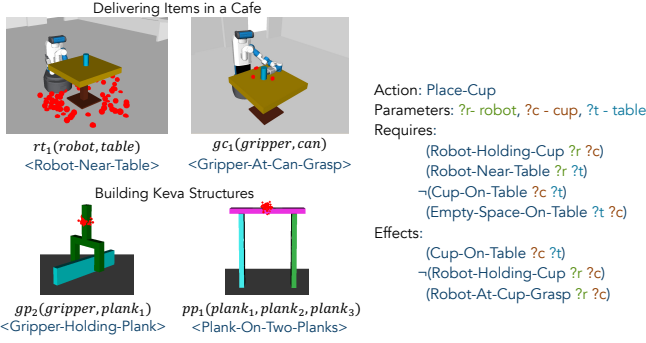


Fig. 3. Examples of relations and an action invented by our approach and their corresponding critical regions. Each image in (a) shows one binary predicate and its semantic interpretation. The red dots show sampled possible poses for the object in the relational critical region. The action in (b) shows auto-invented action with its parameters, preconditions, and effects. Relation names in blue denote the authors’ interpretations of the corresponding invented relations.

strations. To invent high-level actions, it uses the invented relational vocabulary \mathcal{V} to first convert each primitive action trajectory $\langle x_0, \dots, x_n \rangle$ to abstract transitions $\langle s'_0, \dots, s'_n \rangle$, and then lifts it to lifted transitions $\langle s_0, \dots, s_n \rangle$ by replacing object identities with placeholder objects of the object type to identify equivalent transitions. Here, each abstract state $s'_i = \{R^k(o_i, o_j) \mid \forall o_i, o_j \in \mathcal{O}, \forall R^k \in \mathcal{V}, x \models R^k(o_i, o_j)\}$.

Next, for each lifted transition $C_{ij} = s_i \rightarrow s_j$, the AI computes sets of added and deleted relations such that $C_{ij}^+ = s_j \setminus s_i$ and $C_{ij}^- = s_i \setminus s_j$ and identify the set of all transitions from the training demonstrations that induce the same $\langle C_{ij}^+, C_{ij}^- \rangle$. Each of these sets induces a high-level action \bar{a}_{ij} . It repeats this process for every identified set and build the set of high-level actions $\bar{\mathcal{A}}$. The AI then uses associative action model learning to learn symbolic models for these actions (App. C).

An important thing to note is that each action can have spurious preconditions corresponding to static relations that do not change when the action is applied, but are still true in all the pre-states. Therefore, the AI removes relations from the learned precondition that (i) are not parameterized by any of the objects that are changed by the action and (ii) that are not changed at any point in any of the demonstrations. This removes spurious preconditions with respect to the observed data.

To execute learned symbolic actions, robots require interpreters that allow converting abstract actions into sequences of primitive actions. LAMP autonomously constructs these interpreters using learned multivariate Gaussian predictors, whose generative properties enable sampling feasible environmental configurations. Formally, for a grounded symbolic relation R' , let $\Gamma_{R'} = \{x \mid R'(x) = 1\}$ denote its interpretation region. Then, the interpreter for an abstract action \bar{a}' with effects $R'^1 \wedge \dots \wedge R'^k$ is defined as $\Gamma_{\bar{a}'} = \Gamma_{R'^1} \cap \dots \cap \Gamma_{R'^k}$. To execute \bar{a}' , a planner [49] samples from $\Gamma_{\bar{a}'}$ and employs a motion planner to generate a suitable sequence of primitive robot actions.

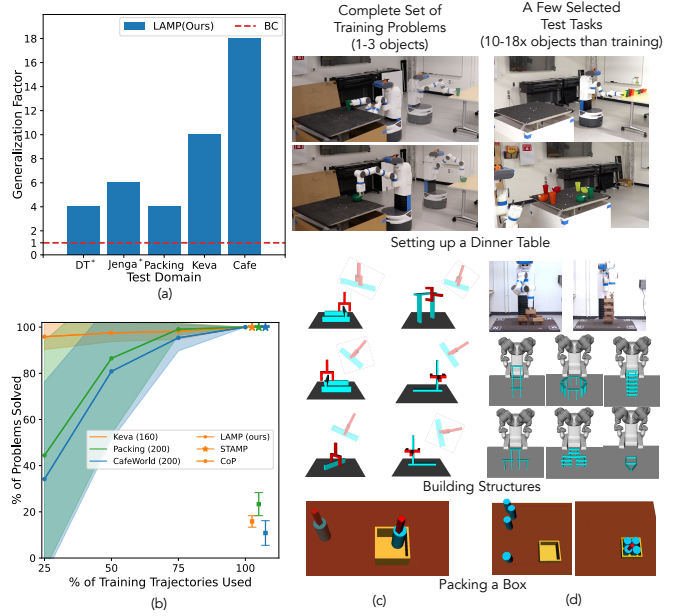


Fig. 4. Empirical assessment of the system. (a) illustrates the generalization achieved with our approach. The x-axis represents the domain, while the y-axis reflects the generalization factor. The red dotted line indicates the zone of generalization (1x) for contemporary approaches for imitation from demonstrations or behavior cloning (BC). (b) depicts the robustness of our approach, along with a comparison to Code-as-policies and STAMP (task and motion planning with oracle-designed abstractions). Here, the x-axis indicates the number of training demonstrations utilized to develop the world model, and the y-axis indicates the proportion of test tasks that our approach can solve. (c) and (d) display generalization across various tasks. (c) shows the training tasks used to learn relational region predictors and high-level actions, and (d) presents the test tasks used to evaluate our approach.

IV. EMPIRICAL EVALUATION

We designed five real-world settings to evaluate this approach in both simulated and real-world environments. These settings feature tasks including packing cans into a small box (200 demonstrations, with one can); the assembly of complex free-standing structures using Keva planks (160 demonstrations with a maximum of three planks), and Jenga planks (160 demonstrations with a maximum of three planks) with the YuMi and Fetch robots respectively; autonomous food delivery in a café environment (200 demonstrations with one item), and setting up a dining table with cups and bowls (200 demonstrations with one cup or bowl). The objective of this evaluation is to determine whether the robot can invent concepts and world models from rudimentary tasks in simulation (Fig. 4(c) and use them to solve larger tasks either in the simulator (for the café, Keva structures, and packing tasks) or in the real world (for the dining table and Jenga structures) (Fig. 4(d)). Fig. 3 illustrates some of the concepts (relations and a high-level action) that the robot invented while solving these tasks.

a) Generalization and transfer to more complex scenarios: We define the *generalization factor* as the ratio of the maximum number of objects in test tasks to the maximum

number of objects in training tasks. Since the number of relevant objects characterizes the size of the state space \mathcal{X} that the robot has to work with in computing plans, this has turned out to be an effective indicator of the complexity of a task; it is directly correlated with the length of planning horizon (the number of decision-making steps that the robot needs to consider to solve a task). We used a maximum of three objects in demonstrations across all test problems. Fig. 4(a) shows the generalization factors for LAMP (blue bar) compared to the zone of generalization for contemporary approaches that use expert demonstrations for imitation (red line), computed using 12 distinct test tasks for each domain with varying numbers of objects or problem settings. Contemporary imitation learning approaches use expert-demonstrations to learn to imitate and therefore only perform tasks that they have been trained on leading to a generalization factor of 1. On the other hand, LAMP achieves a generalization factor of upto 18. In the café domain, LAMP was able to solve problems with 18 (8) objects in simulation (real-world) based on demonstrations with at most two objects resulting in a generalization factor of $18\times$ ($4\times$) in simulated (real-world) tasks. Similarly, for the Keva and Jenga domains, LAMP invented its world models from demonstrations with three planks and successfully built structures with 30 Keva planks in simulated settings (generalization factor of $10\times$) using the YuMi robot and 18 Jenga planks in real-world settings (generalization factor of $6\times$) using the Fetch robot. The maximum possible generalization factor for box packing was $4\times$ as the box can only accommodate four cans, and LAMP achieved this.

b) Performance on novel test tasks: To evaluate generalizability of learning, we evaluate performance on new tasks starting with no knowledge other than demonstration trajectories on simpler tasks with fewer objects (Fig. 4(b)). We compare its performance with a robot equipped with hand-crafted models, and a robot equipped with a foundation model-based reasoner. The latter has emerged as a popular option for creating implicit abstractions [46, 64, 37, 16, 62, 24]. We used prior work on stochastic task and motion planning (STAMP) [49] as a baseline approach for the former and Code as Policies (CoP) [37] for the latter approach. LAMP was able to solve 100% of the unseen test tasks in our evaluation reaching similar performance of STAMP with expert-provided abstractions. On the other hand, CoP was able to solve only the simpler test tasks reaching less than 35% success rate on overall evaluation. We remark that although popular, these baselines solve fundamentally different problems as they require manually crafted inputs for the concepts that our agent needs to invent on its own: STAMP relies on complete world models, while CoP requires Python code for actions, action interpreters, detailed goal descriptions using hand-crafted predicates, and sample solution code. Additionally, CoP was given 25 attempts at each problem with a single successful execution required for the problem to be considered solved (pass @25).

c) Sample efficiency and robustness: Sample efficiency is a critical factor in robot learning. Modern approaches typically

require tens of thousands of training demonstrations, which can be difficult to obtain due to the substantially higher cost of obtaining demonstrations in robotics as compared to learning in other domains such as text and images [8, 65]. We observed that enabling the robot to learn generalizable concepts substantially reduces the burden of facilitating demonstrations. For all experiments in this work, LAMP used a maximum of 200 demonstrations on significantly simpler tasks, *with only half of the demonstrations in each domain completing those tasks*. Figure 4(b) shows how this approach scales as the number of demonstrations is reduced further and illustrates that the robot can effectively learn useful world models using as few as 40 goal-achieving demonstrations.

V. 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. We also aim to extend our approach to account for stochasticity in the environment while providing strong theoretical guarantees on learned world models.

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A. Overview of the LAMP

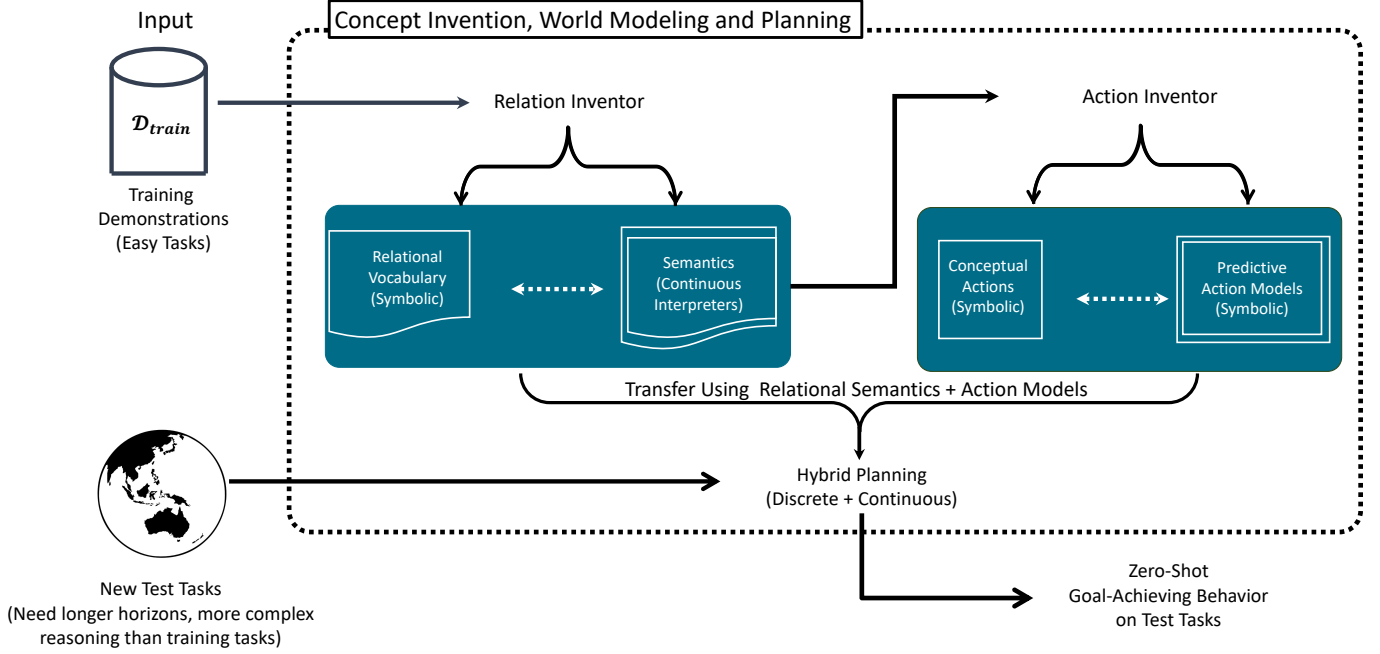


Fig. 5. Overview of the proposed algorithm. The approach comprises of two core components: (i) “Relation Inventor” that uses training demonstrations and generates novel relational vocabularies for robots, and (ii) “Action Inventor” that invents high-level symbolic actions. Together, they enable zero-shot goal-achieving behavior by integrating relational semantics, predictive action models, and hybrid planning.

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} , test tasks T_{test}

Output: Symbolic world model \mathcal{M}

/* Use Alg. 2 to invent relations */

*/

1 $\mathcal{V} \leftarrow \text{Relation_Inventor}(\mathcal{D}_{train});$

/* Use Alg. 3 to invent actions */

*/

2 $\bar{\mathcal{A}} \leftarrow \text{Action_Inventor}(\mathcal{D}_{train}, \mathcal{V});$

3 $\mathcal{M} = \langle \mathcal{V}, \bar{\mathcal{A}} \rangle;$

/* Solve new unseen task with task and motion planning (App. F) */

*/

4 $\Pi_{\mathcal{D}_{test}} \leftarrow \text{task_and_motion_planning}(T_{test}, \mathcal{M});$

5 **return** $\mathcal{M};$

B. Relation Inventor

Algorithm 2: Relation Inventor

Input: Training Demonstrations \mathcal{D}_{train} , set of objects \mathcal{O} , set of object types \mathcal{T}
Output: Set of relations \mathcal{V}

```
/* Prepare data */
1  $\tilde{\mathcal{D}}_{train} \leftarrow \xi(\mathcal{D}_{train}, \mathcal{O})$  */
/* Learn relational critical region predictor */
2  $\Psi \leftarrow \text{learn\_relational\_critical\_regions\_predictor}(\tilde{\mathcal{D}}_{train})$  */
/* Identify binary relations */
3  $\mathcal{V}_{bin} \leftarrow \text{invent\_binary\_relations}(\Psi)$  */
/* Identify additional relations */
4  $\mathcal{V}_{add} \leftarrow \text{invent\_additional\_relations}(\mathcal{V}_{bin}, \Psi)$  */
5  $\mathcal{V} \leftarrow \mathcal{V}_{bin} \cup \mathcal{V}_{add}$ 
6 return  $\mathcal{V}$ 
```

C. Action Inventor

Algorithm 3: Inventing Symbolic Actions

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

```
1  $\bar{\mathcal{D}}'_{train} \leftarrow \text{get\_abstract\_demonstrations}(\mathcal{D}_{train}, \mathcal{V});$ 
2  $\bar{\mathcal{D}}_{train} \leftarrow \text{lift\_demonstrations}(\bar{\mathcal{D}}'_{train});$ 
3  $\text{changed\_predicates} \leftarrow [];$ 
4 foreach  $d^k \in \bar{\mathcal{D}}$  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    $\text{pre} \leftarrow \cap_{s \in S_i} s;$ 
14    $\text{pre} \leftarrow \text{prune\_precondition}(\text{pre});$ 
15    $\text{param} \leftarrow \text{extract\_params}(S_i \rightarrow S_j);$ 
16    $\bar{\mathcal{A}}.\text{add}(\text{create\_action}(\text{param}, \text{pre}, \text{eff}));$ 
17 return  $\bar{\mathcal{A}}$ 
```

After identifying a group of high-level actions denoted by $\bar{\mathcal{A}}$ we employ associative learning along with the training demonstrations \mathcal{D}_{train} to develop a symbolic representation for each action $\bar{a} \in \bar{\mathcal{A}}$. The symbolic model of an action is described through its symbolic effects, symbolic preconditions, and parameters.

a) *Learning effects:* As noted earlier, in our setting, effect of an action \bar{a} is represented as $\text{eff}_{\bar{a}} = \langle \text{add}_{\bar{a}}, \text{del}_{\bar{a}} \rangle$. Each cluster $c_i \in \mathcal{C}$ is generated by clustering transitions the sets of changed relations. These changed relations correspond to added and removed relations 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 relations $C_i = \langle +C_i, -C_i \rangle$, $\text{add}_{\bar{a}_i} = +C_i$ and $\text{del}_{\bar{a}_i} = -C_i$.

b) *Learning preconditions:* To learn the precondition of an action, we take the intersection of all states where the action is applicable. Given a set of relations, this approach generates a maximal precondition that is conservative yet sound [61, 55]. We learn the precondition of an action $\bar{a} \in \bar{\mathcal{A}}$ corresponding to a cluster $c = \langle S_i \rightarrow S_j, C_{ij} \rangle$ $\text{pre}_{\bar{a}} = \cap_{s \in S_i} s$.

Each action can have spurious preconditions corresponding to static relations that do not change when the action is applied, but are still true in all the pre-states. Therefore, we remove relations 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.

c) *Learning 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 relations in precondition and effect are processed in order. These relations are processed in alphanumeric order and each of their parameters is added to the

action's parameter list, if not already added. This process leads to an ordered list of parameters of the action, which can be grounded with compatible objects.

1) *Example of Action Model Learning*: Let the set of predicates invented in Sec. III-B 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.

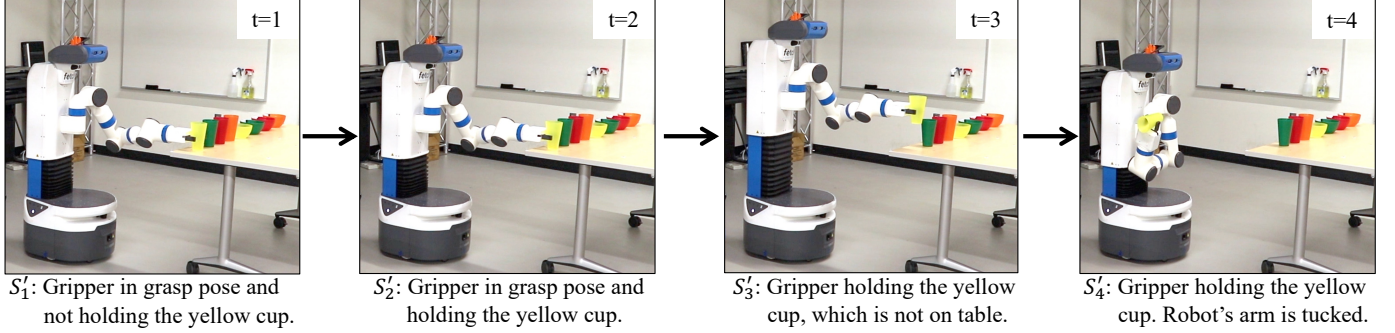


Fig. 6. Trajectory $T_1 = \langle S'_1, S'_2, S'_3, S'_4 \rangle$ corresponding to the process of picking up a yellow cup from the table. The state description below each image explains that image in English. These state descriptions are added here for ease of understanding only.

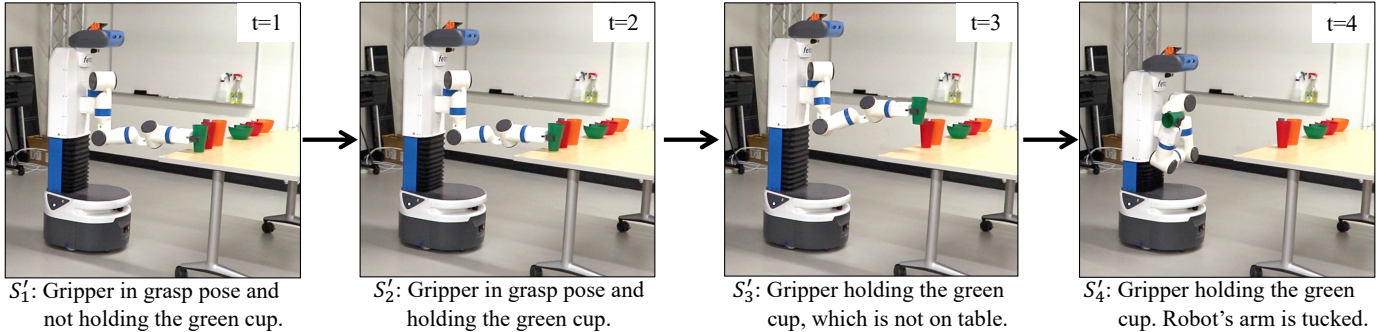


Fig. 7. Trajectory $T_2 = \langle S'_1, S'_2, S'_3, S'_4 \rangle$ corresponding to the process of picking up a green cup from the table. The state description below each image explains that image in English. These state descriptions are added here for ease of understanding only.

Now, consider the two trajectories T_1 and T_2 as shown in Fig. 6 and Fig. 7, 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. 3 in terms of the predicates shown earlier. For T_1 and T_2 both, the lifted states will be:

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

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.

a) *Learning effects*: Alg. 3 creates the following three clusters (lines 4-9) based on these states.

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

b) *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 $C_{12} = \{(\text{table-can1 } ?\text{table } ?\text{can}), (\text{can-gripper1 } ?\text{can } ?\text{gripper}), (\text{base-gripper0 } ?\text{base } ?\text{gripper}), (\text{base-table1 } ?\text{base } ?\text{table})\}$. Alg. 3 will prune out $(\text{base-table1 } ?\text{base } ?\text{table})$ 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:

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

c) *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:

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

D. 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.

a) *Task and motion planning*: Task and motion planning approaches [54, 15, 19, 49] 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 [47, 48] learn state and action abstractions for long-horizon motion planning problems. Orthogonal research [42, 12, 17] learn implicit abstractions (action interpreters or abstract actions) for TAMP 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.

b) *Learning symbolic abstractions*: Several approaches invent symbolic vocabularies given a set of high-level actions (or skills) [30, 56, 31, 4, 32, 7, 27]. Ahmetoglu et al. [1], Asai et al. [5], Liang and Boularias [38] 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 [63, 14, 66, 3, 58] have focused on learning preconditions and effects for high-level actions, i.e., action model. A few approaches [11, 34] have also focused on continually learning action models while collecting experience in the environment. Bryce et al. [9] and Nayyar et al. [44] 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 [51, 59, 13, 52, 33, 53] 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.

c) *Behavior Cloning for Robotics*: Behavior cloning (BC) has been widely explored in robotics as a method for learning control policies from expert demonstrations. Early work by Pomerleau [45] introduced the concept of imitation learning through supervised learning, where a model maps sensor inputs to control actions. Recent years have seen renewed interest in behavior cloning approaches due to the rise in applicability of deep neural networks [36, 8, 18, 65, 6]. However, these approaches are only limited to tackling problems in their training demonstrations as well as often require huge amounts of training demonstrations (in the order of 1000s of demonstrations per task), reducing the applicability of such approaches in real-world settings where the distribution of tasks is not known a priori.

d) *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 [8, 21, 50, 60] 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 [64, 37, 25, 46, 39, 26, 2]. 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. [57] show that LLMs are only $\sim 36\%$ accurate as planners even in simple block stacking settings not involving more than 5 object.

E. Environment Setup

We consider a setting where the environment comprises objects and robots. Each object's state is represented by a 6D pose. A robot, considered a distinct object, is structured as a kinematic chain of links and joints, and its state is $\langle P_{\text{base}}, \Theta \rangle$, where P_{base} indicates the 6D pose of the initial link, and Θ corresponds to the values for each joint. In an environment with objects $\mathcal{O} = \langle o_1, \dots, o_n, r_1, \dots, r_m \rangle$, the state space is denoted by $\mathcal{X} = \mathcal{X}_{r_i} \times \mathcal{X}_{o_j}$ for every robot $r_i \in \mathcal{O}$ and object $o_j \in \mathcal{O}$. A collision function c categorizes the state space \mathcal{X} into two subsets: $\mathcal{X}_{\text{free}}$ (states without collisions) and \mathcal{X}_{obs} (colliding states).

Primitive robot actions allow robots to alter their state, including configuration and base link pose, enabling movement and object manipulation within the environment. A primitive action a is characterized by a deterministic function $a : x \mapsto x'$. Given environment states $x \in \mathcal{X}$ and $x' \in \mathcal{X}$, taking action a in state x leads to state x' . We describe a robot planning problem as follows:

Definition 3: A **robot planning domain** is characterized as a tuple $\langle \mathcal{O}, \mathcal{T}, \mathcal{X}, \mathcal{A}, x_i, \mathcal{X}_g \rangle$ where \mathcal{O} represents a collection of objects, \mathcal{T} is a set of object types, \mathcal{X} denotes a state space, and \mathcal{A} is an uncountably infinite set of deterministic native actions. The initial state of the environment, $x_i \in \mathcal{X}_{\text{free}}$ is an initial state of the environment, and $\mathcal{X}_g \subseteq \mathcal{X}$ is a set of goal states. Solving a planning problem involves finding a sequence of native actions a_0, \dots, a_n such that $a_n(\dots(a_0(x_i))) \in \mathcal{X}_g$.

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 ???. 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.

a) *Symbolic World Models*: We treat symbolic world models as first-order logic frameworks and use PDDL [41] to express these models. The PDDL domain encompasses two key components: $\langle \mathcal{V}, \bar{\mathcal{A}} \rangle$. Here, \mathcal{V} represents a collection of symbolic relationships, while $\bar{\mathcal{A}}$ comprises high-level actions performed by robots. The relations $R \in \mathcal{V}$, defined by typed parameters, establish how objects of one type relate to one another type. These relations $R \in \mathcal{V}$ can be instantiated with specific objects, termed R when uninstantiated and R' when instantiated. Instantiated relations R' serve as Boolean classifiers, meaning they are true in a low-level state x (indicated by $R'_x = 1$) if the relation is valid for the objects in question within the state x . The abstraction function $\alpha : x \mapsto s$ evaluates all instantiated relations in a low-level state $x \in \mathcal{X}$, resulting in an abstract grounded state $s' \in 2^{\mathcal{V}}$ (or $s \in \alpha(\mathcal{X})$). This symbolic grounded state s' comprises the relations that hold true in low-level state x , whereas the symbolic lifted state is denoted by s ($s \in 2^{\mathcal{V}}$).

$\bar{\mathcal{A}}$ outlines symbolic lifted actions using lifted relations \mathcal{V} . Each action $\bar{a} \in \bar{\mathcal{A}}$ has typed symbolic parameters. \bar{a} is defined as a tuple $\langle pre_{\bar{a}}, eff_{\bar{a}} \rangle$, where $pre_{\bar{a}}$ is a conjunctive formula of parameterized relations \mathcal{V} . The action's effect $eff_{\bar{a}}$ is a tuple $eff_{\bar{a}} = \langle add_{\bar{a}}, del_{\bar{a}} \rangle$ adding relations $add_{\bar{a}}$ and removing relations $del_{\bar{a}}$ from the state once the action \bar{a} is executed. Actions \bar{a} can be grounded to specific objects, resulting in grounded actions \bar{a}' , generating grounded precondition $pre_{\bar{a}'}$ and effect $eff_{\bar{a}'}$. A grounded action \bar{a}' is applicable in a state s only if $pre_{\bar{a}'} \models s$. Every deterministic grounded action $\bar{a}' \in \bar{\mathcal{A}}'$ maps each symbolic state s_i to a new state s_j .

The set $\bar{\mathcal{A}}$ delineates symbolic lifted actions utilizing the lifted relations \mathcal{V} . Each action $\bar{a} \in \bar{\mathcal{A}}$ has typed symbolic parameters and is defined using a tuple $\langle pre_{\bar{a}}, eff_{\bar{a}} \rangle$. Here, $pre_{\bar{a}}$ represents a precondition of the action \bar{a} as a conjunction of parameterized relations \mathcal{V} . The effect of the action, $eff_{\bar{a}}$, is detailed as $eff_{\bar{a}} = \langle add_{\bar{a}}, del_{\bar{a}} \rangle$, which involves adding $add_{\bar{a}}$ and removing $del_{\bar{a}}$ relations from the state upon execution of action \bar{a} . These actions \bar{a} can be instantiated with specific objects to obtain grounded actions \bar{a}' , thus producing a grounded precondition $pre_{\bar{a}'}$ and effect $eff_{\bar{a}'}$. An instantiated action \bar{a}' applies in a state s' only if the precondition $pre_{\bar{a}'} \models s'$. Each deterministic grounded action $\bar{a}' \in \bar{\mathcal{A}}'$ defines a deterministic function $a' : s'_i \mapsto s'_j$ that transitions a symbolic state s'_i to another state s'_j .

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 $\bigcap_{p' \in s'} \gamma_{p'}$.

F. Task and Motion Planning with Learned World Models

Task and motion planning [54, 19, 49] combines symbolic world representations and action interpreters to develop an interleaved planning approach. This approach seeks a valid sequence of high-level actions each accompanied by legitimate primitive action refinement. We apply a deterministic form of STAMP [49] for task and motion planning relying on learned world representations. STAMP utilizes the acquired relational vocabulary along with high-level robotic actions to generate a high-level action sequence, subsequently refining these actions using learned interpreters into executable primitive actions.

One of the major challenges in TAMP with automatically learned world models is the overly pessimistic or conservative nature of these models, often leading the planner to a failed search even in the presence of potential plans. To address this, we incorporate predicate abstractions [22] to systematically create a relaxed high-level planning problem that STAMP can work to refine. However, the use of predicate abstractions may result in inaccurate world models, thus permitting high-level plans lacking viable refinements. To counteract this, we enhance the STAMP high-level planner to a top- k [29] version, generating multiple high-level plans. We then progressively refine these k plans until we achieve a plan supporting valid primitive action refinements for each high-level robot activity.

G. Code and Data

Code and data is available with the supplementary material. It would be made publicly available with the accepted paper.

H. Learned Word Models

1) Delivering Items in a Cafe:

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

  (:constants
    goalLoc_Const - goalLoc
  )

  (:predicates
    (freight_surface_0 ?x - freight ?y - surface)
    (freight_surface_1 ?x - freight ?y - surface)
    (gripper_can_0 ?x - gripper ?y - can)
    (gripper_can_1 ?x - gripper ?y - can)
    (gripper_can_2 ?x - gripper ?y - can)
    (freight_gripper_0 ?x - freight ?y - gripper)
    (freight_gripper_1 ?x - freight ?y - gripper)
    (can_surface_0 ?x - can ?y - surface)
    (can_surface_1 ?x - can ?y - surface)
    (freight_can_0 ?x - freight ?y - can)
    (freight_can_1 ?x - freight ?y - can)
    (clear3_gripper_can_1 ?x - gripper)
    (clear3_freight_can_1 ?x - freight)
    (clear3_freight_gripper_1 ?x - freight)
    (clear3_freight_surface_1 ?x - freight)
    (clear3_can_surface_1 ?x - can)
    (clear3_gripper_can_2 ?x - gripper)
```

```

)

(: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)
  (freight_can_0 ?freight_p1 ?can_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (clear3_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))
  (clear3_gripper_can_2 ?gripper_p1)
  (not (clear3_gripper_can_1 ?gripper_p1))
)
)

(:action a2
:parameters ( ?can_p1 - can ?gripper_p1 - gripper ?surface_extra_p1 - surface
              ?freight_p1 - freight )
:precondition (and
  (freight_can_0 ?freight_p1 ?can_p1)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (gripper_can_2 ?gripper_p1 ?can_p1)
  (clear3_freight_can_1 ?freight_p1)
  (clear3_freight_gripper_1 ?freight_p1)
)
:effect (and
  (freight_can_1 ?freight_p1 ?can_p1)
  (freight_gripper_1 ?freight_p1 ?gripper_p1)
  (not (freight_can_0 ?freight_p1 ?can_p1))
  (not (freight_gripper_0 ?freight_p1 ?gripper_p1))
  (not (clear3_freight_can_1 ?freight_p1))
  (not (clear3_freight_gripper_1 ?freight_p1))
)
)

(:action a3
: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)
  (freight_gripper_0 ?freight_p1 ?gripper_p1)
  (freight_surface_1 ?freight_p1 ?surface_extra_p1)
  (gripper_can_1 ?gripper_p1 ?can_p1)
  (clear3_gripper_can_2 ?gripper_p1)
)
:effect (and
  (gripper_can_0 ?gripper_p1 ?can_p1)

```



```

        (not (gripper_can_1 ?gripper_p1 ?can_p1))
        (not (gripper_can_2 ?gripper_p1 ?can_p1))
        (clear3_gripper_can_1 ?gripper_p1)
    )
)

(:action a4
 :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)
            )
 :effect (and
          (freight_gripper_0 ?freight_p1 ?gripper_p1)
          (not (freight_gripper_1 ?freight_p1 ?gripper_p1))
          (clear3_freight_gripper_1 ?freight_p1)
        )
)

(:action a5
 :parameters ( ?gripper_extra_p1 - gripper ?can_p1 - can ?freight_extra_p1 -
               ↪ freight
               ?surface_p1 - surface )
 :precondition (and
                (can_surface_0 ?can_p1 ?surface_p1)
                (freight_can_0 ?freight_extra_p1 ?can_p1)
                (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
                (freight_surface_1 ?freight_extra_p1 ?surface_p1)
                (gripper_can_2 ?gripper_extra_p1 ?can_p1)
            )
 :effect (and
          (can_surface_1 ?can_p1 ?surface_p1)
          (not (can_surface_0 ?can_p1 ?surface_p1))
          (not (clear3_can_surface_1 ?can_p1))
        )
)

(:action a6
 :parameters ( ?can_p1 - can ?gripper_p1 - gripper ?surface_extra_p1 - surface
               ?freight_p1 - freight )
 :precondition (and
                (freight_can_1 ?freight_p1 ?can_p1)
                (freight_gripper_1 ?freight_p1 ?gripper_p1)
                (freight_surface_1 ?freight_p1 ?surface_extra_p1)
                (gripper_can_2 ?gripper_p1 ?can_p1)
            )
 :effect (and
          (freight_can_0 ?freight_p1 ?can_p1)
          (freight_gripper_0 ?freight_p1 ?gripper_p1)
          (not (freight_can_1 ?freight_p1 ?can_p1))
          (not (freight_gripper_1 ?freight_p1 ?gripper_p1))
          (clear3_freight_can_1 ?freight_p1)
          (clear3_freight_gripper_1 ?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)
(freight_gripper_0 ?freight_p1 ?gripper_p1)
(freight_surface_1 ?freight_p1 ?surface_extra_p1)
(gripper_can_1 ?gripper_p1 ?can_p1)
(clear3_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))
(clear3_gripper_can_1 ?gripper_p1)
(not (clear3_gripper_can_2 ?gripper_p1))
)
)

```

```

(:action a8
:parameters ( ?gripper_p1 - gripper ?surface_extra_p1 - surface
?freight_p1 - freight )
:precondition (and
(freight_gripper_0 ?freight_p1 ?gripper_p1)
(freight_surface_1 ?freight_p1 ?surface_extra_p1)
(clear3_freight_gripper_1 ?freight_p1)
)
:effect (and
(freight_gripper_1 ?freight_p1 ?gripper_p1)
(not (freight_gripper_0 ?freight_p1 ?gripper_p1))
(not (clear3_freight_gripper_1 ?freight_p1))
)
)

```

```

(:action a9
:parameters ( ?can_p1 - can ?freight_p1 - freight ?surface_extra_p1 - surface
?gripper_p1 - gripper )
:precondition (and
(can_surface_1 ?can_p1 ?surface_extra_p1)
(freight_can_0 ?freight_p1 ?can_p1)
(freight_gripper_0 ?freight_p1 ?gripper_p1)
(freight_surface_1 ?freight_p1 ?surface_extra_p1)
(gripper_can_0 ?gripper_p1 ?can_p1)
(clear3_gripper_can_1 ?gripper_p1)
(clear3_gripper_can_2 ?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))
(not (clear3_gripper_can_1 ?gripper_p1))
)
)

```

```

(:action a10
  :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)
    (clear3_freight_surface_1 ?freight_p1)
  )
  :effect (and
    (freight_surface_1 ?freight_p1 ?surface_p1)
    (not (freight_surface_0 ?freight_p1 ?surface_p1))
    (not (clear3_freight_surface_1 ?freight_p1))
  )
)

(:action a11
  :parameters ( ?gripper_extra_p1 - gripper ?can_p1 - can ?freight_extra_p1 -
    ↪ freight
                ?surface_p1 - surface )
  :precondition (and
    (can_surface_1 ?can_p1 ?surface_p1)
    (freight_can_0 ?freight_extra_p1 ?can_p1)
    (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
    (freight_surface_1 ?freight_extra_p1 ?surface_p1)
    (gripper_can_2 ?gripper_extra_p1 ?can_p1)
  )
  :effect (and
    (can_surface_0 ?can_p1 ?surface_p1)
    (not (can_surface_1 ?can_p1 ?surface_p1))
    (clear3_can_surface_1 ?can_p1)
  )
)

(:action a12
  :parameters ( ?gripper_p1 - gripper ?surface_p1 - surface
                ?freight_p1 - freight )
  :precondition (and
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (freight_surface_1 ?freight_p1 ?surface_p1)
  )
  :effect (and
    (freight_surface_0 ?freight_p1 ?surface_p1)
    (not (freight_surface_1 ?freight_p1 ?surface_p1))
    (clear3_freight_surface_1 ?freight_p1)
  )
)
))

```

2) Setting Up a Dinner Table:

```

(define (domain DinnerTable)
  (:requirements :strips :typing :equality :conditional-effects
    :existential-preconditions :universal-preconditions)
  (:types
    freight
    gripper
    glass
    bowl
  )
)

```

```

surface
glasstargetLoc
glassinitLoc
bowltargetLoc
bowlinitLoc
)

(:predicates
  (glass_glasstargetLoc_0 ?x - glass ?y - glasstargetLoc)
  (glass_glasstargetLoc_1 ?x - glass ?y - glasstargetLoc)
  (freight_bowl_0 ?x - freight ?y - bowl)
  (freight_bowlinitLoc_0 ?x - freight ?y - bowlinitLoc)
  (freight_bowlinitLoc_1 ?x - freight ?y - bowlinitLoc)
  (bowl_bowlinitLoc_0 ?x - bowl ?y - bowlinitLoc)
  (bowl_bowlinitLoc_1 ?x - bowl ?y - bowlinitLoc)
  (gripper_bowl_0 ?x - gripper ?y - bowl)
  (gripper_bowl_1 ?x - gripper ?y - bowl)
  (gripper_bowl_2 ?x - gripper ?y - bowl)
  (freight_bowltargetLoc_0 ?x - freight ?y - bowltargetLoc)
  (freight_bowltargetLoc_1 ?x - freight ?y - bowltargetLoc)
  (freight_glass_0 ?x - freight ?y - glass)
  (bowl_bowltargetLoc_0 ?x - bowl ?y - bowltargetLoc)
  (bowl_bowltargetLoc_1 ?x - bowl ?y - bowltargetLoc)
  (glass_glassinitLoc_0 ?x - glass ?y - glassinitLoc)
  (glass_glassinitLoc_1 ?x - glass ?y - glassinitLoc)
  (freight_gripper_0 ?x - freight ?y - gripper)
  (freight_gripper_1 ?x - freight ?y - gripper)
  (freight_glassinitLoc_0 ?x - freight ?y - glassinitLoc)
  (freight_glassinitLoc_1 ?x - freight ?y - glassinitLoc)
  (freight_glasstargetLoc_0 ?x - freight ?y - glasstargetLoc)
  (freight_glasstargetLoc_1 ?x - freight ?y - glasstargetLoc)
  (gripper_glass_0 ?x - gripper ?y - glass)
  (gripper_glass_1 ?x - gripper ?y - glass)
  (gripper_glass_2 ?x - gripper ?y - glass)
  (clear3_freight_bowltargetLoc_1 ?x - freight)
  (clear3_gripper_glass_1 ?x - gripper)
  (clear3_gripper_bowl_2 ?x - gripper)
  (clear3_glass_glasstargetLoc_1 ?x - glass)
  (clear3_gripper_bowl_1 ?x - gripper)
  (clear3_gripper_glass_2 ?x - gripper)
  (clear3_freight_glasstargetLoc_1 ?x - freight)
  (clear3_freight_bowlinitLoc_1 ?x - freight)
  (clear3_bowl_bowltargetLoc_1 ?x - bowl)
  (clear3_freight_glassinitLoc_1 ?x - freight)
  (clear3_freight_gripper_1 ?x - freight)
  (clear3_bowl_bowlinitLoc_1 ?x - bowl)
  (clear3_glass_glassinitLoc_1 ?x - glass)
)

(:action a1
  :parameters ( ?bowl_extra_p1 - bowl ?freight_p1 - freight ?
    bowlinitLoc_p1 - bowlinitLoc ?gripper_p1 - gripper )
  :precondition (and
    (bowl_bowlinitLoc_0 ?bowl_extra_p1 ?bowlinitLoc_p1)
    (freight_bowlinitLoc_1 ?freight_p1 ?bowlinitLoc_p1)

```

```

        (freight_gripper_1 ?freight_p1 ?gripper_p1)
        (gripper_bowl_2 ?gripper_p1 ?bowl_extra_p1)
    )
    :effect (and
        (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_p1)
        (not (freight_bowlinitLoc_1 ?freight_p1 ?bowlinitLoc_p1))
        (clear3_freight_bowlinitLoc_1 ?freight_p1)
    )
)

(:action a2
:parameters ( ?glassinitLoc_extra_p1 - glassinitLoc ?gripper_p1 - gripper
    ?glasstargetLoc_p1 - glasstargetLoc ?freight_p1 - freight )
:precondition (and
    (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_extra_p1)
    (freight_glasstargetLoc_1 ?freight_p1 ?glasstargetLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
)
:effect (and
    (freight_glasstargetLoc_0 ?freight_p1 ?glasstargetLoc_p1)
    (not (freight_glasstargetLoc_1 ?freight_p1 ?glasstargetLoc_p1))
    (clear3_freight_glasstargetLoc_1 ?freight_p1)
)
)

(:action a3
:parameters ( ?bowl_p1 - bowl ?gripper_extra_p1 - gripper ?freight_extra_p1 -
    ↪ freight
    ?bowlinitLoc_p1 - bowlinitLoc )
:precondition (and
    (bowl_bowlinitLoc_1 ?bowl_p1 ?bowlinitLoc_p1)
    (freight_bowl_0 ?freight_extra_p1 ?bowl_p1)
    (freight_bowlinitLoc_1 ?freight_extra_p1 ?bowlinitLoc_p1)
    (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
    (gripper_bowl_2 ?gripper_extra_p1 ?bowl_p1)
)
:effect (and
    (bowl_bowlinitLoc_0 ?bowl_p1 ?bowlinitLoc_p1)
    (not (bowl_bowlinitLoc_1 ?bowl_p1 ?bowlinitLoc_p1))
    (clear3_bowl_bowlinitLoc_1 ?bowl_p1)
)
)

(:action a4
:parameters ( ?gripper_p1 - gripper ?bowltargetLoc_p1 - bowltargetLoc
    ?bowlinitLoc_extra_p1 - bowlinitLoc ?freight_p1 - freight )
:precondition (and
    (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_extra_p1)
    (freight_bowltargetLoc_1 ?freight_p1 ?bowltargetLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
)
:effect (and
    (freight_bowltargetLoc_0 ?freight_p1 ?bowltargetLoc_p1)
    (not (freight_bowltargetLoc_1 ?freight_p1 ?bowltargetLoc_p1))
    (clear3_freight_bowltargetLoc_1 ?freight_p1)
)
)

```

```

)

(:action a5
:parameters ( ?bowl_p1 - bowl ?gripper_extra_p1 - gripper ?
bowlinitLoc_extra_p1 - bowlinitLoc ?freight_extra_p1 - freight
?bowltargetLoc_p1 - bowltargetLoc )
:precondition (and
    (bowl_bowlinitLoc_0 ?bowl_p1 ?bowlinitLoc_extra_p1)
    (bowl_bowltargetLoc_0 ?bowl_p1 ?bowltargetLoc_p1)
    (freight_bowl_0 ?freight_extra_p1 ?bowl_p1)
    (freight_bowlinitLoc_0 ?freight_extra_p1 ?bowlinitLoc_extra_p1)
    (freight_bowltargetLoc_1 ?freight_extra_p1 ?bowltargetLoc_p1)
    (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
    (gripper_bowl_2 ?gripper_extra_p1 ?bowl_p1)
    (clear3_bowl_bowltargetLoc_1 ?bowl_p1)
)
:effect (and
    (bowl_bowltargetLoc_1 ?bowl_p1 ?bowltargetLoc_p1)
    (not (bowl_bowltargetLoc_0 ?bowl_p1 ?bowltargetLoc_p1))
    (not (clear3_bowl_bowltargetLoc_1 ?bowl_p1))
)
)

(:action a6
:parameters ( ?glasstargetLoc_extra_p1 - glasstargetLoc ?glass_p1 - glass
?gripper_p1 - gripper ?glassinitLoc_extra_p1 - glassinitLoc ?freight_p1 -
    ↪ freight )
:precondition (and
    (freight_glass_0 ?freight_p1 ?glass_p1)
    (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_extra_p1)
    (freight_glasstargetLoc_1 ?freight_p1 ?glasstargetLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (glass_glassinitLoc_0 ?glass_p1 ?glassinitLoc_extra_p1)
    (glass_glasstargetLoc_1 ?glass_p1 ?glasstargetLoc_extra_p1)
    (gripper_glass_2 ?gripper_p1 ?glass_p1)
    (clear3_gripper_glass_1 ?gripper_p1)
)
:effect (and
    (gripper_glass_1 ?gripper_p1 ?glass_p1)
    (not (gripper_glass_0 ?gripper_p1 ?glass_p1))
    (not (gripper_glass_2 ?gripper_p1 ?glass_p1))
    (clear3_gripper_glass_2 ?gripper_p1)
    (not (clear3_gripper_glass_1 ?gripper_p1))
)
)

(:action a7
:parameters ( ?bowltargetLoc_extra_p1 - bowltargetLoc ?bowl_p1 - bowl
?gripper_p1 - gripper ?bowlinitLoc_extra_p1 - bowlinitLoc ?freight_p1 -
    ↪ freight )
:precondition (and
    (bowl_bowlinitLoc_0 ?bowl_p1 ?bowlinitLoc_extra_p1)
    (bowl_bowltargetLoc_1 ?bowl_p1 ?bowltargetLoc_extra_p1)
    (freight_bowl_0 ?freight_p1 ?bowl_p1)
    (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_extra_p1)
    (freight_bowltargetLoc_1 ?freight_p1 ?bowltargetLoc_extra_p1)

```



```

        (freight_gripper_0 ?freight_p1 ?gripper_p1)
        (gripper_bowl_1 ?gripper_p1 ?bowl_p1)
        (clear3_gripper_bowl_2 ?gripper_p1)
    )
    :effect (and
        (gripper_bowl_0 ?gripper_p1 ?bowl_p1)
        (not (gripper_bowl_1 ?gripper_p1 ?bowl_p1))
        (not (gripper_bowl_2 ?gripper_p1 ?bowl_p1))
        (clear3_gripper_bowl_1 ?gripper_p1)
    )
)

(:action a8
  :parameters ( ?bowltargetLoc_extra_p1 - bowltargetLoc ?bowl_p1 - bowl
    ?gripper_p1 - gripper ?bowlinitLoc_extra_p1 - bowlinitLoc ?freight_p1 -
      ↪ freight )
  :precondition (and
    (bowl_bowlinitLoc_0 ?bowl_p1 ?bowlinitLoc_extra_p1)
    (bowl_bowltargetLoc_1 ?bowl_p1 ?bowltargetLoc_extra_p1)
    (freight_bowl_0 ?freight_p1 ?bowl_p1)
    (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_extra_p1)
    (freight_bowltargetLoc_1 ?freight_p1 ?bowltargetLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (gripper_bowl_2 ?gripper_p1 ?bowl_p1)
    (clear3_gripper_bowl_1 ?gripper_p1)
  )
  :effect (and
    (gripper_bowl_1 ?gripper_p1 ?bowl_p1)
    (not (gripper_bowl_0 ?gripper_p1 ?bowl_p1))
    (not (gripper_bowl_2 ?gripper_p1 ?bowl_p1))
    (clear3_gripper_bowl_2 ?gripper_p1)
    (not (clear3_gripper_bowl_1 ?gripper_p1))
  )
)

(:action a9
  :parameters ( ?glasstargetLoc_p1 - glasstargetLoc ?glass_p1 - glass
    ?freight_extra_p1 - freight ?glassinitLoc_extra_p1 - glassinitLoc
    ?gripper_extra_p1 - gripper )
  :precondition (and
    (freight_glass_0 ?freight_extra_p1 ?glass_p1)
    (freight_glassinitLoc_0 ?freight_extra_p1 ?glassinitLoc_extra_p1)
    (freight_glasstargetLoc_1 ?freight_extra_p1 ?glasstargetLoc_p1)
    (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
    (glass_glassinitLoc_0 ?glass_p1 ?glassinitLoc_extra_p1)
    (glass_glasstargetLoc_0 ?glass_p1 ?glasstargetLoc_p1)
    (gripper_glass_2 ?gripper_extra_p1 ?glass_p1)
    (clear3_glass_glasstargetLoc_1 ?glass_p1)
  )
  :effect (and
    (glass_glasstargetLoc_1 ?glass_p1 ?glasstargetLoc_p1)
    (not (glass_glasstargetLoc_0 ?glass_p1 ?glasstargetLoc_p1))
    (not (clear3_glass_glasstargetLoc_1 ?glass_p1))
  )
)

```

```

(:action a10
  :parameters ( ?bowltargetLoc_p1 - bowltargetLoc  ?bowl_extra_p1 - bowl
    ?gripper_p1 - gripper  ?bowlinitLoc_extra_p1 - bowlinitLoc  ?freight_p1 -
      ↪ freight )
  :precondition (and
    (bowl_bowlinitLoc_0 ?bowl_extra_p1 ?bowlinitLoc_extra_p1)
    (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_extra_p1)
    (freight_bowltargetLoc_0 ?freight_p1 ?bowltargetLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (gripper_bowl_2 ?gripper_p1 ?bowl_extra_p1)
    (clear3_freight_bowltargetLoc_1 ?freight_p1)
  )
  :effect (and
    (freight_bowltargetLoc_1 ?freight_p1 ?bowltargetLoc_p1)
    (not (freight_bowltargetLoc_0 ?freight_p1 ?bowltargetLoc_p1))
    (not (clear3_freight_bowltargetLoc_1 ?freight_p1))
  )
)

(:action a11
  :parameters ( ?glassinitLoc_p1 - glassinitLoc  ?gripper_p1 - gripper
    ?freight_p1 - freight )
  :precondition (and
    (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (clear3_freight_glassinitLoc_1 ?freight_p1)
  )
  :effect (and
    (freight_glassinitLoc_1 ?freight_p1 ?glassinitLoc_p1)
    (not (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_p1))
    (not (clear3_freight_glassinitLoc_1 ?freight_p1))
  )
)

(:action a12
  :parameters ( ?bowl_p1 - bowl  ?gripper_p1 - gripper
    ?bowlinitLoc_extra_p1 - bowlinitLoc  ?freight_p1 - freight )
  :precondition (and
    (bowl_bowlinitLoc_1 ?bowl_p1 ?bowlinitLoc_extra_p1)
    (freight_bowl_0 ?freight_p1 ?bowl_p1)
    (freight_bowlinitLoc_1 ?freight_p1 ?bowlinitLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (gripper_bowl_1 ?gripper_p1 ?bowl_p1)
    (clear3_gripper_bowl_2 ?gripper_p1)
  )
  :effect (and
    (gripper_bowl_2 ?gripper_p1 ?bowl_p1)
    (not (gripper_bowl_0 ?gripper_p1 ?bowl_p1))
    (not (gripper_bowl_1 ?gripper_p1 ?bowl_p1))
    (clear3_gripper_bowl_1 ?gripper_p1)
    (not (clear3_gripper_bowl_2 ?gripper_p1))
  )
)

(:action a13
  :parameters ( ?gripper_p1 - gripper  ?bowl_p1 - bowl

```

```

    ?bowlinitLoc_extra_p1 - bowlinitLoc  ?freight_p1 - freight )
:precondition (and
    (bowl_bowlinitLoc_1 ?bowl_p1 ?bowlinitLoc_extra_p1)
    (freight_bowl_0 ?freight_p1 ?bowl_p1)
    (freight_bowlinitLoc_1 ?freight_p1 ?bowlinitLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (gripper_bowl_0 ?gripper_p1 ?bowl_p1)
    (clear3_gripper_bowl_1 ?gripper_p1)
    (clear3_gripper_bowl_2 ?gripper_p1)
)
:effect (and
    (gripper_bowl_1 ?gripper_p1 ?bowl_p1)
    (not (gripper_bowl_0 ?gripper_p1 ?bowl_p1))
    (not (gripper_bowl_2 ?gripper_p1 ?bowl_p1))
    (not (clear3_gripper_bowl_1 ?gripper_p1))
)
)

(:action a14
:parameters ( ?glasstargetLoc_extra_p1 - glasstargetLoc  ?glass_p1 - glass
    ?freight_p1 - freight  ?glassinitLoc_extra_p1 - glassinitLoc  ?gripper_p1 -
    → gripper )
:precondition (and
    (freight_glass_0 ?freight_p1 ?glass_p1)
    (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_extra_p1)
    (freight_glasstargetLoc_1 ?freight_p1 ?glasstargetLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (glass_glassinitLoc_0 ?glass_p1 ?glassinitLoc_extra_p1)
    (glass_glasstargetLoc_1 ?glass_p1 ?glasstargetLoc_extra_p1)
    (gripper_glass_1 ?gripper_p1 ?glass_p1)
    (clear3_gripper_glass_2 ?gripper_p1)
)
:effect (and
    (gripper_glass_0 ?gripper_p1 ?glass_p1)
    (not (gripper_glass_1 ?gripper_p1 ?glass_p1))
    (not (gripper_glass_2 ?gripper_p1 ?glass_p1))
    (clear3_gripper_glass_1 ?gripper_p1)
)
)

(:action a15
:parameters ( ?glasstargetLoc_p1 - glasstargetLoc  ?glassinitLoc_extra_p1 -
    → glassinitLoc
    ?freight_p1 - freight  ?glass_extra_p1 - glass  ?gripper_p1 - gripper )
:precondition (and
    (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_extra_p1)
    (freight_glasstargetLoc_0 ?freight_p1 ?glasstargetLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (glass_glassinitLoc_0 ?glass_extra_p1 ?glassinitLoc_extra_p1)
    (gripper_glass_2 ?gripper_p1 ?glass_extra_p1)
    (clear3_freight_glasstargetLoc_1 ?freight_p1)
)
:effect (and
    (freight_glasstargetLoc_1 ?freight_p1 ?glasstargetLoc_p1)
    (not (freight_glasstargetLoc_0 ?freight_p1 ?glasstargetLoc_p1))
    (not (clear3_freight_glasstargetLoc_1 ?freight_p1))
)
)

```

```

)
)

(:action a16
:parameters ( ?gripper_p1 - gripper ?freight_p1 - freight )
:precondition (and
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (clear3_freight_gripper_1 ?freight_p1)
)
:effect (and
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (not (freight_gripper_0 ?freight_p1 ?gripper_p1))
    (not (clear3_freight_gripper_1 ?freight_p1))
)
)

(:action a17
:parameters ( ?glassinitLoc_extra_p1 - glassinitLoc ?gripper_p1 - gripper
    ?glass_p1 - glass ?freight_p1 - freight )
:precondition (and
    (freight_glass_0 ?freight_p1 ?glass_p1)
    (freight_glassinitLoc_1 ?freight_p1 ?glassinitLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (glass_glassinitLoc_1 ?glass_p1 ?glassinitLoc_extra_p1)
    (gripper_glass_1 ?gripper_p1 ?glass_p1)
    (clear3_gripper_glass_2 ?gripper_p1)
)
:effect (and
    (gripper_glass_2 ?gripper_p1 ?glass_p1)
    (not (gripper_glass_0 ?gripper_p1 ?glass_p1))
    (not (gripper_glass_1 ?gripper_p1 ?glass_p1))
    (clear3_gripper_glass_1 ?gripper_p1)
    (not (clear3_gripper_glass_2 ?gripper_p1))
)
)

(:action a18
:parameters ( ?glassinitLoc_p1 - glassinitLoc ?glass_p1 - glass
    ?freight_extra_p1 - freight ?gripper_extra_p1 - gripper )
:precondition (and
    (freight_glass_0 ?freight_extra_p1 ?glass_p1)
    (freight_glassinitLoc_1 ?freight_extra_p1 ?glassinitLoc_p1)
    (freight_gripper_0 ?freight_extra_p1 ?gripper_extra_p1)
    (glass_glassinitLoc_1 ?glass_p1 ?glassinitLoc_p1)
    (gripper_glass_2 ?gripper_extra_p1 ?glass_p1)
)
:effect (and
    (glass_glassinitLoc_0 ?glass_p1 ?glassinitLoc_p1)
    (not (glass_glassinitLoc_1 ?glass_p1 ?glassinitLoc_p1))
    (clear3_glass_glassinitLoc_1 ?glass_p1)
)
)

(:action a19
:parameters ( ?gripper_p1 - gripper ?freight_p1 - freight )
:precondition (and

```

```

        (freight_gripper_1 ?freight_p1 ?gripper_p1)
    )
    :effect (and
        (freight_gripper_0 ?freight_p1 ?gripper_p1)
        (not (freight_gripper_1 ?freight_p1 ?gripper_p1))
        (clear3_freight_gripper_1 ?freight_p1)
    )
)

(:action a20
  :parameters ( ?glassinitLoc_p1 - glassinitLoc ?freight_p1 - freight
    ?glass_extra_p1 - glass ?gripper_p1 - gripper )
  :precondition (and
    (freight_glassinitLoc_1 ?freight_p1 ?glassinitLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (glass_glassinitLoc_0 ?glass_extra_p1 ?glassinitLoc_p1)
    (gripper_glass_2 ?gripper_p1 ?glass_extra_p1)
  )
  :effect (and
    (freight_glassinitLoc_0 ?freight_p1 ?glassinitLoc_p1)
    (not (freight_glassinitLoc_1 ?freight_p1 ?glassinitLoc_p1))
    (clear3_freight_glassinitLoc_1 ?freight_p1)
  )
)

(:action a21
  :parameters ( ?glassinitLoc_extra_p1 - glassinitLoc ?gripper_p1 - gripper
    ?glass_p1 - glass ?freight_p1 - freight )
  :precondition (and
    (freight_glass_0 ?freight_p1 ?glass_p1)
    (freight_glassinitLoc_1 ?freight_p1 ?glassinitLoc_extra_p1)
    (freight_gripper_0 ?freight_p1 ?gripper_p1)
    (glass_glassinitLoc_1 ?glass_p1 ?glassinitLoc_extra_p1)
    (gripper_glass_0 ?gripper_p1 ?glass_p1)
    (clear3_gripper_glass_1 ?gripper_p1)
    (clear3_gripper_glass_2 ?gripper_p1)
  )
  :effect (and
    (gripper_glass_1 ?gripper_p1 ?glass_p1)
    (not (gripper_glass_0 ?gripper_p1 ?glass_p1))
    (not (gripper_glass_2 ?gripper_p1 ?glass_p1))
    (not (clear3_gripper_glass_1 ?gripper_p1))
  )
)

(:action a22
  :parameters ( ?gripper_p1 - gripper ?bowlinitLoc_p1 - bowlinitLoc ?freight_p1 -
    freight )
  :precondition (and
    (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_p1)
    (freight_gripper_1 ?freight_p1 ?gripper_p1)
    (clear3_freight_bowlinitLoc_1 ?freight_p1)
  )
  :effect (and
    (freight_bowlinitLoc_1 ?freight_p1 ?bowlinitLoc_p1)
    (not (freight_bowlinitLoc_0 ?freight_p1 ?bowlinitLoc_p1))
  )
)

```

```

        (not (clear3_freight_bowlinitLoc_1 ?freight_p1))
    )
))

```

3) Building Structures with Keva Planks:

```

(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)
    (plank_plank_0 ?x - plank ?y - plank)
    (plank_plank_1 ?x - plank ?y - plank)
    (plank_plank_2 ?x - plank ?y - plank)
    (plank_plank_3 ?x - plank ?y - plank)
    (plank_plank_4 ?x - plank ?y - plank)
    (plank_plank_5 ?x - plank ?y - plank)
    (plank_plank_6 ?x - plank ?y - plank)
    (plank_plank_7 ?x - plank ?y - plank)
    (plank_plank_8 ?x - plank ?y - plank)
    (plank_plank_9 ?x - plank ?y - plank)
    (goalLoc_plank_0 ?x - goalLoc ?y - plank)
    (goalLoc_plank_1 ?x - goalLoc ?y - plank)
    (clear3_plank_plank_2 ?x - plank)
    (clear3_gripper_plank_2 ?x - gripper)
    (clear3_plank_plank_6 ?x - plank)
    (clear3_plank_plank_8 ?x - plank)
    (clear3_plank_plank_5 ?x - plank)
    (clear3_plank_plank_7 ?x - plank)
    (clear3_plank_plank_9 ?x - plank)
    (clear3_plank_plank_4 ?x - plank)
    (clear3_gripper_plank_1 ?x - gripper)
    (clear3_plank_plank_1 ?x - plank)
    (clear3_plank_plank_3 ?x - plank)
  )

  (:action a1
    :parameters ( ?gripper_extra_p1 - gripper ?plank_p2 - plank
      ?plank_p1 - plank )
    :precondition (and
      (not (= ?plank_p2 ?plank_p1))
      (goalLoc_plank_0 goalLoc_Const ?plank_p1)
      (goalLoc_plank_1 goalLoc_Const ?plank_p2)
      (gripper_plank_0 ?gripper_extra_p1 ?plank_p2)
    )
  )
)

```



```

(gripper_plank_1 ?gripper_extra_p1 ?plank_p1)
(plank_plank_0 ?plank_p1 ?plank_p1)
(plank_plank_0 ?plank_p1 ?plank_p2)
(plank_plank_0 ?plank_p2 ?plank_p1)
(plank_plank_0 ?plank_p2 ?plank_p2)
(clear3_plank_plank_4 ?plank_p1)
(clear3_plank_plank_4 ?plank_p2)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (plank_plank_4 ?plank_p2 ?plank_p1)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p1))
  (not (plank_plank_0 ?plank_p2 ?plank_p1))
  (not (plank_plank_1 ?plank_p2 ?plank_p1))
  (not (plank_plank_2 ?plank_p2 ?plank_p1))
  (not (plank_plank_3 ?plank_p2 ?plank_p1))
  (not (plank_plank_5 ?plank_p2 ?plank_p1))
  (not (plank_plank_6 ?plank_p2 ?plank_p1))
  (not (plank_plank_7 ?plank_p2 ?plank_p1))
  (not (plank_plank_8 ?plank_p2 ?plank_p1))
  (not (plank_plank_9 ?plank_p2 ?plank_p1))
  (not (clear3_plank_plank_4 ?plank_p2))
)
)

(:action a2
:parameters ( ?gripper_extra_p1 - gripper ?plank_p3 - plank ?plank_p2 - plank
               ?plank_p1 - plank )
:precondition (and
  (not (= ?plank_p3 ?plank_p2))
  (not (= ?plank_p3 ?plank_p1))
  (not (= ?plank_p2 ?plank_p1))
  (goalLoc_plank_0 goalLoc_Const ?plank_p2)
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (goalLoc_plank_1 goalLoc_Const ?plank_p3)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
  (gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
  (plank_plank_0 ?plank_p1 ?plank_p1)
  (plank_plank_0 ?plank_p1 ?plank_p2)
  (plank_plank_0 ?plank_p1 ?plank_p3)
  (plank_plank_0 ?plank_p2 ?plank_p1)
  (plank_plank_0 ?plank_p2 ?plank_p2)
  (plank_plank_0 ?plank_p2 ?plank_p3)
  (plank_plank_0 ?plank_p3 ?plank_p2)
  (plank_plank_0 ?plank_p3 ?plank_p3)
  (plank_plank_4 ?plank_p3 ?plank_p1)
  (clear3_plank_plank_1 ?plank_p1)
  (clear3_plank_plank_1 ?plank_p2)
  (clear3_plank_plank_1 ?plank_p3)
  (clear3_plank_plank_3 ?plank_p1)
  (clear3_plank_plank_3 ?plank_p2)
  (clear3_plank_plank_3 ?plank_p3)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)

```

```

(plank_plank_1 ?plank_p1 ?plank_p2)
(plank_plank_3 ?plank_p3 ?plank_p2)
(not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
(not (plank_plank_0 ?plank_p1 ?plank_p2))
(not (plank_plank_0 ?plank_p3 ?plank_p2))
(not (plank_plank_1 ?plank_p3 ?plank_p2))
(not (plank_plank_2 ?plank_p1 ?plank_p2))
(not (plank_plank_2 ?plank_p3 ?plank_p2))
(not (plank_plank_3 ?plank_p1 ?plank_p2))
(not (plank_plank_4 ?plank_p1 ?plank_p2))
(not (plank_plank_4 ?plank_p3 ?plank_p2))
(not (plank_plank_5 ?plank_p1 ?plank_p2))
(not (plank_plank_5 ?plank_p3 ?plank_p2))
(not (plank_plank_6 ?plank_p1 ?plank_p2))
(not (plank_plank_6 ?plank_p3 ?plank_p2))
(not (plank_plank_7 ?plank_p1 ?plank_p2))
(not (plank_plank_7 ?plank_p3 ?plank_p2))
(not (plank_plank_8 ?plank_p1 ?plank_p2))
(not (plank_plank_8 ?plank_p3 ?plank_p2))
(not (plank_plank_9 ?plank_p1 ?plank_p2))
(not (plank_plank_9 ?plank_p3 ?plank_p2))
(not (clear3_plank_plank_1 ?plank_p1))
(not (clear3_plank_plank_3 ?plank_p3))
)
)

(:action a3
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
(gripper_plank_2 ?gripper_p1 ?plank_p1)
(clear3_gripper_plank_1 ?gripper_p1)
)
:effect (and
(gripper_plank_1 ?gripper_p1 ?plank_p1)
(not (gripper_plank_0 ?gripper_p1 ?plank_p1))
(not (gripper_plank_2 ?gripper_p1 ?plank_p1))
(clear3_gripper_plank_2 ?gripper_p1)
(not (clear3_gripper_plank_1 ?gripper_p1))
)
)

(:action a4
:parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
:precondition (and
(gripper_plank_0 ?gripper_p1 ?plank_p1)
(clear3_gripper_plank_1 ?gripper_p1)
(clear3_gripper_plank_2 ?gripper_p1)
)
:effect (and
(gripper_plank_2 ?gripper_p1 ?plank_p1)
(not (gripper_plank_0 ?gripper_p1 ?plank_p1))
(not (gripper_plank_1 ?gripper_p1 ?plank_p1))
(not (clear3_gripper_plank_2 ?gripper_p1))
)
)
)

```

```

(:action a5
  :parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
  :precondition (and
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (gripper_plank_2 ?gripper_p1 ?plank_p1)
    (clear3_gripper_plank_1 ?gripper_p1)
  )
  :effect (and
    (gripper_plank_0 ?gripper_p1 ?plank_p1)
    (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_2 ?gripper_p1 ?plank_p1))
    (clear3_gripper_plank_2 ?gripper_p1)
  )
)

(:action a6
  :parameters ( ?plank_p1 - plank ?gripper_p1 - gripper )
  :precondition (and
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (gripper_plank_1 ?gripper_p1 ?plank_p1)
    (clear3_gripper_plank_2 ?gripper_p1)
  )
  :effect (and
    (gripper_plank_2 ?gripper_p1 ?plank_p1)
    (not (gripper_plank_0 ?gripper_p1 ?plank_p1))
    (not (gripper_plank_1 ?gripper_p1 ?plank_p1))
    (clear3_gripper_plank_1 ?gripper_p1)
    (not (clear3_gripper_plank_2 ?gripper_p1))
  )
)

(:action a7
  :parameters ( ?gripper_extra_p1 - gripper ?plank_p3 - plank ?plank_p2 - plank
    ?plank_p1 - plank )
  :precondition (and
    (not (= ?plank_p3 ?plank_p2))
    (not (= ?plank_p3 ?plank_p1))
    (not (= ?plank_p2 ?plank_p1))
    (goalLoc_plank_0 goalLoc_Const ?plank_p2)
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (goalLoc_plank_1 goalLoc_Const ?plank_p3)
    (gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
    (gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
    (gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
    (plank_plank_0 ?plank_p1 ?plank_p1)
    (plank_plank_0 ?plank_p1 ?plank_p2)
    (plank_plank_0 ?plank_p1 ?plank_p3)
    (plank_plank_0 ?plank_p2 ?plank_p1)
    (plank_plank_0 ?plank_p2 ?plank_p2)
    (plank_plank_0 ?plank_p2 ?plank_p3)
    (plank_plank_0 ?plank_p3 ?plank_p2)
    (plank_plank_0 ?plank_p3 ?plank_p3)
    (plank_plank_4 ?plank_p3 ?plank_p1)
    (clear3_plank_plank_8 ?plank_p1)
    (clear3_plank_plank_8 ?plank_p2)
    (clear3_plank_plank_8 ?plank_p3)
  )
)

```

```

(clear3_plank_plank_9 ?plank_p1)
(clear3_plank_plank_9 ?plank_p2)
(clear3_plank_plank_9 ?plank_p3)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_8 ?plank_p1 ?plank_p2)
  (plank_plank_9 ?plank_p3 ?plank_p2)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (plank_plank_0 ?plank_p3 ?plank_p2))
  (not (plank_plank_1 ?plank_p1 ?plank_p2))
  (not (plank_plank_1 ?plank_p3 ?plank_p2))
  (not (plank_plank_2 ?plank_p1 ?plank_p2))
  (not (plank_plank_2 ?plank_p3 ?plank_p2))
  (not (plank_plank_3 ?plank_p1 ?plank_p2))
  (not (plank_plank_3 ?plank_p3 ?plank_p2))
  (not (plank_plank_4 ?plank_p1 ?plank_p2))
  (not (plank_plank_4 ?plank_p3 ?plank_p2))
  (not (plank_plank_5 ?plank_p1 ?plank_p2))
  (not (plank_plank_5 ?plank_p3 ?plank_p2))
  (not (plank_plank_6 ?plank_p1 ?plank_p2))
  (not (plank_plank_6 ?plank_p3 ?plank_p2))
  (not (plank_plank_7 ?plank_p1 ?plank_p2))
  (not (plank_plank_7 ?plank_p3 ?plank_p2))
  (not (plank_plank_8 ?plank_p3 ?plank_p2))
  (not (plank_plank_9 ?plank_p1 ?plank_p2))
  (not (clear3_plank_plank_8 ?plank_p1))
  (not (clear3_plank_plank_9 ?plank_p3))
)
)

(:action a8
  :parameters ( ?gripper_extra_p1 - gripper ?plank_p3 - plank ?plank_p2 - plank
    ?plank_p1 - plank )
  :precondition (and
    (not (= ?plank_p3 ?plank_p2))
    (not (= ?plank_p3 ?plank_p1))
    (not (= ?plank_p2 ?plank_p1))
    (goalLoc_plank_0 goalLoc_Const ?plank_p2)
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (goalLoc_plank_1 goalLoc_Const ?plank_p3)
    (gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
    (gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
    (gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
    (plank_plank_0 ?plank_p1 ?plank_p1)
    (plank_plank_0 ?plank_p1 ?plank_p2)
    (plank_plank_0 ?plank_p1 ?plank_p3)
    (plank_plank_0 ?plank_p2 ?plank_p1)
    (plank_plank_0 ?plank_p2 ?plank_p2)
    (plank_plank_0 ?plank_p2 ?plank_p3)
    (plank_plank_0 ?plank_p3 ?plank_p2)
    (plank_plank_0 ?plank_p3 ?plank_p3)
    (plank_plank_4 ?plank_p3 ?plank_p1)
    (clear3_plank_plank_2 ?plank_p1)
    (clear3_plank_plank_2 ?plank_p2)
  )
)

```

```

(clear3_plank_plank_2 ?plank_p3)
(clear3_plank_plank_6 ?plank_p1)
(clear3_plank_plank_6 ?plank_p2)
(clear3_plank_plank_6 ?plank_p3)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_2 ?plank_p3 ?plank_p2)
  (plank_plank_6 ?plank_p1 ?plank_p2)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (plank_plank_0 ?plank_p3 ?plank_p2))
  (not (plank_plank_1 ?plank_p1 ?plank_p2))
  (not (plank_plank_1 ?plank_p3 ?plank_p2))
  (not (plank_plank_2 ?plank_p1 ?plank_p2))
  (not (plank_plank_3 ?plank_p1 ?plank_p2))
  (not (plank_plank_3 ?plank_p3 ?plank_p2))
  (not (plank_plank_4 ?plank_p1 ?plank_p2))
  (not (plank_plank_4 ?plank_p3 ?plank_p2))
  (not (plank_plank_5 ?plank_p1 ?plank_p2))
  (not (plank_plank_5 ?plank_p3 ?plank_p2))
  (not (plank_plank_6 ?plank_p3 ?plank_p2))
  (not (plank_plank_7 ?plank_p1 ?plank_p2))
  (not (plank_plank_7 ?plank_p3 ?plank_p2))
  (not (plank_plank_8 ?plank_p1 ?plank_p2))
  (not (plank_plank_8 ?plank_p3 ?plank_p2))
  (not (plank_plank_9 ?plank_p1 ?plank_p2))
  (not (plank_plank_9 ?plank_p3 ?plank_p2))
  (not (clear3_plank_plank_2 ?plank_p3))
  (not (clear3_plank_plank_6 ?plank_p1))
)
)

(:action a9
:parameters ( ?gripper_extra_p1 - gripper ?plank_p2 - plank
               ?plank_p1 - plank )
:precondition (and
  (not (= ?plank_p2 ?plank_p1))
  (goalLoc_plank_0 goalLoc_Const ?plank_p1)
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p2)
  (gripper_plank_1 ?gripper_extra_p1 ?plank_p1)
  (plank_plank_0 ?plank_p1 ?plank_p1)
  (plank_plank_0 ?plank_p1 ?plank_p2)
  (plank_plank_0 ?plank_p2 ?plank_p1)
  (plank_plank_0 ?plank_p2 ?plank_p2)
  (clear3_plank_plank_5 ?plank_p1)
  (clear3_plank_plank_5 ?plank_p2)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (plank_plank_5 ?plank_p2 ?plank_p1)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p1))
  (not (plank_plank_0 ?plank_p2 ?plank_p1))
  (not (plank_plank_1 ?plank_p2 ?plank_p1))
  (not (plank_plank_2 ?plank_p2 ?plank_p1))

```

```

        (not (plank_plank_3 ?plank_p2 ?plank_p1))
        (not (plank_plank_4 ?plank_p2 ?plank_p1))
        (not (plank_plank_6 ?plank_p2 ?plank_p1))
        (not (plank_plank_7 ?plank_p2 ?plank_p1))
        (not (plank_plank_8 ?plank_p2 ?plank_p1))
        (not (plank_plank_9 ?plank_p2 ?plank_p1))
        (not (clear3_plank_plank_5 ?plank_p2))
    )
)

(:action a10
 :parameters ( ?gripper_extra_p1 - gripper ?plank_p2 - plank
               ?plank_p1 - plank )
 :precondition (and
                (not (= ?plank_p2 ?plank_p1))
                (goalLoc_plank_0 goalLoc_Const ?plank_p1)
                (goalLoc_plank_1 goalLoc_Const ?plank_p2)
                (gripper_plank_0 ?gripper_extra_p1 ?plank_p2)
                (gripper_plank_1 ?gripper_extra_p1 ?plank_p1)
                (plank_plank_0 ?plank_p1 ?plank_p1)
                (plank_plank_0 ?plank_p1 ?plank_p2)
                (plank_plank_0 ?plank_p2 ?plank_p1)
                (plank_plank_0 ?plank_p2 ?plank_p2)
                (clear3_plank_plank_7 ?plank_p1)
                (clear3_plank_plank_7 ?plank_p2)
            )
 :effect (and
          (goalLoc_plank_1 goalLoc_Const ?plank_p1)
          (plank_plank_7 ?plank_p2 ?plank_p1)
          (not (goalLoc_plank_0 goalLoc_Const ?plank_p1))
          (not (plank_plank_0 ?plank_p2 ?plank_p1))
          (not (plank_plank_1 ?plank_p2 ?plank_p1))
          (not (plank_plank_2 ?plank_p2 ?plank_p1))
          (not (plank_plank_3 ?plank_p2 ?plank_p1))
          (not (plank_plank_4 ?plank_p2 ?plank_p1))
          (not (plank_plank_5 ?plank_p2 ?plank_p1))
          (not (plank_plank_6 ?plank_p2 ?plank_p1))
          (not (plank_plank_8 ?plank_p2 ?plank_p1))
          (not (plank_plank_9 ?plank_p2 ?plank_p1))
          (not (clear3_plank_plank_7 ?plank_p2))
      )
)

(:action a11
 :parameters ( ?gripper_extra_p1 - gripper ?plank_p1 - plank )
 :precondition (and
                (goalLoc_plank_0 goalLoc_Const ?plank_p1)
                (gripper_plank_1 ?gripper_extra_p1 ?plank_p1)
            )
 :effect (and
          (goalLoc_plank_1 goalLoc_Const ?plank_p1)
          (not (goalLoc_plank_0 goalLoc_Const ?plank_p1))
      )
)

(:action a12

```

```

:parameters ( ?gripper_extra_p1 - gripper ?plank_p3 - plank ?plank_p2 - plank
              ?plank_p1 - plank )
:precondition (and
  (not (= ?plank_p3 ?plank_p2))
  (not (= ?plank_p3 ?plank_p1))
  (not (= ?plank_p2 ?plank_p1))
  (goalLoc_plank_0 goalLoc_Const ?plank_p2)
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (goalLoc_plank_1 goalLoc_Const ?plank_p3)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
  (gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
  (plank_plank_0 ?plank_p1 ?plank_p1)
  (plank_plank_0 ?plank_p1 ?plank_p2)
  (plank_plank_0 ?plank_p2 ?plank_p1)
  (plank_plank_0 ?plank_p2 ?plank_p2)
  (plank_plank_0 ?plank_p2 ?plank_p3)
  (plank_plank_0 ?plank_p3 ?plank_p1)
  (plank_plank_0 ?plank_p3 ?plank_p2)
  (plank_plank_0 ?plank_p3 ?plank_p3)
  (plank_plank_7 ?plank_p1 ?plank_p3)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_4 ?plank_p3 ?plank_p2)
  (plank_plank_5 ?plank_p1 ?plank_p2)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (plank_plank_0 ?plank_p3 ?plank_p2))
  (not (plank_plank_1 ?plank_p1 ?plank_p2))
  (not (plank_plank_1 ?plank_p3 ?plank_p2))
  (not (plank_plank_2 ?plank_p1 ?plank_p2))
  (not (plank_plank_2 ?plank_p3 ?plank_p2))
  (not (plank_plank_3 ?plank_p1 ?plank_p2))
  (not (plank_plank_3 ?plank_p3 ?plank_p2))
  (not (plank_plank_4 ?plank_p1 ?plank_p2))
  (not (plank_plank_5 ?plank_p3 ?plank_p2))
  (not (plank_plank_6 ?plank_p1 ?plank_p2))
  (not (plank_plank_6 ?plank_p3 ?plank_p2))
  (not (plank_plank_7 ?plank_p1 ?plank_p2))
  (not (plank_plank_7 ?plank_p3 ?plank_p2))
  (not (plank_plank_8 ?plank_p1 ?plank_p2))
  (not (plank_plank_8 ?plank_p3 ?plank_p2))
  (not (plank_plank_9 ?plank_p1 ?plank_p2))
  (not (plank_plank_9 ?plank_p3 ?plank_p2))
  (not (clear3_plank_plank_4 ?plank_p3))
  (not (clear3_plank_plank_5 ?plank_p1))
)
)

(:action a13
:parameters ( ?gripper_extra_p1 - gripper ?plank_p3 - plank ?plank_p2 - plank
              ?plank_p1 - plank )
:precondition (and
  (not (= ?plank_p3 ?plank_p2))
  (not (= ?plank_p3 ?plank_p1))

```

```

(not (= ?plank_p2 ?plank_p1))
(goalLoc_plank_0 goalLoc_Const ?plank_p2)
(goalLoc_plank_1 goalLoc_Const ?plank_p1)
(goalLoc_plank_1 goalLoc_Const ?plank_p3)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
(gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
(plank_plank_0 ?plank_p1 ?plank_p1)
(plank_plank_0 ?plank_p1 ?plank_p2)
(plank_plank_0 ?plank_p1 ?plank_p3)
(plank_plank_0 ?plank_p2 ?plank_p1)
(plank_plank_0 ?plank_p2 ?plank_p2)
(plank_plank_0 ?plank_p2 ?plank_p3)
(plank_plank_0 ?plank_p3 ?plank_p2)
(plank_plank_0 ?plank_p3 ?plank_p3)
(plank_plank_4 ?plank_p3 ?plank_p1)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_8 ?plank_p1 ?plank_p2)
  (plank_plank_9 ?plank_p3 ?plank_p2)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (plank_plank_0 ?plank_p3 ?plank_p2))
  (not (plank_plank_1 ?plank_p1 ?plank_p2))
  (not (plank_plank_1 ?plank_p3 ?plank_p2))
  (not (plank_plank_2 ?plank_p1 ?plank_p2))
  (not (plank_plank_2 ?plank_p3 ?plank_p2))
  (not (plank_plank_3 ?plank_p1 ?plank_p2))
  (not (plank_plank_3 ?plank_p3 ?plank_p2))
  (not (plank_plank_4 ?plank_p1 ?plank_p2))
  (not (plank_plank_4 ?plank_p3 ?plank_p2))
  (not (plank_plank_5 ?plank_p1 ?plank_p2))
  (not (plank_plank_5 ?plank_p3 ?plank_p2))
  (not (plank_plank_6 ?plank_p1 ?plank_p2))
  (not (plank_plank_6 ?plank_p3 ?plank_p2))
  (not (plank_plank_7 ?plank_p1 ?plank_p2))
  (not (plank_plank_7 ?plank_p3 ?plank_p2))
  (not (plank_plank_8 ?plank_p3 ?plank_p2))
  (not (plank_plank_9 ?plank_p1 ?plank_p2))
  (not (clear3_plank_plank_8 ?plank_p1))
  (not (clear3_plank_plank_9 ?plank_p3))
)
)

(:action a14
:parameters ( ?gripper_extra_p1 - gripper ?plank_p4 - plank ?plank_p3 - plank
?plank_p2 - plank ?plank_p1 - plank )
:precondition (and
  (not (= ?plank_p4 ?plank_p3))
  (not (= ?plank_p4 ?plank_p2))
  (not (= ?plank_p4 ?plank_p1))
  (not (= ?plank_p3 ?plank_p2))
  (not (= ?plank_p3 ?plank_p1))
  (not (= ?plank_p2 ?plank_p1))
  (goalLoc_plank_0 goalLoc_Const ?plank_p2)

```



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(goalLoc_plank_1 goalLoc_Const ?plank_p1)
(goalLoc_plank_1 goalLoc_Const ?plank_p3)
(goalLoc_plank_1 goalLoc_Const ?plank_p4)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p4)
(gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
(plank_plank_0 ?plank_p1 ?plank_p1)
(plank_plank_0 ?plank_p1 ?plank_p2)
(plank_plank_0 ?plank_p2 ?plank_p1)
(plank_plank_0 ?plank_p2 ?plank_p2)
(plank_plank_0 ?plank_p2 ?plank_p3)
(plank_plank_0 ?plank_p2 ?plank_p4)
(plank_plank_0 ?plank_p3 ?plank_p1)
(plank_plank_0 ?plank_p3 ?plank_p2)
(plank_plank_0 ?plank_p3 ?plank_p3)
(plank_plank_0 ?plank_p4 ?plank_p1)
(plank_plank_0 ?plank_p4 ?plank_p2)
(plank_plank_0 ?plank_p4 ?plank_p3)
(plank_plank_0 ?plank_p4 ?plank_p4)
(plank_plank_2 ?plank_p1 ?plank_p4)
(plank_plank_4 ?plank_p1 ?plank_p3)
(plank_plank_6 ?plank_p3 ?plank_p4)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_1 ?plank_p3 ?plank_p2)
  (plank_plank_3 ?plank_p1 ?plank_p2)
  (plank_plank_4 ?plank_p4 ?plank_p2)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (plank_plank_0 ?plank_p3 ?plank_p2))
  (not (plank_plank_0 ?plank_p4 ?plank_p2))
  (not (plank_plank_1 ?plank_p1 ?plank_p2))
  (not (plank_plank_1 ?plank_p4 ?plank_p2))
  (not (plank_plank_2 ?plank_p1 ?plank_p2))
  (not (plank_plank_2 ?plank_p3 ?plank_p2))
  (not (plank_plank_2 ?plank_p4 ?plank_p2))
  (not (plank_plank_3 ?plank_p3 ?plank_p2))
  (not (plank_plank_3 ?plank_p4 ?plank_p2))
  (not (plank_plank_4 ?plank_p1 ?plank_p2))
  (not (plank_plank_4 ?plank_p3 ?plank_p2))
  (not (plank_plank_5 ?plank_p1 ?plank_p2))
  (not (plank_plank_5 ?plank_p3 ?plank_p2))
  (not (plank_plank_5 ?plank_p4 ?plank_p2))
  (not (plank_plank_6 ?plank_p1 ?plank_p2))
  (not (plank_plank_6 ?plank_p3 ?plank_p2))
  (not (plank_plank_6 ?plank_p4 ?plank_p2))
  (not (plank_plank_7 ?plank_p1 ?plank_p2))
  (not (plank_plank_7 ?plank_p3 ?plank_p2))
  (not (plank_plank_7 ?plank_p4 ?plank_p2))
  (not (plank_plank_8 ?plank_p1 ?plank_p2))
  (not (plank_plank_8 ?plank_p3 ?plank_p2))
  (not (plank_plank_8 ?plank_p4 ?plank_p2))
  (not (plank_plank_9 ?plank_p1 ?plank_p2))
  (not (plank_plank_9 ?plank_p3 ?plank_p2))
)

```

```

        (not (plank_plank_9 ?plank_p4 ?plank_p2))
        (not (clear3_plank_plank_1 ?plank_p3))
        (not (clear3_plank_plank_3 ?plank_p1))
        (not (clear3_plank_plank_4 ?plank_p4))
    )
)

(:action a15
:parameters ( ?gripper_extra_p1 - gripper  ?plank_p3 - plank  ?plank_p2 - plank
               ?plank_p1 - plank )
:precondition (and
    (not (= ?plank_p3 ?plank_p2))
    (not (= ?plank_p3 ?plank_p1))
    (not (= ?plank_p2 ?plank_p1))
    (goalLoc_plank_0 goalLoc_Const ?plank_p2)
    (goalLoc_plank_1 goalLoc_Const ?plank_p1)
    (goalLoc_plank_1 goalLoc_Const ?plank_p3)
    (gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
    (gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
    (gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
    (plank_plank_0 ?plank_p1 ?plank_p1)
    (plank_plank_0 ?plank_p1 ?plank_p2)
    (plank_plank_0 ?plank_p2 ?plank_p1)
    (plank_plank_0 ?plank_p2 ?plank_p2)
    (plank_plank_0 ?plank_p2 ?plank_p3)
    (plank_plank_0 ?plank_p3 ?plank_p1)
    (plank_plank_0 ?plank_p3 ?plank_p2)
    (plank_plank_0 ?plank_p3 ?plank_p3)
    (plank_plank_4 ?plank_p1 ?plank_p3)
)
:effect (and
    (goalLoc_plank_1 goalLoc_Const ?plank_p2)
    (plank_plank_1 ?plank_p3 ?plank_p2)
    (plank_plank_3 ?plank_p1 ?plank_p2)
    (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
    (not (plank_plank_0 ?plank_p1 ?plank_p2))
    (not (plank_plank_0 ?plank_p3 ?plank_p2))
    (not (plank_plank_1 ?plank_p1 ?plank_p2))
    (not (plank_plank_2 ?plank_p1 ?plank_p2))
    (not (plank_plank_2 ?plank_p3 ?plank_p2))
    (not (plank_plank_3 ?plank_p3 ?plank_p2))
    (not (plank_plank_4 ?plank_p1 ?plank_p2))
    (not (plank_plank_4 ?plank_p3 ?plank_p2))
    (not (plank_plank_5 ?plank_p1 ?plank_p2))
    (not (plank_plank_5 ?plank_p3 ?plank_p2))
    (not (plank_plank_6 ?plank_p1 ?plank_p2))
    (not (plank_plank_6 ?plank_p3 ?plank_p2))
    (not (plank_plank_7 ?plank_p1 ?plank_p2))
    (not (plank_plank_7 ?plank_p3 ?plank_p2))
    (not (plank_plank_8 ?plank_p1 ?plank_p2))
    (not (plank_plank_8 ?plank_p3 ?plank_p2))
    (not (plank_plank_9 ?plank_p1 ?plank_p2))
    (not (plank_plank_9 ?plank_p3 ?plank_p2))
    (not (clear3_plank_plank_1 ?plank_p3))
    (not (clear3_plank_plank_3 ?plank_p1))
)
)

```

```

)

(:action a16
:parameters ( ?gripper_extra_p1 - gripper ?plank_p4 - plank ?plank_p3 - plank
  ↳ ?plank_p2 - plank
    ?plank_p1 - plank )
:precondition (and
  (not (= ?plank_p4 ?plank_p3))
  (not (= ?plank_p4 ?plank_p2))
  (not (= ?plank_p4 ?plank_p1))
  (not (= ?plank_p3 ?plank_p2))
  (not (= ?plank_p3 ?plank_p1))
  (not (= ?plank_p2 ?plank_p1))
  (goalLoc_plank_0 goalLoc_Const ?plank_p2)
  (goalLoc_plank_1 goalLoc_Const ?plank_p1)
  (goalLoc_plank_1 goalLoc_Const ?plank_p3)
  (goalLoc_plank_1 goalLoc_Const ?plank_p4)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
  (gripper_plank_0 ?gripper_extra_p1 ?plank_p4)
  (gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
  (plank_plank_0 ?plank_p1 ?plank_p1)
  (plank_plank_0 ?plank_p1 ?plank_p2)
  (plank_plank_0 ?plank_p1 ?plank_p3)
  (plank_plank_0 ?plank_p1 ?plank_p4)
  (plank_plank_0 ?plank_p2 ?plank_p1)
  (plank_plank_0 ?plank_p2 ?plank_p2)
  (plank_plank_0 ?plank_p2 ?plank_p3)
  (plank_plank_0 ?plank_p2 ?plank_p4)
  (plank_plank_0 ?plank_p3 ?plank_p1)
  (plank_plank_0 ?plank_p3 ?plank_p2)
  (plank_plank_0 ?plank_p3 ?plank_p3)
  (plank_plank_0 ?plank_p3 ?plank_p4)
  (plank_plank_0 ?plank_p4 ?plank_p2)
  (plank_plank_0 ?plank_p4 ?plank_p3)
  (plank_plank_0 ?plank_p4 ?plank_p4)
  (plank_plank_4 ?plank_p4 ?plank_p1)
)
:effect (and
  (goalLoc_plank_1 goalLoc_Const ?plank_p2)
  (plank_plank_2 ?plank_p4 ?plank_p2)
  (plank_plank_4 ?plank_p3 ?plank_p2)
  (plank_plank_6 ?plank_p1 ?plank_p2)
  (not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
  (not (plank_plank_0 ?plank_p1 ?plank_p2))
  (not (plank_plank_0 ?plank_p3 ?plank_p2))
  (not (plank_plank_0 ?plank_p4 ?plank_p2))
  (not (plank_plank_1 ?plank_p1 ?plank_p2))
  (not (plank_plank_1 ?plank_p3 ?plank_p2))
  (not (plank_plank_1 ?plank_p4 ?plank_p2))
  (not (plank_plank_2 ?plank_p1 ?plank_p2))
  (not (plank_plank_2 ?plank_p3 ?plank_p2))
  (not (plank_plank_3 ?plank_p1 ?plank_p2))
  (not (plank_plank_3 ?plank_p3 ?plank_p2))
  (not (plank_plank_3 ?plank_p4 ?plank_p2))
  (not (plank_plank_4 ?plank_p1 ?plank_p2))
)

```

```

(not (plank_plank_4 ?plank_p4 ?plank_p2))
(not (plank_plank_5 ?plank_p1 ?plank_p2))
(not (plank_plank_5 ?plank_p3 ?plank_p2))
(not (plank_plank_5 ?plank_p4 ?plank_p2))
(not (plank_plank_6 ?plank_p3 ?plank_p2))
(not (plank_plank_6 ?plank_p4 ?plank_p2))
(not (plank_plank_7 ?plank_p1 ?plank_p2))
(not (plank_plank_7 ?plank_p3 ?plank_p2))
(not (plank_plank_7 ?plank_p4 ?plank_p2))
(not (plank_plank_8 ?plank_p1 ?plank_p2))
(not (plank_plank_8 ?plank_p3 ?plank_p2))
(not (plank_plank_8 ?plank_p4 ?plank_p2))
(not (plank_plank_9 ?plank_p1 ?plank_p2))
(not (plank_plank_9 ?plank_p3 ?plank_p2))
(not (plank_plank_9 ?plank_p4 ?plank_p2))
(not (clear3_plank_plank_2 ?plank_p4))
(not (clear3_plank_plank_4 ?plank_p3))
(not (clear3_plank_plank_6 ?plank_p1))
)
)

(:action a17
:parameters ( ?gripper_extra_p1 - gripper ?plank_p3 - plank ?plank_p2 - plank
?plank_p1 - plank )
:precondition (and
(not (= ?plank_p3 ?plank_p2))
(not (= ?plank_p3 ?plank_p1))
(not (= ?plank_p2 ?plank_p1))
(goalLoc_plank_0 goalLoc_Const ?plank_p2)
(goalLoc_plank_1 goalLoc_Const ?plank_p1)
(goalLoc_plank_1 goalLoc_Const ?plank_p3)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p1)
(gripper_plank_0 ?gripper_extra_p1 ?plank_p3)
(gripper_plank_1 ?gripper_extra_p1 ?plank_p2)
(plank_plank_0 ?plank_p1 ?plank_p1)
(plank_plank_0 ?plank_p1 ?plank_p2)
(plank_plank_0 ?plank_p1 ?plank_p3)
(plank_plank_0 ?plank_p2 ?plank_p1)
(plank_plank_0 ?plank_p2 ?plank_p2)
(plank_plank_0 ?plank_p2 ?plank_p3)
(plank_plank_0 ?plank_p3 ?plank_p1)
(plank_plank_0 ?plank_p3 ?plank_p2)
(plank_plank_0 ?plank_p3 ?plank_p3)
)
:effect (and
(goalLoc_plank_1 goalLoc_Const ?plank_p2)
(plank_plank_4 ?plank_p1 ?plank_p2)
(plank_plank_7 ?plank_p3 ?plank_p2)
(not (goalLoc_plank_0 goalLoc_Const ?plank_p2))
(not (plank_plank_0 ?plank_p1 ?plank_p2))
(not (plank_plank_0 ?plank_p3 ?plank_p2))
(not (plank_plank_1 ?plank_p1 ?plank_p2))
(not (plank_plank_1 ?plank_p3 ?plank_p2))
(not (plank_plank_2 ?plank_p1 ?plank_p2))
(not (plank_plank_2 ?plank_p3 ?plank_p2))
(not (plank_plank_3 ?plank_p1 ?plank_p2))
)
)

```

```

(not (plank_plank_3 ?plank_p3 ?plank_p2))
(not (plank_plank_4 ?plank_p3 ?plank_p2))
(not (plank_plank_5 ?plank_p1 ?plank_p2))
(not (plank_plank_5 ?plank_p3 ?plank_p2))
(not (plank_plank_6 ?plank_p1 ?plank_p2))
(not (plank_plank_6 ?plank_p3 ?plank_p2))
(not (plank_plank_7 ?plank_p1 ?plank_p2))
(not (plank_plank_8 ?plank_p1 ?plank_p2))
(not (plank_plank_8 ?plank_p3 ?plank_p2))
(not (plank_plank_9 ?plank_p1 ?plank_p2))
(not (plank_plank_9 ?plank_p3 ?plank_p2))
(not (clear3_plank_plank_4 ?plank_p1))
(not (clear3_plank_plank_7 ?plank_p3))
)
))

```

4) Building Structures with Jenga Planks:

```

(define (domain Jenga)
  (:requirements :strips :typing :equality
:conditional-effects :existential-preconditions :universal-preconditions)
  (:types
    goalLoc
    jenga
    tabletop
    gripper
    pickupstation
  )

  (:constants
    goalLoc_Const - goalLoc
  )

  (:predicates
    (goalLoc_jenga_0 ?x - goalLoc ?y - jenga)
    (goalLoc_jenga_1 ?x - goalLoc ?y - jenga)
    (goalLoc_jenga_2 ?x - goalLoc ?y - jenga)
    (jenga_jenga_0 ?x - jenga ?y - jenga)
    (jenga_jenga_1 ?x - jenga ?y - jenga)
    (jenga_jenga_2 ?x - jenga ?y - jenga)
    (jenga_jenga_3 ?x - jenga ?y - jenga)
    (jenga_jenga_4 ?x - jenga ?y - jenga)
    (jenga_jenga_5 ?x - jenga ?y - jenga)
    (jenga_jenga_6 ?x - jenga ?y - jenga)
    (jenga_jenga_7 ?x - jenga ?y - jenga)
    (jenga_jenga_8 ?x - jenga ?y - jenga)
    (gripper_jenga_0 ?x - gripper ?y - jenga)
    (gripper_jenga_1 ?x - gripper ?y - jenga)
    (gripper_jenga_2 ?x - gripper ?y - jenga)
    (clear3_gripper_jenga_1 ?x - gripper)
    (clear3_jenga_jenga_6 ?x - jenga)
    (clear3_jenga_jenga_2 ?x - jenga)
    (clear3_jenga_jenga_3 ?x - jenga)
    (clear3_jenga_jenga_1 ?x - jenga)
    (clear3_jenga_jenga_8 ?x - jenga)
    (clear3_gripper_jenga_2 ?x - gripper)
    (clear3_jenga_jenga_4 ?x - jenga)
  )

```

```

        (clear3_jenga_jenga_7 ?x - jenga)
        (clear3_jenga_jenga_5 ?x - jenga)
    )

(:action a1
 :parameters ( ?jenga_p1 - jenga ?gripper_extra_p1 - gripper )
 :precondition (and
    (goalLoc_jenga_0 goalLoc_Const ?jenga_p1)
    (gripper_jenga_1 ?gripper_extra_p1 ?jenga_p1)
 )
 :effect (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (not (goalLoc_jenga_0 goalLoc_Const ?jenga_p1))
    (not (goalLoc_jenga_2 goalLoc_Const ?jenga_p1))
 )
 )

(:action a2
 :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
 :precondition (and
    (gripper_jenga_0 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_1 ?gripper_p1)
    (clear3_gripper_jenga_2 ?gripper_p1)
 )
 :effect (and
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (not (gripper_jenga_0 ?gripper_p1 ?jenga_p1))
    (not (gripper_jenga_1 ?gripper_p1 ?jenga_p1))
    (not (clear3_gripper_jenga_2 ?gripper_p1))
 )
 )

(:action a3
 :parameters ( ?jenga_p2 - jenga ?jenga_p3 - jenga ?jenga_p1 - jenga
    ?gripper_extra_p1 - gripper )
 :precondition (and
    (not (= ?jenga_p2 ?jenga_p3))
    (not (= ?jenga_p2 ?jenga_p1))
    (not (= ?jenga_p3 ?jenga_p1))
    (goalLoc_jenga_0 goalLoc_Const ?jenga_p2)
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p3)
    (gripper_jenga_0 ?gripper_extra_p1 ?jenga_p1)
    (gripper_jenga_0 ?gripper_extra_p1 ?jenga_p3)
    (gripper_jenga_1 ?gripper_extra_p1 ?jenga_p2)
    (jenga_jenga_0 ?jenga_p1 ?jenga_p2)
    (jenga_jenga_0 ?jenga_p3 ?jenga_p2)
    (clear3_jenga_jenga_1 ?jenga_p1)
    (clear3_jenga_jenga_1 ?jenga_p2)
    (clear3_jenga_jenga_1 ?jenga_p3)
    (clear3_jenga_jenga_3 ?jenga_p1)
    (clear3_jenga_jenga_3 ?jenga_p2)
    (clear3_jenga_jenga_3 ?jenga_p3)
 )
 :effect (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p2)

```

```

(jenga_jenga_1 ?jenga_p1 ?jenga_p2)
(jenga_jenga_3 ?jenga_p3 ?jenga_p2)
(not (goalLoc_jenga_0 goalLoc_Const ?jenga_p2))
(not (goalLoc_jenga_2 goalLoc_Const ?jenga_p2))
(not (jenga_jenga_0 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_0 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_1 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_2 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_2 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_3 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_4 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_4 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_5 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_5 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_6 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_6 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_7 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_7 ?jenga_p3 ?jenga_p2))
(not (jenga_jenga_8 ?jenga_p1 ?jenga_p2))
(not (jenga_jenga_8 ?jenga_p3 ?jenga_p2))
(not (clear3_jenga_jenga_1 ?jenga_p1))
(not (clear3_jenga_jenga_3 ?jenga_p3))
)
)

(:action a4
:parameters ( ?jenga_p2 - jenga ?jenga_p3 - jenga ?jenga_p1 - jenga
?gripper_extra_p1 - gripper )
:precondition (and
(not (= ?jenga_p2 ?jenga_p3))
(not (= ?jenga_p2 ?jenga_p1))
(not (= ?jenga_p3 ?jenga_p1))
(goalLoc_jenga_0 goalLoc_Const ?jenga_p1)
(goalLoc_jenga_1 goalLoc_Const ?jenga_p2)
(goalLoc_jenga_1 goalLoc_Const ?jenga_p3)
(gripper_jenga_0 ?gripper_extra_p1 ?jenga_p2)
(gripper_jenga_0 ?gripper_extra_p1 ?jenga_p3)
(gripper_jenga_1 ?gripper_extra_p1 ?jenga_p1)
(jenga_jenga_0 ?jenga_p2 ?jenga_p1)
(jenga_jenga_0 ?jenga_p3 ?jenga_p1)
(clear3_jenga_jenga_2 ?jenga_p1)
(clear3_jenga_jenga_2 ?jenga_p2)
(clear3_jenga_jenga_2 ?jenga_p3)
(clear3_jenga_jenga_8 ?jenga_p1)
(clear3_jenga_jenga_8 ?jenga_p2)
(clear3_jenga_jenga_8 ?jenga_p3)
)
:effect (and
(goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
(jenga_jenga_2 ?jenga_p2 ?jenga_p1)
(jenga_jenga_8 ?jenga_p3 ?jenga_p1)
(not (goalLoc_jenga_0 goalLoc_Const ?jenga_p1))
(not (goalLoc_jenga_2 goalLoc_Const ?jenga_p1))
(not (jenga_jenga_0 ?jenga_p2 ?jenga_p1))
(not (jenga_jenga_0 ?jenga_p3 ?jenga_p1))
(not (jenga_jenga_1 ?jenga_p2 ?jenga_p1))

```

```

        (not (jenga_jenga_1 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_2 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_3 ?jenga_p2 ?jenga_p1))
        (not (jenga_jenga_3 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_4 ?jenga_p2 ?jenga_p1))
        (not (jenga_jenga_4 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_5 ?jenga_p2 ?jenga_p1))
        (not (jenga_jenga_5 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_6 ?jenga_p2 ?jenga_p1))
        (not (jenga_jenga_6 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_7 ?jenga_p2 ?jenga_p1))
        (not (jenga_jenga_7 ?jenga_p3 ?jenga_p1))
        (not (jenga_jenga_8 ?jenga_p2 ?jenga_p1))
        (not (clear3_jenga_jenga_2 ?jenga_p2))
        (not (clear3_jenga_jenga_8 ?jenga_p3))
    )
)

(:action a5
 :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
 :precondition (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (gripper_jenga_1 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_2 ?gripper_p1)
 )
 :effect (and
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (not (gripper_jenga_0 ?gripper_p1 ?jenga_p1))
    (not (gripper_jenga_1 ?gripper_p1 ?jenga_p1))
    (clear3_gripper_jenga_1 ?gripper_p1)
    (not (clear3_gripper_jenga_2 ?gripper_p1))
 )
)

(:action a6
 :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
 :precondition (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_1 ?gripper_p1)
 )
 :effect (and
    (gripper_jenga_0 ?gripper_p1 ?jenga_p1)
    (not (gripper_jenga_1 ?gripper_p1 ?jenga_p1))
    (not (gripper_jenga_2 ?gripper_p1 ?jenga_p1))
    (clear3_gripper_jenga_2 ?gripper_p1)
 )
)

(:action a7
 :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
 :precondition (and
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_1 ?gripper_p1)
 )
 :effect (and

```



```

        (gripper_jenga_1 ?gripper_p1 ?jenga_p1)
        (not (gripper_jenga_0 ?gripper_p1 ?jenga_p1))
        (not (gripper_jenga_2 ?gripper_p1 ?jenga_p1))
        (clear3_gripper_jenga_2 ?gripper_p1)
        (not (clear3_gripper_jenga_1 ?gripper_p1))
    )
)

(:action a8
:parameters ( ?jenga_p2 - jenga ?jenga_p3 - jenga ?jenga_p1 - jenga
?gripper_extra_p1 - gripper )
:precondition (and
    (not (= ?jenga_p2 ?jenga_p3))
    (not (= ?jenga_p2 ?jenga_p1))
    (not (= ?jenga_p3 ?jenga_p1))
    (goalLoc_jenga_0 goalLoc_Const ?jenga_p2)
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p3)
    (gripper_jenga_0 ?gripper_extra_p1 ?jenga_p1)
    (gripper_jenga_0 ?gripper_extra_p1 ?jenga_p3)
    (gripper_jenga_1 ?gripper_extra_p1 ?jenga_p2)
    (jenga_jenga_0 ?jenga_p1 ?jenga_p2)
    (jenga_jenga_0 ?jenga_p3 ?jenga_p2)
    (clear3_jenga_jenga_4 ?jenga_p1)
    (clear3_jenga_jenga_4 ?jenga_p2)
    (clear3_jenga_jenga_4 ?jenga_p3)
    (clear3_jenga_jenga_6 ?jenga_p1)
    (clear3_jenga_jenga_6 ?jenga_p2)
    (clear3_jenga_jenga_6 ?jenga_p3)
)
:effect (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p2)
    (jenga_jenga_4 ?jenga_p1 ?jenga_p2)
    (jenga_jenga_6 ?jenga_p3 ?jenga_p2)
    (not (goalLoc_jenga_0 goalLoc_Const ?jenga_p2))
    (not (goalLoc_jenga_2 goalLoc_Const ?jenga_p2))
    (not (jenga_jenga_0 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_0 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_1 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_1 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_2 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_2 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_3 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_3 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_4 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_5 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_5 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_6 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_7 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_7 ?jenga_p3 ?jenga_p2))
    (not (jenga_jenga_8 ?jenga_p1 ?jenga_p2))
    (not (jenga_jenga_8 ?jenga_p3 ?jenga_p2))
    (not (clear3_jenga_jenga_4 ?jenga_p1))
    (not (clear3_jenga_jenga_6 ?jenga_p3))
)
)
)

```

```

(:action a9
  :parameters ( ?jenga_p2 - jenga ?jenga_p3 - jenga ?jenga_p1 - jenga
    ?gripper_extra_p1 - gripper )
  :precondition (and
    (not (= ?jenga_p2 ?jenga_p3))
    (not (= ?jenga_p2 ?jenga_p1))
    (not (= ?jenga_p3 ?jenga_p1))
    (goalLoc_jenga_0 goalLoc_Const ?jenga_p1)
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p2)
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p3)
    (gripper_jenga_0 ?gripper_extra_p1 ?jenga_p2)
    (gripper_jenga_0 ?gripper_extra_p1 ?jenga_p3)
    (gripper_jenga_1 ?gripper_extra_p1 ?jenga_p1)
    (jenga_jenga_0 ?jenga_p2 ?jenga_p1)
    (jenga_jenga_0 ?jenga_p3 ?jenga_p1)
    (clear3_jenga_jenga_5 ?jenga_p1)
    (clear3_jenga_jenga_5 ?jenga_p2)
    (clear3_jenga_jenga_5 ?jenga_p3)
    (clear3_jenga_jenga_7 ?jenga_p1)
    (clear3_jenga_jenga_7 ?jenga_p2)
    (clear3_jenga_jenga_7 ?jenga_p3)
  )
  :effect (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (jenga_jenga_5 ?jenga_p2 ?jenga_p1)
    (jenga_jenga_7 ?jenga_p3 ?jenga_p1)
    (not (goalLoc_jenga_0 goalLoc_Const ?jenga_p1))
    (not (goalLoc_jenga_2 goalLoc_Const ?jenga_p1))
    (not (jenga_jenga_0 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_0 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_1 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_1 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_2 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_2 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_3 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_3 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_4 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_4 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_5 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_6 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_6 ?jenga_p3 ?jenga_p1))
    (not (jenga_jenga_7 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_8 ?jenga_p2 ?jenga_p1))
    (not (jenga_jenga_8 ?jenga_p3 ?jenga_p1))
    (not (clear3_jenga_jenga_5 ?jenga_p2))
    (not (clear3_jenga_jenga_7 ?jenga_p3))
  )
)

(:action a10
  :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
  :precondition (and
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_1 ?gripper_p1)
  )
)

```

```

    :effect (and
        (gripper_jenga_1 ?gripper_p1 ?jenga_p1)
        (not (gripper_jenga_0 ?gripper_p1 ?jenga_p1))
        (not (gripper_jenga_2 ?gripper_p1 ?jenga_p1))
        (clear3_gripper_jenga_2 ?gripper_p1)
        (not (clear3_gripper_jenga_1 ?gripper_p1))
    )
)

(:action a11
  :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
  :precondition (and
    (gripper_jenga_0 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_1 ?gripper_p1)
    (clear3_gripper_jenga_2 ?gripper_p1)
  )
  :effect (and
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (not (gripper_jenga_0 ?gripper_p1 ?jenga_p1))
    (not (gripper_jenga_1 ?gripper_p1 ?jenga_p1))
    (not (clear3_gripper_jenga_2 ?gripper_p1))
  )
)

(:action a12
  :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
  :precondition (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (gripper_jenga_1 ?gripper_p1 ?jenga_p1)
    (clear3_gripper_jenga_2 ?gripper_p1)
  )
  :effect (and
    (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
    (not (gripper_jenga_0 ?gripper_p1 ?jenga_p1))
    (not (gripper_jenga_1 ?gripper_p1 ?jenga_p1))
    (clear3_gripper_jenga_1 ?gripper_p1)
    (not (clear3_gripper_jenga_2 ?gripper_p1))
  )
)

(:action a13
  :parameters ( ?jenga_p1 - jenga ?gripper_extra_p1 - gripper )
  :precondition (and
    (goalLoc_jenga_0 goalLoc_Const ?jenga_p1)
    (gripper_jenga_1 ?gripper_extra_p1 ?jenga_p1)
  )
  :effect (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)
    (not (goalLoc_jenga_0 goalLoc_Const ?jenga_p1))
  )
)

(:action a14
  :parameters ( ?jenga_p1 - jenga ?gripper_p1 - gripper )
  :precondition (and
    (goalLoc_jenga_1 goalLoc_Const ?jenga_p1)

```

```

        (gripper_jenga_2 ?gripper_p1 ?jenga_p1)
        (clear3_gripper_jenga_1 ?gripper_p1)
    )
    :effect (and
        (gripper_jenga_0 ?gripper_p1 ?jenga_p1)
        (not (gripper_jenga_1 ?gripper_p1 ?jenga_p1))
        (not (gripper_jenga_2 ?gripper_p1 ?jenga_p1))
        (clear3_gripper_jenga_2 ?gripper_p1)
    )
))

```

5) Packing a Box:

```

(define (domain Packing)
  (:requirements :strips :typing :equality :conditional-effects
    → :existential-preconditions
      :universal-preconditions)
  (:types
    gripper
    can
    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)
    (clear3_gripper_can_1 ?x - gripper)
    (clear3_gripper_can_2 ?x - gripper)
  )

  (:action a1
    :parameters ( ?can_p1 - can ?surface_extra_p1 - surface
      ?gripper_p1 - gripper )
    :precondition (and
      (can_surface_1 ?can_p1 ?surface_extra_p1)
      (gripper_can_2 ?gripper_p1 ?can_p1)
      (clear3_gripper_can_1 ?gripper_p1)
    )
    :effect (and
      (gripper_can_0 ?gripper_p1 ?can_p1)
      (not (gripper_can_1 ?gripper_p1 ?can_p1))
      (not (gripper_can_2 ?gripper_p1 ?can_p1))
      (clear3_gripper_can_2 ?gripper_p1)
    )
  )

  (:action a2
    :parameters ( ?can_p1 - can ?gripper_p1 - gripper )
    :precondition (and
      (gripper_can_2 ?gripper_p1 ?can_p1)
      (clear3_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))
        (clear3_gripper_can_2 ?gripper_p1)
        (not (clear3_gripper_can_1 ?gripper_p1))
    )
)

(:action a3
 :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)
                (clear3_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))
          (clear3_gripper_can_1 ?gripper_p1)
          (not (clear3_gripper_can_2 ?gripper_p1))
      )
)

(:action a4
 :parameters ( ?can_p1 - can ?gripper_p1 - gripper )
 :precondition (and
                (gripper_can_0 ?gripper_p1 ?can_p1)
                (clear3_gripper_can_1 ?gripper_p1)
                (clear3_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))
          (not (clear3_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))
      )
))

```

I. Code as Policies Evaluation Prompts

1) Delivering Items in a Cafe:

Domain-specific Prompt for Robot Actions:

```

jointnames = ("torso_lift_joint", "shoulder_pan_joint", "shoulder_lift_joint",
              "upperarm_roll_joint", "elbow_flex_joint", "forearm_roll_joint",
              "wrist_flex_joint", "wrist_roll_joint"])

# define function: openGripper(robot)
def openGripper(robot):
    taskmanip = interfaces.TaskManipulation(robot)
    with robot:
        taskmanip.ReleaseFingers()
    robot.WaitForController(0)

# define function: grab_success_flag = grab_object(object_name)
def grab_object(object_to_grab):
    o = env.GetKinBody(object_to_grab)
    ot = o.GetTransform()
    robot_t = robot.GetLink("wrist_roll_link").GetTransform()
    euclidean_distance = np.linalg.norm(robot_t[:3,3]-ot[:3,3])
    obj_type = object_to_grab.split("_")[0]
    grab_range = [0.20,0.24]
    if euclidean_distance<grab_range[1] and euclidean_distance>grab_range[0]:
        robot.Grab(o)
        return True
    else:
        print("object out of grasp range")
        return False

# define function: un_grab(object_name)
def un_grab(object_name):
    robot.ReleaseAllGrabbed()

# define function: current_pose_of_object = get_current_pose_of_object(object_name)
def get_current_pose_of_object(object_name):
    obj = env.GetKinBody(object_name)
    obj_T = obj.GetTransform()
    obj_pose = get_pose_from_transform(obj_T)

    return obj_pose

# define function: robot_ik = get_ik(pose)
def get_ik(pose):
    end_effector_solution = get_transform_from_pose(pose)
    activate_manip_joints()
    # filter_option = IkFilterOptions.CheckEnvCollisions
    filter_option = IkFilterOptions.IgnoreEndEffectorCollisions

    with env:
        ikmodel = databases.inversekinematics.InverseKinematicsModel(robot,
                                                                    iktype=IkParameterization.Type.Transform6D)

        if not ikmodel.load():
            ikmodel.autogenerate()
        try:
            solutions = ikmodel.manip.FindIKSolutions(end_effector_solution, filter_option)
        except:
            print("error")

    if len(solutions) == 0:
        print("NO IKs found, Probably Un-reachable transform")

    if len(solutions) > 0:
        if len(solutions) == 1:
            i = 0
        else:
            i = np.random.randint(0,len(solutions))
    else:
        return []

```

```

        return solutions[i]

# define function: go_to_gripper_pose(pose)
def go_to_gripper_pose(pose):
    activate_manip_joints()
    robot.SetActiveDOFValues(pose)

# define function: go_to_base_pose(pose)
def go_to_base_pose(pose):
    activate_base_joints()
    robot.SetActiveDOFValues(pose)

# define function: current_arm_joint_values = get_current_arm_joint_values_of_robot()
def get_current_arm_joint_values_of_robot():
    activate_manip_joints()
    return robot.GetActiveDOFValues()

# define function: current_base_joint_values = get_current_base_joint_values()
def get_current_base_joint_values_of_robot():
    activate_base_joints()
    return robot.GetActiveDOFValues()

# define function: pose = get_pose_from_transform(transform)
def get_pose_from_transform(transform):
    quat = poseFromMatrix(transform)[4:]
    eul = axisAngleFromQuat(quat)
    pose = []
    pose.extend(poseFromMatrix(transform)[4:])
    pose.extend(eul)

    return pose

# define function: collision_flag = collision_check(object_name)
def collision_check(object_name):
    collision_flag = False
    obj = env.GetKinBody(object_name)

    for obj2 in env.GetBodies():
        if obj != obj2:
            collision = env.CheckCollision(obj, obj2)
            if collision:
                if (obj2 == robot and obj in robot.GetGrabbed()) or
                    (obj == robot and obj2 in robot.GetGrabbed()):
                    collision = False
                    continue
                collision_flag = True
                break
    return collision_flag

# define function: activate_base_joints()
def activate_base_joints():
    robot.SetActiveDOFs([], DOFAffine.X | DOFAffine.Y | DOFAffine.RotationAxis)

# define function: activate_arm_joints()
def activate_manip_joints():
    robot.SetActiveDOFs([robot.GetJoint(name).GetDOFIndex() for name in jointnames])

# define function: grasp_pose_for_object = generate_grasp_pose(object_to_grab)
def generate_grasp_pose(object_to_grab):
    activate_manip_joints()
    rot_Z = matrixFromAxisAngle([0, 0, -np.pi/2])
    gripper_offset = -0.04
    world_T_obj = env.GetKinBody(object_to_grab).GetTransform()

    rot_ang = np.random.uniform(low = -np.pi, high = np.pi)

```

```

obj_T_gripper = matrixFromPose([1, 0, 0, 0, gripper_offset, 0, 0.2/2.0])
rot_mat = matrixFromAxisAngle([0, 0, rot_ang])

wrist_roll_pose = robot.GetLink("wrist_roll_link").GetTransform()
gripper_pose = robot.GetLink("gripper_link").GetTransform()
wrist_pose_wrt_gripper = np.matmul(np.linalg.inv(gripper_pose), wrist_roll_pose)

grasp_T = world_T_obj.dot(rot_mat).dot(rot_Z).dot(obj_T_gripper)
grasp_T = np.matmul(grasp_T, wrist_pose_wrt_gripper)

grasp_pose = get_pose_from_transform(grasp_T)

return grasp_pose

# define function: transform = get_tranform_from_pose(pose)
def get_transform_from_pose(pose):
    quat = quatFromAxisAngle(pose[3:])
    pos = pose[:3]
    pose = []
    pose.extend(quat)
    pose.extend(pos)
    transform = matrixFromPose(pose)

    return transform

# define function: putdown_pose_for_object =
    generate_put_down_pose(object_name, target_name)
def generate_put_down_pose(object_name, target_name):
    target_id = int(target_name.split("_")[1])
    obj = env.GetKinBody(object_name)
    can_radius = 0.03
    sampling_range = [[-0.175, 0.175], [-0.175, 0.175]]
    target_t = env.GetKinBody(target_name).GetTransform()

    x = np.random.uniform(low=sampling_range[0][0]+can_radius,
                           high=sampling_range[0][1]-can_radius)
    y = np.random.uniform(low=sampling_range[1][0]+can_radius,
                           high=sampling_range[1][1]-can_radius)

    target_id = int(target_name.split("_")[1])
    if target_id == 0:
        z = 0
        rot_z = np.eye(4)
    else:
        z = (0.1/2.0) + 0.005
        rot_angle = np.random.uniform(low=-np.pi, high=np.pi)
        rot_z = matrixFromAxisAngle([0, 0, rot_angle])

    t = matrixFromPose([1, 0, 0, 0, x, y, z])
    t = target_t.dot(t)
    t = t.dot(rot_z)

    rot_Z = matrixFromAxisAngle([0, 0, -np.pi/2])
    gripper_offset = -0.04
    world_T_obj = t

    rot_ang = np.random.uniform(low = -np.pi, high = np.pi)
    obj_T_gripper = matrixFromPose([1, 0, 0, 0, gripper_offset, 0, 0.2/2.0])
    rot_mat = matrixFromAxisAngle([0, 0, rot_ang])

    wrist_roll_pose = robot.GetLink("wrist_roll_link").GetTransform()

```



```

gripper_pose = robot.GetLink("gripper_link").GetTransform()
wrist_pose_wrt_gripper = np.matmul(np.linalg.inv(gripper_pose), wrist_roll_pose)

grasp_T = world_T_obj.dot(rot_mat).dot(rot_Z).dot(obj_T_gripper)
grasp_T = np.matmul(grasp_T, wrist_pose_wrt_gripper)

pose = get_pose_from_transform(grasp_T)

return pose

# define function: base_pose_around_surface =
    generate_base_pose_around_surface(target_name)
def generate_base_pose_around_surface(target_name):
    target_id = int(target_name.split("_")[1])
    diff = 0.35
    x_dim = 0.45
    x_offset = -diff-x_dim
    y_offset = 0
    target_t = env.GetKinBody(target_name).GetTransform()
    diff_translation_matrix = matrixFromPose([1,0,0,0,x_offset,y_offset,0])

    if target_id == 0:
        rot_angle = (2*np.pi) / 4.0
    else:
        rot_angle = np.random.uniform(low=-np.pi,high=np.pi)

    rot_Z = matrixFromAxisAngle([0, 0, -np.pi/2])
    rot_mat = matrixFromAxisAngle([0,0,rot_angle])
    t = np.eye(4)
    t = target_t.dot(rot_mat).dot(rot_Z).dot(diff_translation_matrix)

    _x = t[0,3]
    _y = t[1,3]
    _yaw = axisAngleFromRotationMatrix(t[:3,:3])[-1]
    pose = [_x,_y,_yaw]

    return pose

# define function: tuck_arm()
def tuck_arm():
    activate_manip_joints()
    dof_values = [0, 1.32, 1.4, -0.2, 1.72, 0, 1.3599999999999999, 0.0]

    robot.SetActiveDOFValues(dof_values)

grabbed_armTuckDOFs = [0, 1.32, 1.4, -0.2, 1.72, 0, 1.3599999999999999, 0.0]

# example: tuck the robot arm to a tuck pose.
tuck_arm()

# example: go to "surface_1"
p = generate_base_pose_around_surface("surface_1")
go_to_base_pose(p)

# example: grab can_1 which is currently on "surface_0".
p = generate_base_pose_around_surface("surface_2")
go_to_base_pose(p)
p_g = generate_grasp_pose("can_1")
ik = get_ik(p_g)
if len(ik) != 0:
    go_to_gripper_pose(ik)
grabbed_flag = grab_object("can_1")

# example: pickup a grabbed object "can_2", which is on "surface_1"

```

```

        when robot is near "surface_1".
p_g = generate_grasp_pose("can_2")
ik = get_ik(p_g)
if len(ik) != 0:
    go_to_gripper_pose(ik)
grabbed_flag = grab_object("can_2")
if grabbed_flag:
    tuck_arm()

# example: put down "can_1", which is already being held by the
# robot gripper on "surface_1".
p = generate_base_pose_around_surface("surface_1")
go_to_base_pose(p)
p_g = generate_put_down_pose("can_1", "surface_1")
ik = get_ik(p_g)
if len(ik) != 0:
    go_to_gripper_pose(ik)
un_grab("can_1")
tuck_arm()

# example: check collisions for "can_1".
collision_flag = collision_check("can_1")

# example: pickup can_1, which is on surface_0 and place it on surface_2
p = generate_base_pose_around_surface("surface_0")
go_to_base_pose(p)
p_g = generate_grasp_pose("can_1")
ik = get_ik(p_g)
if len(ik) != 0:
    go_to_gripper_pose(ik)
grabbed_flag = grab_object("can_1")
if grabbed_flag:
    tuck_arm()
p = generate_base_pose_around_surface("surface_2")
go_to_base_pose(p)
p_g = generate_put_down_pose("can_1", "surface_2")
ik = get_ik(p_g)
if len(ik) != 0:
    go_to_gripper_pose(ik)
un_grab("can_1")
tuck_arm()

```

Prompt for Delivering 1 Item:

Using the functions given above solve the following problem: #
 There are 2 cans, can_1, and can_2, and three surfaces, surface_1, surface_2, and surface_0 in the environment. In the initial state, both the cans, can_1 and can_2 are on the surface - surface_2. the function returns True if robot has successfully picked up both cans from surface_2 and placed can_1 on surface_0 and can_2 on surface_1. success_flag is True if the function succeeds in task and there is no object in collision with any other object in the environemnt.
 # The signature for the function required is:
 success_flag = place_cans_on_goal_surfaces().
 # only give the code and no other text including comments, markdowns or for which language the code is given. Also, at the end call the function as well.

Prompt for Delivering 2 Item:

Using the functions given above solve the following problem: #
 There are 2 cans, can_1, and can_2, and three surfaces, surface_1, surface_2, and surface_0 in the environment. In the initial state, can_1 is on surface_2 and can_2 is on surface_1. the function returns True if robot has successfully picked up can_1 from surface_2 and placed it on surface_1, and also has picked can_2 from surface_1 and placed it on surface_0. success_flag is True if the function succeeds in task and there is no object in collision with any other object in the environemnt.
 # The signature for the function required is:

```
success_flag = place_cans_on_goal_surfaces().  
# only give the code and no other text including comments, markdowns or for which  
language the code is given. Also, at the end call the function as well.
```

2) Building Keva Structures:

Domain-specific Prompt for Robot Actions:

```
# define function: success_flag = tuck_arm()  
def tuck_arm(arm="left"):  
    release(arm)  
    if arm == "left":  
        solution = left_arm_tuck_DOFs  
    elif arm == "right":  
        solution = right_arm_tuck_DOFs  
  
    try:  
        robot.SetActiveDOFValues(solution)  
    except:  
        pass  
  
    openGripper()  
    return True  
  
# define function: grab(object_name)  
def grab(obj, arm="left"):  
    o = env.GetKinBody(obj)  
    if arm == "left":  
        gripper_link = left_gripper_link  
    elif arm == "right":  
        gripper_link = right_gripper_link  
  
    robot_t = gripper_link.GetTransform()  
    ot = o.GetTransform()  
    euclidean_distance = np.linalg.norm(robot_t[:3,3]-ot[:3,3])  
    if euclidean_distance < grab_range[1] and euclidean_distance > grab_range[0]:  
        robot.Grab(o)  
    else:  
        print("object out of grasp range")  
  
# define function: release(object_name)  
def release(object_name="object_name", arm="left"):  
    robot.ReleaseAllGrabbed()  
  
# define function: collision_flag = collision_check(object_name)  
def collision_check(object_name):  
    collision_flag = False  
    obj = env.GetKinBody(object_name)  
  
    for obj2 in env.GetBodies():  
        if obj != obj2:  
            collision = env.CheckCollision(obj, obj2)  
            if collision:  
                if (obj2 == robot and obj in robot.GetGrabbed()) or  
                    (obj == robot and obj2 in robot.GetGrabbed()):  
                    collision = False  
                    continue  
                collision_flag = True  
                break  
  
    return collision_flag  
  
# define function: robot_ik = get_ik_solutions(pose)  
def get_ik_solutions(end_effector_solution, robot_param="left"):  
    end_effector_solution = get_transform_from_pose(end_effector_solution)  
    current_state = robot.SetActiveDOFValues()  
    collision = True  
    if robot_param not in manipulator_groups:
```

```

    robot_param = "left"

    if robot_param == "left":
        ik_solver = left_ik_solver
    elif robot_param == "right":
        ik_solver = right_ik_solver

    ik_count = 0

    required_T = np.linalg.pinv(robot_init_transform).dot(end_effector_solution)
    pose = get_pose_from_transform(required_T)
    pos = pose[:3]
    orn = quatFromAxisAngle(pose[3:])

    while collision:
        seed_state = [np.random.uniform(-3.14, 3.14)] * ik_solver.number_of_joints
        joint_values = ik_solver.get_ik(seed_state,
                                       pos[0], pos[1], pos[2],
                                       orn[1], orn[2], orn[3], orn[0]
                                       )

        if joint_values is not None:
            robot.SetActiveDOFValues(joint_values)
            if collision_check(str(robot.GetName())):
                collision=True
            else:
                collision = False
        else:
            print("no joint_values")
            joint_values = []
            break

    robot.SetActiveDOFValues(current_state)
    return joint_values

# define function: pose = get_pose_from_transform(transform)
def get_pose_from_transform(transform):
    quat = poseFromMatrix(transform)[:4]
    eul = axisAngleFromQuat(quat)
    pose = []
    pose.extend(poseFromMatrix(transform)[4:])
    pose.extend(eul)

    return pose

# define function: go_to_gripper_pose(pose)
def go_to_gripper_pose(pose, arm="left"):
    robot.SetActiveDOFValues(pose)

# define function: current_pose_of_object = get_current_pose_of_object(object_name)
def get_current_pose_of_object(object_name):
    obj = env.GetKinBody(object_name)
    obj_T = obj.GetTransform()
    obj_pose = get_pose_from_transform(obj_T)

    return obj_pose

# define function: transform = get_tranform_from_pose(pose)
def get_transform_from_pose(pose):
    quat = quatFromAxisAngle(pose[3:])
    pos = pose[:3]
    pose = []
    pose.extend(quat)
    pose.extend(pos)
    transform = matrixFromPose(pose)

```

```

    return transform

# define function: p = sample_grasp_pose(object_name)
def sample_grasp_pose(object_name):
    world_T_obj = env.GetKinBody(object_name).GetTransform()

    world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
    robot_T_world = np.linalg.inv(world_T_robot)

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

# define function: set_plank(object_name)
def set_plank(plank_name):
    plank = env.GetKinBody(plank_name)
    x_offsets=[0.15,0.45]
    y_offsets=[0.65,0.05]

    while True:
        t = np.eye(4)
        t[0,3] = np.random.uniform(low = -0.45+x_offsets[0], high = 0.45-x_offsets[1])
        t[1,3] = np.random.uniform(low = -0.45+y_offsets[0], high = 0.45-y_offsets[1])
        t[2,3] = 0.0135

        t1 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])
        t = t.dot(t1)
        plank.SetTransform(t)
        t2 = orpy.matrixFromAxisAngle([0,-np.pi/2, 0])
        plank.SetTransform(t.dot(t2))
        if not(collision_check(plank_name)):
            break

# define function: p = get_goal_put_down_pose_for_plank_1()
def get_goal_put_down_pose_for_plank_1():
    world_T_obj = env.GetKinBody("goalLoc_1").GetTransform()

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

# define function: p = sample_plank_on_left_of_other_plank(plank_1,plank_2)
def sample_plank_on_left_of_other_plank(plank_1,plank_2):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform = get_transform_from_pose([0, 0, 0.077474999073727457, 0, 0, 0])

    required_t = plank_1.GetTransform().dot(relative_transform)

    world_T_obj = required_t

```

```

world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
robot_T_world = np.linalg.inv(world_T_robot)

obj_T_robot = np.eye(4)
obj_T_robot[1,3]= grasping_offset

t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
t = np.matmul(world_T_obj,obj_T_robot)
pose = get_pose_from_transform(t)

return pose

# define function: p = sample_plank_on_right_of_other_plank(plank_1,plank_2)
def sample_plank_on_right_of_other_plank(plank_1,plank_2):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform =
        get_transform_from_pose([0, 0, -0.077474999073727457, 0, 0, 0])

    required_t = plank_1.GetTransform().dot(relative_transform)

    world_T_obj = required_t

    world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
    robot_T_world = np.linalg.inv(world_T_robot)

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

# define function: p =
sample_plank_horizontally_on_top_of_other_two_vertical_planks
    ("plank_1","plank_2","plank_3")
def sample_plank_horizontally_on_top_of_other_two_vertical_planks
    (plank_1,plank_2,plank_3):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform = get_transform_from_pose([0.059907747268674261, 0,
        0.04373009875416578, 0, 1.5707963267948959, 0])
    required_t = plank_1.GetTransform().dot(relative_transform)

    world_T_obj = required_t

    world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
    robot_T_world = np.linalg.inv(world_T_robot)

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

```

```

# define function: p =
sample_plank_horizontally_on_top_of_other_two_horizontal_planks_on_
    left_side("plank_1","plank_2","plank_3")
def sample_plank_horizontally_on_top_of_other_two_horizontal_planks_on_
    left_side(plank_1,plank_2,plank_3):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform = get_transform_from_pose([0.04, -0.023439999999999989, 0.04,
        0, 1.5707963267948963, 0])
    required_t = plank_1.GetTransform().dot(relative_transform)

    world_T_obj = required_t

    world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
    robot_T_world = np.linalg.inv(world_T_robot)

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)
    return pose

# define function: p =
sample_plank_horizontally_on_top_of_other_two_horizontal_planks_on_
    right_side("plank_1","plank_2","plank_3")
def sample_plank_horizontally_on_top_of_other_two_horizontal_planks_on_
    right_side(plank_1,plank_2,plank_3):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform = get_transform_from_pose([-0.04, -0.023999999999999935,
        0.04, 0, 1.5707963267948968, 0])

    required_t = plank_1.GetTransform().dot(relative_transform)

    world_T_obj = required_t

    world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
    robot_T_world = np.linalg.inv(world_T_robot)

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

# define function: p =
sample_plank_perpendicularly_on_top_of_a_horizontal_plank_on_its_left_side
    (plank_1,plank_2)
def sample_plank_perpendicularly_on_top_of_a_horizontal_plank_on_its_
    left_side(plank_1,plank_2):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform = get_transform_from_pose([-0.033744900319561663,
        -4.9568220254682954e-16, 0.066504776477813554, 1.0368663869534288e-14,
        -1.5707963267948974, -9.9776971655314691e-15])

    required_t = plank_1.GetTransform().dot(relative_transform)

```

```

world_T_obj = required_t

world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
robot_T_world = np.linalg.inv(world_T_robot)

obj_T_robot = np.eye(4)
obj_T_robot[1,3]= grasping_offset

t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
t = np.matmul(world_T_obj,obj_T_robot)
pose = get_pose_from_transform(t)
return pose

# define function: p =
sample_plank_perpendicularly_on_top_of_a_horizontal_plank_on_its_
    right_side(plank_1,plank_2)
def sample_plank_perpendicularly_on_top_of_a_horizontal_plank_on_its_
    right_side(plank_1,plank_2):
    plank_1 = env.GetKinBody(plank_1)
    relative_transform = get_transform_from_pose([0.04373009875416739,
        -4.7544147175681199e-16, 0.066334486007690402, 1.0368663869534288e-14,
        -1.5707963267948974, -9.9776971655314691e-15])

    required_t = plank_1.GetTransform().dot(relative_transform)

    world_T_obj = required_t

    world_T_robot = get_transform_from_pose(robot.GetActiveDOFValues())
    robot_T_world = np.linalg.inv(world_T_robot)

    obj_T_robot = np.eye(4)
    obj_T_robot[1,3]= grasping_offset

    t1 = orpy.matrixFromAxisAngle([ 0, -np.pi/2, 0])
    t2 = orpy.matrixFromAxisAngle([-np.pi/2, 0, 0])

    obj_T_robot = np.matmul(np.matmul(obj_T_robot,t1),t2)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)
    return pose

# example: place plank_1 and plank_2 parallel to each other
set_plank("plank_1")
p = sample_grasp_pose("plank_1")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_1")
p = get_goal_put_down_pose_for_plank_1()
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
release()
set_plank("plank_2")
p = sample_grasp_pose("plank_2")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_2")
p = sample_plank_on_left_of_other_plank("plank_1","plank_2")
ik = get_ik_solutions(p)
if len(ik) > 0:

```



```

    go_to_gripper_pose(ik)
release()

# example: place plank_3 horizontally on top of vertically placed plank_1 and plank_2
set_plank("plank_3")
p = sample_grasp_pose("plank_3")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_3")
p = sample_plank_on_top_of_other_planks_in_pose_1("plank_1", "plank_2", "plank_3")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
release()

# example: place plank_2 vertically on plank_1 on the left
set_plank("plank_2")
p = sample_grasp_pose("plank_2")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_2")
p = sample_plank_perpendicularly_on_top_of_a_horizontal_plank_on_its_
    left_side("plank_1", "plank_2")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
release()

# example: place plank_2 vertically on plank_1 on the right
set_plank("plank_2")
p = sample_grasp_pose("plank_2")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_2")
p = sample_plank_perpendicularly_on_top_of_a_horizontal_plank_on_its_
    right_side("plank_1", "plank_2")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
release()

# example: place plank_3 horizontally on top of horizontally placed
    plank_1 and plank_2
set_plank("plank_3")
p = sample_grasp_pose("plank_3")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_3")
p = sample_plank_on_top_of_other_planks_in_pose_2("plank_1", "plank_2", "plank_3")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
release()

# example: place plank_3 horizontally on top of horizontally placed
    plank_1 and plank_2
set_plank("plank_3")
p = sample_grasp_pose("plank_3")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
grab("plank_3")

```

```

p = sample_plank_on_top_of_other_planks_in_pose_3("plank_1", "plank_2", "plank_3")
ik = get_ik_solutions(p)
if len(ik) > 0:
    go_to_gripper_pose(ik)
release()

# example: tuck the robot arm to a tuck pose.
tuck_arm()

# example: check collisions for plank_1
collision_flag = collision_check("plank_1")

```

Prompt for Building Structure 1:

Using the functions given above solve the following problem: #
There are 3 planks in the environment. The function should arrange these planks such that all the planks are kept at their corresponding goal locations. plank_1 being at goal location corresponding to itself. I.e., plank_1 and plank_2 are placed vertically on the table parallel from each other and plank_3 should be placed horizontally on both of these planks. The function returns true if the planks are placed in a collision-free configuration, otherwise returns false.
The signature for the function required is:
success_flag = place_planks_in_a_goal_structure().
only give the code and no other text including comments, markdowns or for which language the code is given. Also, at the end call the function as well.

Prompt for Building Structure 2:

Using the functions given above solve the following problem: #
There are 4 planks in the environment. The function should arrange these planks such that all the planks are kept at their corresponding goal locations. plank_1 and plank_2 are placed horizontally on top of the table, with plank_1 being at goal location corresponding to itself and plank_2 placed parallelly on left of plank_1. plank_4 is placed on the plank_2 and plank_1 horizontally on its side on the left and plank_3 is placed on the plank_2 and plank_1 horizontally on its side on the right. plank_3 is also placed parallelly on the left of the plank_4.
The signature for the function required is:
success_flag = place_planks_in_a_goal_structure().
only give the code and no other text including comments, markdowns or for which language the code is given. Also, at the end call the function as well.

Prompt for Building Structure 3:

Using the functions given above solve the following problem: #
There are 6 planks in the environment. The function should arrange these planks such that all the planks are kept at their corresponding goal locations such that when kept together, the planks create a structure of a 2D drawing of a house.
The signature for the function required is:
success_flag = place_planks_in_a_goal_structure().
only give the code and no other text including comments, markdowns or for which language the code is given. Also, at the end call the function as well.

Prompt for Building Structure 4:

Using the functions given above solve the following problem: #
There are 6 planks in the environment. The function should arrange these planks such that all the planks are kept at their corresponding goal locations.
plank_1 and plank_2 are placed horizontally on top of the table, with plank_1 being at goal location corresponding to itself and plank_2 placed parallelly on left of plank_1. plank_3 is placed on the plank_2 and plank_1 horizontally on its side on the left and plank_4 is placed on the plank_2 and plank_1 horizontally on its side on the right. plank_4 is also placed parallelly on the left of the plank_3. plank_4 and plank_5 are kept parallelly and vertically on top of plank_3, with plank_4 kept on right side and plank_5 placed on left side of plank_4. plank_6 is placed horizontally on plank_4 and plank_5.
The signature for the function required is:
success_flag = place_planks_in_a_goal_structure().
only give the code and no other text including comments, markdowns or for which language the code is given. Also, at the end call the function as well.

3) Packing a Box:

Domain-specific Prompt for Robot Actions:

```
# define function: grab_object(object_to_grab)
def grab_object(object_to_grab):
    o = env.GetKinBody(object_to_grab)
    robot.Grab(o)

# define function: un_grab(object_name)
def un_grab(object_name):
    robot.ReleaseAllGrabbed()

# define function: grasp_pose_for_object = generate_grasp_pose(object_to_grab)
def generate_grasp_pose(object_to_grab):
    world_T_obj = env.GetKinBody(object_to_grab).GetTransform()
    obj_T_robot = np.eye(4)
    obj_T_robot[2,3] = 0.21
    t1 = matrixFromAxisAngle([0, 0, -np.pi/4.0])
    obj_T_robot = obj_T_robot.dot(t1)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

# define function: putdown_pose_for_object = generate_putdown_pose
# (object_name,target_name)
def generate_putdown_pose(object_name,target_name):
    obj_dims = [0.0325,0.0325]
    droparea_dims = 0.075

    drop = env.GetKinBody(target_name)
    drop_t = drop.GetTransform()

    x_edge_offset = abs(droparea_dims-obj_dims[0])
    y_edge_offset = abs(droparea_dims-obj_dims[1])

    x = np.random.uniform(low=-x_edge_offset,high=x_edge_offset)
    y = np.random.uniform(low=-y_edge_offset,high=y_edge_offset)
    z = 0.001

    world_T_obj = matrixFromPose([1,0,0,0,x,y,z])
    world_T_obj = drop_t.dot(world_T_obj)

    obj_T_robot = np.eye(4)
    obj_T_robot[2,3] = 0.21
    t1 = matrixFromAxisAngle([0, 0, -np.pi/4.0])
    obj_T_robot = obj_T_robot.dot(t1)
    t = np.matmul(world_T_obj,obj_T_robot)
    pose = get_pose_from_transform(t)

    return pose

# define function: current_pose_of_object = get_current_pose_of_object(object_name)
def get_current_pose_of_object(object_name):
    obj = env.GetKinBody(object_name)
    obj_T = obj.GetTransform()
    obj_pose = get_pose_from_transform(obj_T)

    return obj_pose

# define function: robot_ik = get_ik(pose)
def get_ik(pose):
    return pose

# define function: go_to_pose(pose)
```

```

def go_to_pose(pose):
    ik = get_ik(pose)
    robot.SetActiveDOFValues(ik)

# define function: current_joint_values = get_current_joint_values_of_robot()
def get_current_joint_values_of_robot():
    return robot.SetActiveDOFValues()

# define function: pose = get_pose_from_transform(transform)
def get_pose_from_transform(transform):
    quat = poseFromMatrix(transform)[4]
    eul = axisAngleFromQuat(quat)
    pose = []
    pose.extend(poseFromMatrix(transform)[4:])
    pose.extend(eul)

    return pose

# define function: collision_flag = collision_check(object_name)
def collision_check(object_name):
    collision_flag = False
    obj = env.GetKinBody(object_name)

    for obj2 in env.GetBodies():
        if obj != obj2:
            collision = env.CheckCollision(obj, obj2)
            if collision:
                if (obj2 == robot and obj in robot.GetGrabbed())
                    or (obj == robot and obj2 in robot.GetGrabbed()):
                    collision = False
                    continue
                collision_flag = True
                break

    return collision_flag

# example: go to grasp pose of can_1.
p = generate_grasp_pose("can_1")
go_to_pose(p)

# example: grab can_1.
grab_object("can_1")

# example: pickup can_1.
p = generate_grasp_pose("can_1")
go_to_pose(p)
grab_object("can_1")

# example: putdown can_1 in box.
p = generate_putdown_pose("can_1", "box")
go_to_pose(p)
un_grab("can_1")

# example: check collisions for can_1.
collision_flag = collision_check("can_1")
\end{promptbox}
\subsection*{Prompt For Packing 1 Can}
\begin{promptbox}
Using the functions given above solve the following problem: #
There is 1 can, can_1, on the table. The function returns true if it can accommodate
all the cans in a box at a pose such that each can is not in collision with every
other can in the box. The function needs to accommodate all objects in the box.
# The signature for the function required is:
collision_flag = put_all_cans_in_box("box").
# only give the code and no other text including comments, markdowns or for which
language the code is given. Also, at the end call the function as well.

```

Prompt For Packing 2 Can:

```
Using the functions given above solve the following problem: #
There are 2 cans, can_1, and can_2, on the table. The function returns true if it can
accommodate all the cans in a box at a pose such that each can is not in collision
with every other can in the box. The function needs to accommodate all objects in
the box.
# The signature for the function required is:
collision_flag = put_all_cans_in_box("box").
# only give the code and no other text including comments, markdowns or for which
language the code is given. Also, at the end call the function as well.
```

Prompt For Packing 3 Can:

```
Using the functions given above solve the following problem: #
There are 3 cans, can_1, can_2, and can_3 on the table. The function returns true
if it can accommodate all the cans in a box at a pose such that each can is not
in collision with every other can in the box. The function needs to accommodate all
objects in the box.
# The signature for the function required is:
collision_flag = put_all_cans_in_box("box").
# only give the code and no other text including comments, markdowns or for which
language the code is given. Also, at the end call the function as well.
```

Prompt For Packing 4 Can:

```
Using the functions given above solve the following problem: #
There are 3 cans, can_1, can_2, and can_3 on the table. The function returns true
if it can accommodate all the cans in a box at a pose such that each can is not
in collision with every other can in the box. The function needs to accommodate all
objects in the box.
# The signature for the function required is:
collision_flag = put_all_cans_in_box("box").
# only give the code and no other text including comments, markdowns or for which
language the code is given. Also, at the end call the function as well.
```