Active Task Randomization: Learning Visuomotor Skills for Sequential Manipulation by Proposing Feasible and Novel Tasks

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Abstract—Solving real-world sequential manipulation tasks requires robots to have a repertoire of skills applicable to a wide range of circumstances. To acquire such skills using data-driven approaches, we need massive and diverse training data which is often labor-intensive and non-trivial to collect and curate. In this work, we introduce Active Task Randomization (ATR), an approach that learns visuomotor skills for sequential manipulation by automatically creating feasible and novel tasks in simulation. During training, our approach procedurally generates tasks using a graph-based task parameterization. To adaptively estimate the feasibility and novelty of sampled tasks, we develop a relational neural network that maps each task parameter into a compact embedding. We demonstrate that our approach can automatically create suitable tasks for efficiently training the skill policies to handle diverse scenarios with a variety of objects. We evaluate our method on simulated and real-world sequential manipulation tasks by composing the learned skills using a task planner. Compared to baseline methods, the skills learned using our approach consistently achieve better success rates. Videos are available at sites.google.com/view/active-task-randomization/

I. INTRODUCTION

Performing sequential manipulation tasks in the real world requires the robot to interact with the environment in a variety of ways based on the raw sensory observations. Fig. 1 shows an example task in which the robot is asked to store the salt can in a container under the rack. At the beginning of this task, the container is in front of the rack and the soda can is beyond reach of the robot. To achieve task success, the robot needs to sequentially execute these steps: pick up a hook, use it to pull the salt can closer, grasp the can, put it into the container, and finally push the container under the rack. Handcrafted primitive skills have been traditionally used in robotics to solve such tasks given known states and environment dynamics [1–3]. However, to address the vast variety and complexity of sequential manipulation tasks in the real world, the robot would need to acquire a repertoire of skills that can generalize to a wide range of environment configurations and goals.

In light of this challenge, a variety of data-driven approaches have been developed to acquire skills through self-supervised learning [4,5], imitation learning [6], and reinforcement learning [7,8]. While these approaches alleviate the need to manually design skills, the ability of the learned skills to generalize to novel scenarios highly depends on the scale and quality of the training data. Recently, simulated environments created through domain randomization [9,10] have been widely used for collecting training data to enable generalization to unseen environments. To solve hard exploration problems for which simple domain randomization is inefficient, an increasing number of works have proposed to adaptively select diverse tasks from parameterized task spaces to accelerate the learning progress [11–16]. Despite of success achieved in simple simulated environments, it is often challenging to apply these methods to complicated domains like sequential manipulation, where the choice of object properties, arrangements, and task goals have a complex effect on how the task can be solved. Randomizing the environments will often result in invalid tasks or fail to cover the full range of task variations the skill policies will need to be trained on. It would also be hard to estimate the feasibility and novelty of the sampled tasks from the object properties and relationships in complex task spaces.

In this work, we present Active Task Randomization (ATR), an approach that learns to solve real-world sequential manipulation tasks using procedurally generated tasks in simulation. At the heart of our approach is a task sampler that proposes simulated tasks for training the skill policies, as shown in Fig. 1. The sampling is performed in a parameterized task space that uses scene graphs to
represent the environment configurations to cover a wide range of environment configurations and goals. To enable sampling in a continuous and smooth space, we design a relational neural network that projects each task parameter sample to a compact embedding by learning from the past experiences. From the learned task embedding, we adaptively estimate feasibility and novelty of tasks to select the suitable candidate to facilitate learning. During testing, the learned skills are composed by a high-level task planner to solve unseen sequential manipulation tasks.

Our contributions are as follows: 1) We introduce a system that adaptively generates training tasks of various environment configurations and task goals in simulation using a graph-based task parameterization. 2) We propose a method that learns a compact task embedding for adaptively estimating the feasibility and novelty of sampled tasks. 3) We demonstrate that the skills learned using our method can be composed to solve various sequential manipulation tasks in the simulation and the real world. To the best of our knowledge, this work is the first to learn visuomotor skills for real-world sequential manipulation tasks by adaptively proposing simulated tasks in simulation.

II. RELATED WORK

A. Sequential Manipulation

Our goal is to learn composable skills that can generalize to a wide variety of sequential manipulation tasks. A common approach for solving sequential manipulation tasks is Task and Motion Planning (TAMP) [2,3,17–21]. TAMP algorithms leverage task planners that can reason over long horizons and generalize to any sequential manipulation task expressed as a symbolic goal for the task planner. However, TAMP algorithms often rely on hand-crafted policies with full knowledge of the environment state and dynamics for motion planning, and are also computationally expensive. While a few recent works introduce TAMP algorithms that take raw observations such as images or point clouds as input [22,23], these methods still require fully known dynamics and are computationally expensive.

Replacing hand-crafted policies with learned policies offers a potential solution for handling raw observations and unknown dynamics while avoiding the computational expense at runtime of traditional planning. Many works frame sequential manipulation as a reinforcement learning (RL) problem, where a high level policy selects low level policies to accomplish subtasks in the sequential manipulation task. The low level policies can be RL policies themselves (hierarchical RL) [24–26], or parameterized skills [27–34]. However, these methods offer limited generalization ability, often only working on small variations of a particular sequential manipulation task. Generalizing to a wide variety of sequential manipulation tasks requires training policies on diverse environments and tasks during training [22,35,36]. By automatically learning suitable tasks for training policies, our task proposal framework alleviates the engineering effort required to manually set up training curricula. Although we combine our task proposal framework with task planning and parameterized actions in our experiments for their ability to easily generalize to new tasks, our task proposal framework could be applied to other sequential manipulation frameworks as well.

B. Skill Learning

Skill learning has been widely studied in robotics. When the object properties and environment dynamics are known, handcrafted controllers can be designed and used as low-level skills to allow the robot to perform a variety of interactions with the environment [2,37–40]. In complicated real-world environments, the manual design of skills often involves a significant amount of time and human expertise, and these handcrafted skills will fall short if such privileged information is not available. Learning-based methods are a promising alternative to acquire skills. Given large-scale datasets [6,41–48], a variety of skills can be learned for tasks such as grasping, pushing, rotating, and insertion. In well-designed simulated and real-world environments [4,49–54], the skills can also be learned in a self-supervised manner, in which the trained policy is used to continuously collect data to bootstrap its performance. Skills can also take the form of goal-conditioned policies [55], latent-conditioned policies [56,57], and options [58,59], trained with reinforcement learning paradigms [60–64]. Although these works have shown promising results towards learning generalizable skills, it would be challenging to manually scale up the datasets and environments to cover the vast diversity and complexity of real-world scenarios. In this work, we follow prior work to learn skill policies through self-supervised learning. However, instead of training skills on fixed, hand-designed environments, we train them on a diverse set of environments that are adaptively generated based on their novelty and the current proficiency of the skills, which facilitates generalization to new scenarios.

C. Domain Randomization and Procedural Generation

There has been an increasing number of works that use procedural content generation for robotics [65–67]. Several works use procedurally generated environments in simulation with randomized object properties and dynamics [9,68]. More complex environments can also be generated using predefined probabilistic programming languages [69–71]. Most of these works use hand-designed procedural generation processes, which requires non-trivial expertise and labor. Recent works aim to learn generative models to capture the distribution of realistic environments, goals, and tasks given previously collected datasets [72–74]. Given a target task, [10] and [75] actively randomize the hyperparameters of the simulated environments to facilitate domain adaptation. However, large-scale datasets or target environments are often unavailable beforehand and data distributions chosen by human experts might not always reflect the suitable difficulty and diversity required by the learning algorithm. A growing number of works adaptively generate environments and tasks as curricula through the interplay between the trained policy and an adversarial policy [15,76,77] or a
generator [13,14,78–84], [11,16,85,86] propose to reuse and evolve previously learned environments to learn increasingly difficult and diverse skills. Despite their successes, most of these methods are only applied to simple grid world and simulated domains, in which the metric of difficulty and diversity can be easily defined or learned. In contrast, we propose to learn a graph-based representation for estimating the feasibility and diversity of complicated environments for sequential manipulation tasks. Our work is one of the first open-ended procedural generation methods applied to real-world robotics tasks in complex environments involving multiple objects and diverse skills.

III. PROBLEM FORMULATION

In each sequential manipulation task, the robot aims to reach a goal \( g \) through interactions with the objects in the environment. At each time \( t \), the robot receives a state \( s_t \) and chooses action \( a_t \). Task success is achieved when the constraint specified by \( g \) is satisfied. We aim to solve sequential manipulation tasks using a high-level task planner \( h \) and a low-level skill policy \( \pi \). Given the current state \( s \) and a goal \( g \), the planner \( h(s, g) \) produces a task plan that consists of a sequence of context variables \( c_1, c_2, \ldots \). Then the policy \( \pi(a_t|s_t, c_t) \) computes the action conditioned on the context \( c_t \). When solving a multi-step task, \( h \) re-plans at every time step so that the robot can recover from failures.

Our states \( s_t \) are comprised by a segmented point cloud \( x_t \) and scene graph \( G_t \) with corresponding object indices \( 1, \ldots, n \), computed from the observed depth image. The point cloud segmentation is performed by an external module which is orthogonal to the contributions of this paper. The goal \( g = G_{\text{goal}} \) is defined as the desired scene graph at the completion of the task. Each scene graph is defined over a set of object categories and relationships. Each vertex in the scene graph represents an object of a predefined type with directed links representing the relationship. Each object has a single parent node and arbitrary number of child nodes. The context is defined as \( c = (k, i, j) \) where \( k \) is the skill index, and \( i \) and \( j \) are the indices of target objects (we assume each skill interacts with two target objects). The task-planning problem is formulated and solved using Planning Domain Description Language (PDDL) [87]. Given \((G_t, G_{\text{goal}})\), the task planner \( h \) produces the task plan using first-order logic.

We would like to train the policy \( \pi \) to solve sequential manipulation tasks in diverse unseen scenarios. Since large-scale data collection in the real world is prohibitive, we train the policy in procedurally generated environments in simulation [66]. Following [51,88], we parameterize the task space \( T \) of sequential manipulation tasks in a given environment using a parameterized task space \( \mathcal{W} \) with a procedural generation module \( M(\cdot) \). Given each task parameter \( w \in \mathcal{W} \), the initial state and the goal of a sequential manipulation task can be instantiated by \( M(w) \). At each time step, the policy receives a reward \( r = R(s_{t+1}, c_t) \) which returns 1 when the resulting state satisfies the constraint specified by \( c_t \) and 0 otherwise. We train the policy to imitate successful transitions for which the reward is 1. Our goal is to find suitable task parameters that will optimize the learning progress of the policy.

IV. ACTIVE TASK RANDOMIZATION FOR LEARNING SEQUENTIAL MANIPULATION

We present Active Task Randomization (ATR), an approach that learns skill policies for solving sequential manipulation tasks using procedurally generated tasks in simulation. For each training episode, tasks are selected by the task sampler to facilitate the training of the skill policy. Sequential manipulation tasks can encompass a broad range of scenarios. To cover this space, a meaningful task selection mechanism would require selecting from a large set of object properties, arrangements, and goals. Furthermore, naive task selection strategies can result in task parameters that violate physical constraints or goals that are infeasible to reach. This is in contrast to prior work [11,88], which assumes that task parameters are low-dimensional and form a continuous space. In this work, we seek to develop a task sampling mechanism suitable for sequential manipulation.

In this section, we first introduce a task parameterization that enables procedural generation of sequential manipulation tasks. Then we describe the adaptive task randomization procedure. Finally, we explain how to learn the compact task embeddings that facilitate proposing suitable tasks.
A. Parameterization of Sequential Manipulation Tasks

Our task parameterization should be expressive enough to represent a wide range of environments and goals. Inspired by [14, 88], we define a parameter space \( \mathcal{W} \) that represents the inter-task variation of the task space \( \mathcal{T} \) (e.g. the symbolic relationships of the objects, the object types, and the object sizes) and use a predefined black-box procedural generation module \( M(\cdot) \) to instantiate each task \( M(w) \).

To represent the object properties and symbolic relationships between objects, we devise a graph-based parameterization based on PDDL. Each sequential manipulation task is defined as a tuple \( w = (O_{1:n}, G_{\text{init}}, G_{\text{goal}}) \), where \( O_{1:n} \) represents the intrinsic attributes of each object \( i = 1, \ldots, n \) that do not change across time (e.g. type and size), and \( G_{\text{init}} \) and \( G_{\text{goal}} \) denote the scene graphs of the initial and goal state, respectively. \( \rho(w) \) is the prior probability from which \( w \) can be sampled. In the simplest case, this can be a uniform distribution. More details can be found in Sec. IV-B.

B. Estimation of Task Feasibility and Novelty

During training, we collect data in procedurally generated tasks in simulation. In each episode, a task parameter \( w \in \mathcal{W} \) is proposed for instantiating the sequential manipulation task. The robot takes the action \( a \) produced by the policy conditioned on the given state \( s \) and context \( c = (k, i, j) \) (where \( k \) is the skill index and \( i, j \) are object indices) and receives the reward \( r \). We store the collected experience \( \{(w, s_i, a_i, r_i, t_i, s_{i+1})\} \) in the replay buffer \( \mathcal{D} \) for training the policy \( \pi \). We now describe how to select task \( w \) by adaptively estimating the task feasibility and the task novelty.

The task feasibility gauges if a task \( w \) can be solved by policy \( \pi \). Following [14], we define the task feasibility as the expected return \( \mathbb{E}_{\pi}[r|w] \) of unrolling the policy \( \pi \) in the task specified by \( w \). We train a value function \( V(w) \) to estimate the expected return by minimizing the mean squared error

\[
\mathcal{L} = \mathbb{E}_{r,w \sim \mathcal{D}} [||V(w) - r||^2]
\] (1)

Inspired by recent work on unsupervised exploration [89], we measure the task novelty of a sampled \( w \) through density estimation. Specifically, let \( p(\cdot) \) be the density of task parameters that the policy has been trained on, the task novelty is defined as the negative log density \( -\log p(w) \). While directly computing the density \( p(w) \) is intractable, we use particle-based estimation [90, 91] as \( \hat{p}(w) \). For each sampled \( w \), we denote \( w_K \) to be the \( K \)-th nearest neighbor (KNN) of \( w \) in the set of all task parameters stored in the replay buffer \( \mathcal{D} \). The distance between two task parameter vectors is computed with the distance metric \( d(\cdot, \cdot) \), which is described in Sec. IV-C. The particle-based approximation of the task parameter density can then be computed as

\[
\hat{p}(w) = -\frac{K}{mV_K}
\] (2)

where \( V_K \) is the volume of the hyper-sphere of radius \( d(w, w_K) \). To maximize the novelty, we sample a batch of task parameters and choose the one that maximizes \( d(w, w_K) \). Intuitively, this can be considered to be searching for the \( w \) that is most distinguishable from previous task parameters stored in \( \mathcal{D} \). In practice, we compute the nearest neighbors \( w_K \) from a sampled subset from \( \mathcal{D} \) rather than the entire dataset for computational efficiency.

At the start of each episode, we sample a batch of task parameters and compute the score for each \( w \) as

\[
f(w) = V(w) + \beta d(w, w_K)
\] (3)

where \( \beta = 0.1 \) is a weight that balances the two terms. This score is used to construct a categorical distribution with logits \( f(w) \), which can be used to sample \( w \). To encourage exploration, we use an epsilon-greedy strategy that directly samples from the prior distribution \( p(w) \) with 10% probability and from the categorical distribution otherwise.

C. Learning Compact Task Embeddings

We learn a compact representation of the task parameter \( w \) to effectively estimate task feasibility and task novelty. To extract information from the heterogeneous task parameter, we design a task encoder \( \phi(w) \) (as shown in Fig. 2) with a relational network [92] that makes use of the compositionality of task parameters. Given each \( w = (O_{1:n}, G_{\text{init}}, G_{\text{goal}}) \), we first use the task planner \( h \) to compute the task plan \( c_{1:T} \) and convert \( w \) into \( (O_{1:n}, G_{\text{init}}, c_{1:T}) \). In this work, we propose single-step tasks during training and thus use \( T = 1 \). We encode the properties of each object separately as \( \phi_o(a_i) \) where \( \phi_o \) is implemented as a single fully-connected (FC) layer. To represent the initial condition, the object embeddings are merged by the relational network based on the edges of the initial scene graph \( G_{\text{init}} \). To represent each step in the task plan, we encode the skill index and the target objects as \( \phi_k(k) \), \( \phi_o(a_i) \), and \( \phi_o(a_j) \) using the encoders \( \phi_k \) and \( \phi_o \). With \( \phi(w) \), we can now compute the task density using the Euclidean distance in the learned embedding space as \( d(\cdot, \cdot) \). And the value network computes \( V(w) \) using a fully-connected (FC) layer on top of the computed \( \phi(w) \). \( \phi \) is trained through the objective function Eq. 1.

V. Experiments

The goal of our experimental evaluation is to answer the following questions: 1) Can ATR procedurally generate feasible and novel tasks during training? 2) Can the tasks proposed by ATR improve skill learning performance? 3) How well can the learned skills perform in unseen sequential manipulation tasks?

A. Experimental Setup

Environment. Our experiments are conducted in a sequential manipulation domain, in which a 7-DoF Franka Emika robot arm interacts with multiple objects in a configurable table-top environment. Our simulated environments are implemented using the Bullet simulator [93]. At the beginning of each episode, up to five objects of various types (racks, containers, hooks, boxes, and cans) and sizes are placed in the environment. At each step, an RGBD image of the environment is captured by a Kinect2 sensor and converted into a point cloud given the camera extrinsics and intrinsics.
Our PDDL domain \((\Phi, A)\) contains four predicates \(\Phi = \{\text{on}(a, b), \text{nextto}(a, b), \text{under}(a, b), \text{reachable}(a)\}\) and four actions \(A = \{\text{place-onto}(a, b), \text{place-nextto}(a, b), \text{push-under}(a, b), \text{pull-with}(a, b)\}\). The predicates \(\Phi\) are computed based on the segmented point cloud to represent spatial relationships between objects. For example, \(\text{on}(a, b)\) is true if the bounding box of \(a\) is above and supported by the bounding box of \(b\). We leave the integration of image-based predicate classifiers such as \([95]\) to future work. During training, the task proposal module generates a task parameter \(w = (O_{1:n}, G_{\text{init}}, G_{\text{goal}})\) that can be directly translated into a PDDL problem. The task planner produces for a sequence of skills through depth-first search to solve the proposed PDDL problem, and each skill in the sequence is then executed one after another.

**Skills.** A skill policy is trained for each PDDL action using our task proposal approach. Each skill takes as input the current scene graph, a point cloud observation, and a segmentation mask of the objects in the scene. To transfer well to the real world, the skills have to be robust to noise in the observed point clouds, segmentation masks, and detected object poses. Artificial noise are added to the simulated observations during training to mitigate the reality gap. Each skill receives a binary reward according to whether its post-conditions have been satisfied according to the heuristic predicate classifiers. For example, \(\text{push-under}(a, b)\) receives a reward of 1 if \(\text{under}(a, b)\) is true after the step. In our experiments, a separate policy network is used for each skill and independently trained on data collected for the corresponding skills.

**Baselines.** We compare our method with three domain randomization and task generation baselines and evaluate the success rates. **Uniform** naively creates random environments by directly sampling from the parameterized task space without considering the feasibility or diversity of the tasks. **VDS** \([81]\) uses disagreement among an ensemble of task value networks as a metric of the epistemic uncertainty for selecting the optimal task among the sampled candidates. The original VDS is designed for sampling 2D goal coordinates and uses a simple MLP to compute the value, which is unlikely to learn structured representations for high-dimensional heterogeneous task parameters. Instead, we upgrade VDS with task value networks defined in Sec. \([IV]\). **PLR** \([96]\) re-samples previous tasks stored in the replay buffer based on a scoring function which measures the learning potential of replaying the task in the future. We also analyze two ablations of our method which consider only feasibility or only novelty when sampling tasks. All methods use the same policy learning algorithm and hyperparameters for a fair comparison.

**Implementation Details.** Adapted from \([51]\), the policy network takes the segmented point cloud and the target object indices as inputs and produces the mean and standard deviation of the predicted positional offsets. The task value network first uses 16D fully-connected (FC) layers to embed each vertex and each edge and then merges the information using a 64D FC layer. Each method is trained for 10,000 iterations.
training iterations. In each iteration, one environment step is collected from the simulated environment. For all experiments, we use a learning rate of $3 \times 10^{-4}$ and a batch size of 128. We use closed-loop task planning to recover from skill failures. If recovery from a failure is impossible (e.g. an object falls over and rolls away) or the time runs out, we consider the task to be a failure.

### B. Proposed Tasks

Examples of proposed tasks in simulation are shown in Fig. 4. During training, our method successfully proposes tasks with various object types, shapes, and symbolic relationships. In each task, there exists a feasible planned action to achieve the goal state by interacting with the target objects. In contrast, using baseline methods or uniformly sampling from the task space often results in infeasible tasks such as grasping objects that are beyond reach, pulling distant objects with a hook that is too short, pushing objects that are too large to fit beneath the rack, and stacking too many objects on a small surface.

### C. Skill Learning

During training, we evaluate the performance of the skill policies in simulation. Every 1,000 training iterations, each skill policy is evaluated on five hand-designed single-step tasks that need to be solved by the trained skill for 50 episodes. For all four skills, our full ATR method achieves success rates that are comparable or superior to baselines and ablations. The average success rates evaluated across five random seeds are presented in Fig. 5 in which the standard deviation is denoted by the shaped region. The baseline methods often fail to find tasks with valid configurations and their exploration of the task space is less efficient. The highest performance improvements are achieved in place-onto and pull-with since these two skills have the most stringent requirements for the types and scales of the two target objects. The performance of ATR depends on taking both the feasibility and novelty of the task into consideration; using only one of the two terms leads to worse performance.

### D. Sequential Manipulation

For the evaluation sequential manipulation tasks, we run closed-loop planning and consider a task successful if it can be completed within 10 steps. In simulation, we evaluate each target task with five random seeds for 1,000 episodes per seed. In the real world, each task is evaluated for 10 episodes. The success rates are presented in Fig. 5. As shown in the bar charts, our ATR method outperforms baselines on all three evaluation tasks in both simulation and in the real world, given the superior performance of individual learned skills. The baseline methods do not train the skill policies on a diverse enough range of objects and thus often cannot complete the tasks within 10 steps.

### VI. DISCUSSION AND FUTURE WORK

We presented ATR, a method that adaptively proposes feasible and novel tasks from a parameterized task space to learn skills for sequential manipulation. Our experiments demonstrated that ATR can effectively estimate feasibility by learning a compact representation and can generate suitable tasks for training. The learned skills can generalize to unseen environments and be composed for solving sequential manipulation tasks in simulation and in the real world. To the best of our knowledge, this work is the first to solve real-world sequential manipulation tasks given visual inputs by learning to procedurally generate tasks in simulation. We hope this will open up opportunities to use procedurally generated tasks for scaling up real-world robot learning approaches.

One limitation of ATR is that the set of skills is predefined. We intend to extend the current method to enable unsupervised skill discovery in the future. Another limitation is that the high-level task planner is hand-defined and requires an external segmentation pipeline, which could be replaced with a learned high-level policy in future work.
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