Abstract—Manipulation and assembly tasks require non-trivial planning of actions depending on the environment and the final goal. Previous work in this domain often assembles particular instances of objects from known sets of primitives. In contrast, we aim to handle varying sets of primitives and to construct different objects of a shape category. Given a single object instance of a category, e.g., an arch, and a binary shape classifier, we learn a visual policy to assemble other instances of the same category. Given a single object instance of a category, e.g., an arch, and a binary shape classifier, we learn a visual policy to assemble other instances of the same category. We then render simulated states in the observation space and learn a heatmap representation to predict alternative actions from a given input image. To validate our approach, we first demonstrate its efficiency for building object categories in state space. We then show the success of our visual policies for building arches from different primitives. Moreover, we demonstrate (i) the reactive ability of our method to re-assemble objects using additional primitives and (ii) the robust performance of our policy for unseen primitives resembling building blocks used during training. Our visual assembly policies are trained with no real images and reach up to 95% success rate when evaluated on a real robot.

I. INTRODUCTION

Our daily physical activities such as cooking, dressing or navigation require complex sequences of actions which people successfully and seamlessly plan based on sensory input. Action planning typically depends on the goal and constraints provided by the environment. Despite extensive prior work, existing autonomous agents are still far from the human-level planning performance, especially in unknown and cluttered environments [11], [56].

Action planning is a hard problem due to the large action spaces, exponential complexity and partial observability [27], [28]. To simplify the problem, existing work on task planning [19], [37], [50], [55] typically operates in the state space assuming the full knowledge of the environment. While such an assumption can be practical in structured and controlled environments, full state reconstruction for common scenes remains a highly challenging problem [20]. Arguably, the precise recovery of scene parameters such as its geometry, composition, friction coefficients, etc., is more difficult than the primary planning task itself. It is therefore desirable to design sensor-based planning policies that do not rely on explicit scene geometry and full state estimation.

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Fig. 1: Primitives on the left are assembled by our learned policy into arches on the right. We assemble objects of similar shapes in the simulator and learn visual manipulation policies that can build real 3D shapes from unseen primitives resembling building blocks used during training.

Vision-based control policies have recently become popular for robotic manipulation [2], [33], [59] and navigation [6], [16]. While this line of work shows promise, it has mostly been applied to the low-level motion planning such as predicting next motion direction. In our work we aim to learn visual policies for high-level task planning. Given visual input, our task planning policies for building 3D shapes output control sequences of primitive actions such as picking, rotating and placing.

Object manipulation has a long history in robotics. In particular, assembling objects from a given set of primitives has been addressed, for example, in [5], [45]. Prior work in this domain often aims to build particular object instances for which the structure is pre-defined [51], specified by demonstrations [10], [25] or given by a goal image [29]. Here we go further and learn to assemble different objects of a shape category. Such a task is significantly more complex compared to building particular object instances as it requires generalization to varying sets of building primitives. Moreover, we show empirically that our method is able to generalize to new primitives unseen during training (see Fig. 1).

Our approach contains two stages as illustrated in Fig. 2. In the first stage we discover new object instances and learn their assembling policies in state space. To this end, we propose a disassembling procedure and generate assembly trajectories by (a) unbuilding objects and (b) reverting action sequences. We then learn a value function and apply it to build new object instances. We iterate the disassembling and
learning steps to obtain a policy assembling a 3D shape. In the second stage we assemble objects given images of observed scenes. We render states from assembly trajectories obtained in the first stage and learn visual assembly policies with Behaviour Cloning (BC) [44]. To enable predictions of multiple valid actions at any given time, we propose a heatmap representation for the output of visual policies. While all our policies are learned in a simulated environment, we enable their direct transfer to a real robot using sim2real augmentation [41].

As main contributions of this work, we (i) propose a novel disassembly algorithm for building shape categories in state space, (ii) design and learn visual policies with heatmap outputs to address multi-modality of predicted actions, (iii) demonstrate a successful application of the method to a new task of building shape categories on a real UR5 robot. Moreover, our policies are learned with no human demonstrations, can re-assemble partially built objects, and adapt to unseen primitives resembling building blocks used during training.

II. RELATED WORK

Assembly tasks such as constructing IKEA furniture [51] remain to be a hard robotics challenge. Learning-based methods usually address simpler tasks such as cube stacking [40], [48]. Duan et al. [10] use demonstrations and attention modules to build a tower instance shown by an expert. Janner et al. [29] learn an object-centric representation of the scene to reproduce a tower instance from a goal image with an MPC-like control. Huang et al. [25] train a Graph Network to build a tower instance specified by a demonstration. We go beyond specific object instances and aim to assemble multiple objects from a given shape category, such as an arch. Moreover, we learn to build objects from different sets of possibly unseen primitives. To facilitate the learning, we propose to use disassembling to generate assembly trajectories. While the idea of reversible actions has been explored e.g., in [15], [24], [38], [53], our method differs from the work on disassembling object instances [58] by computing multiple disassembly paths and accounting for alternative valid actions.

Our work is related to methods of Task and Motion Planning (TAMP) [17], [35], [50], [55]. Long-term task planning prohibits costly rollouts, hence, TAMP methods deploy preconditions and postconditions to actions and optimize symbolic planners [14]. While some of these methods solve impressive tasks, conditions require manual and task-specific design [12], [22], [42]. Moreover, TAMP methods typically operate in state-space [18], hence, their generalization to sensor-based input in the real world requires non-trivial scene understanding [9]. In our work we learn visual policies and directly predict control sequences from image inputs.

Convolutions Neural Networks (CNNs) have significantly advanced visual recognition [23], [39], [47] and robotics, for example in tasks such as tossing objects [59], cube stacking [45], grasping [31] and opening doors [21]. Direct methods for visual control avoid explicit scene reconstruction and derive actions directly from image observations. Such methods typically use Reinforcement Learning (RL) [30] with auxiliary rewards [48] or Imitation Learning (IL) [4], [49] relying on large amounts of demonstrations [46], [60]. Indirect methods first estimate scene parameters [3], [13] such as object positions and orientations, and then deploy state-based planning strategies. Scene reconstruction from images, however, might be a more challenging task than solving a control task itself [20], [43]. We avoid drawbacks of direct and indirect methods and first solve the task in the simulated state space. We then use obtained solutions as automatic supervision for learning visual policies in the observation space. Inspired by [33], [36], we render states and train visual policies for a real robot using BC [44] and sim2real [41], [54].

III. APPROACH

We address the problem of building a 3D object shape by manipulating a set of available primitives with a robot. The configuration of the primitives on the table defines the state, \( s \in S \). We assume to have access to a shape classifier
function $f_C : S \rightarrow \{0, 1\}$. We define the shape as a subset of the state space, $C = \{s \in S | f_C(s) = 1\}$. Given $f_C$ and a single shape instance $\hat{s} \in C$, our method learns a visual policy $\pi$ that generates a robot action given a camera observation $o \in \mathcal{O}$. The resulting sequence of actions is then used to assemble a shape instance from available primitives. Our policy operates in the observation space $\mathcal{O}$, i.e., it only has access to the image of a current scene before deciding on the next action. Moreover, the policy is expected to build new object configurations from unseen primitives that resemble building blocks used during training.

**Algorithm 1** Pseudo-code of our approach. The input of the method is a single instance $\hat{s}$ and a binary shape classifier $f_C$. We also assume access to a simulator $T$ and a learned augmentation function $f_{\text{sim2real}}$ for sim2real transfer $f_{\text{sim2real}}$.

```
1: Input: instance $\hat{s}$, classifier $f_C$, simulator $T$, augmentation $f_{\text{sim2real}}$
2: function UNMAKE(state $s$, simulator $T$)
3:    $D = \{s : \text{value} = 1, \text{actions} = \{\}\}$
4:    for $s \in D$
5:        *** Disassemble by moving non-blocked objects ***
6:         $\hat{s} = T(s, \hat{a})$
7:         $V = D[\hat{s}], \text{value} \ast \gamma \implies \text{upper bound for the value}$
8:         $\hat{D} = \{\hat{s} : (\text{value} = V, \text{actions} = \{\hat{a}^{-1}\})\}$
9:         $D = \text{MERGE}_\text{SIMILAR}_\text{STATES}(D, \hat{D})$
10: if $\hat{s}$ is initial then return $D$
11: *** Train the value function $V$ ***
12: $C_V^i = \{\hat{s}\}$
13: for $k \in \{0, \ldots, K - 1\}$ do
14:    $D_V^k = \{}$ \text{State-value pairs dataset}\n15:    $D_{\text{unmake}} = \text{UNMAKE}(s_i)$
16:    $D_{\text{merge}} = \text{EXPAND}_\text{WITH}_\text{RANDOM}_\text{ACTIONS}(D_{\text{unmake}})$
17:    $D_{\text{merge}} = \text{MERGE}_\text{SIMILAR}_\text{STATES}(D_V^k, D_{\text{unmake}})$
18:    $V_k = \text{TRAIN}(D_V^k, \text{fully connected})$
19:    $\mu_k = \text{GREEDY}_\text{POLICY}(V_k)$
20:    $C_{k+1}^i = \{}$ \text{Set of instances discovered with $\mu_k$}\n21:    for $s_{i} \in \{1, \ldots, \text{building attempts}\}$ do
22:        $s_{i} = \text{BUILD}_\text{INSTANCE}(T, \mu_k)$
23:        if $f_C(s_i) = 1$ then
24:            $C_{k+1}^i$.append($s_i$)
25:    $D_{\text{n}} = \{}$ \text{Dataset of observation-heatmap pairs}\n26:    $\sigma_{\text{pick}}, \sigma_{\text{place}} = \text{RENDER}(s_i)$
27:    $h_{\text{pick}}, h_{\text{place}} = \text{GENERATE}_\text{HEATMAPS}(\alpha_i)$
28:    $D_{\pi}$.append($\sigma_{\text{pick}}, h_{\text{pick}}, \sigma_{\text{place}}, h_{\text{place}}$)
29:    $\pi = \text{TRAIN}(D_{\pi}, \text{hourglass}, f_{\text{sim2real}})$
30: Output: assembly policy $\pi$ for a real robot
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### A. Overview of the method

Our method has two stages: (i) generating action sequences in the state space and (ii) learning visual policies in the observation space. We use a simulated environment for both stages, however, our visual policies are trained with sim2real data augmentation [41] and directly transfer to the real robot. The overview and pseudo-code of the method are presented in Fig. 2 and Algorithm 1.

The first stage aims to find new shape instances and to construct action sequences for building them. It takes as input one 3D shape and a shape classifier. We propose to use an unmake procedure to generate valid action sequences. We disassemble the given shape instance and interpret the resulting sequences as reversed assembly demonstrations. We disassemble objects in multiple ways to find all assembly actions that are possible in the same state. We refer to the shape classifier $f_C$ as a sparse reward signal which we use to learn a state-value function $V_k$. We generate new shape instances using a state policy $\mu_k$ which is greedy with respect to the learned $V_k$. For a fixed number of iterations, we repeat the unmake procedure using the new set of instances and train an updated value function $V_{k+1}$. This part of our approach is described in Section III-B.

In the second stage we learn a visual policy that infers appropriate actions from image observations. We convert states $s_i$ into observations $o_i = R(s_i)$ using a graphics renderer $R$ and train a CNN policy $\pi$ with Behaviour Cloning (BC). Given the assembly trajectories produced by the first stage, each state is associated with a valid set of actions $\alpha_i$ that we turn into a heatmap $h_i$ to predict all possible actions simultaneously. Then $\pi$ is trained in a supervised manner using observation-heatmap pairs $(\alpha_i, h_i)$. This part of our approach is described in Section III-C.

### B. Building objects in state space

We define the state of our environment by the vector $s = (x^1, \ldots, x^m)^T$ with $x \in \mathbb{R}^{12}$ representing parameters for $m$ primitive shapes (our building blocks) in the scene. Each primitive is defined by three position coordinates, three orientation angles in the 3D space, three color channels, and three spatial extents (width, height and depth). A robot action $a \in A$ corresponds to a high-level skill of picking, placing and rotation of a primitive: $a = (x, p, o)$ where $x \in \{x_1, \ldots, x_m\}$ is the primitive to pick, $p \in \mathbb{R}^3$ is the position to place it, and $o \in \mathbb{R}^3$ is the orientation $x$ is placed in. We restrict orientations of primitives to the three axis-parallel directions and assume that all primitives are located on the surface of a table or on top of each other. Assuming access to the simulator $T$, applying action $a_i$ in the state $s_i$ would result into $s_{i+1} = T(s_i, a_i)$.

Building an object from a given set of primitives requires finding an appropriate sequence of actions $a_{1:n} = \{a_1, \ldots, a_n\}$ that transforms an initial state $s_0$ into the desired shape state $s_n \in C$. Finding a correct sequence $a_{1:n}$ is not trivial even in the state space. Given the large space of possible actions and the exponential growth of the number of action sequences depending on $n$, the naive brute-force search works only for building simple objects.

**Making objects by unmaking.** For an object example defined by the state $\hat{s} \in C$ we propose to find valid building sequences $a_{1:n}$ via disassembling or *unmaking* $\hat{s}$. We first
find a sequence of unmake actions $\tilde{a}_{1:m} = \{\tilde{a}_1, \ldots, \tilde{a}_n\}$, where $\tilde{a}_i$ moves a random non-blocked primitive on an object to a random non-occupied location on the table. If $m$ is the number of primitives constituting object $s$, we can disassemble $s$ by a sequence of $n = m - 1$ unmake actions. Unmake actions are invertible, i.e., for each unmake action $\tilde{a}$ such that $T(s_i, \tilde{a}) = s_j$ there is an inverse action $a = \tilde{a}^{-1}$ such that $T(s_j, a) = s_i$. By inverting and reordering all unmake actions, we obtain a valid sequence of actions for building $\hat{s}$ as $a_{1:n} = \{\tilde{a}_n, \ldots, \tilde{a}_1\}$.

We use the above randomized unmake procedure to generate a large and diverse set of valid action sequences. While each action $a_i$ in such sequences is associated with a single initial state $s_i$, there might be multiple correct assembly actions in the state $s_i$. For example, when building an arch, the same cube could be placed both to the left and to the right pillars (see Fig. 3). To each state $s_i$, we associate a set of actions $a_i$ available in all states which differ only in positions of primitives located on the table surface (denoted as $\approx$), namely, $a_i = \{a_j | s_j \approx s_i\}$.

Given $M$ action sequences of length $N$ we collect a dataset $D_\mu$ with state-actions pairs $D_\mu = \{(s_i, a_i)\}_{i=1}^{n=1n+1}$ that can be readily used to train a policy for assembling an object instance defined by state $s$.

Finding new object instances. To generalize our policies to build new objects of the similar shape given any set of primitives, we construct new instances through learning a value function $V_k$ for assembling an object instance defined by state $s$.

Learning value function. The value function $V_k$ is learned iteratively using instances found with the greedy policy $\mu_k$. In the first stage of training, we learn $V_0$ using the input instance $s$ only. We run the unmake procedure for all discovered instances in $C_k^\mu$. Given a sequence of state-actions pairs $\{(s_1, a_1), \ldots, (s_n, a_n)\}$, the value function estimate for state $s_i$ is $\hat{V}(s_i) = \gamma^{n-1}$. We also estimate values of states obtained by applying random disassembly actions $\tilde{a}_i$ to trajectory states $s_i$: $\hat{V}(s_i) = T(s_i, \tilde{a}_j)$. The value estimate $\hat{V}(s_i)$ is known if there exists $s_j \in \{s_1, \ldots, s_n\}$ such that $s_j \approx s_i$. Otherwise, we set the value as $\hat{V}(s_j) = \gamma^{n-1}$. We record all state-value pairs to the dataset $D_k^\mu$ and learn the value function by minimizing the loss $\tilde{h}_k = \arg \min_{\gamma} \text{MSE}(V_k(s_i), \hat{V}(s_i))$, where $V_k$ is implemented as a fully connected neural network with parameters $\tilde{h}_k$ and MSE is the mean square error. Once the training is converged, we discover new shape instances with $\mu_k$, unmake them, recollect $D_{k+1}$, and learn $V_{k+1}$. After $K$ phases, we run the unmake procedure on the set of discovered instances $C_k^\mu$ and record all state-actions pairs to the dataset $D_\mu$. The overview of our approach in the state space is illustrated by the left part of Fig. 2 and lines 14-28 of Algorithm 1.

C. Learning in observation space

We want to learn a visual policy $\pi$ for assembling objects from diverse sets of primitives by a real robot. The sole input of the policy is the camera observation of the scene. We learn the image-action association with a supervised learning approach, Behaviour Cloning (BC) [44], where we obtain supervision with solutions found in the state space. Given the dataset $D_\mu$ with state-actions pairs $\{(s_i, a_i)\}$, we use a pybullet [8] graphics renderer $R$ to generate an RGB-D image $o_i = R(s_i)$ for each state $s_i$ in $D_\mu$. In order to allow multiple actions for each observation $o_i$, we generate an action-heatmap $h_i \in H$ given the list of actions $a_i = \{a^1_i, \ldots, a^l_i\}$. We record the observation-heatmap pairs to the dataset $D_\pi$. The policy $\pi : \mathcal{O} \rightarrow \mathcal{H}$ is implemented as a CNN and is trained to predict correct action-heatmaps $\pi(o_i) = h_i$ for all $(o_i, h_i) \in D_\pi$. We show an advantage of the heatmaps-based architecture over a network that directly predicts positions and orientations in Section IV-D.1.

For the task of building objects with a real robot, we consider separate pick and place actions that are parameterized by positions and orientations of primitives on the 2D plane of a table. For simplicity, we assume that the elevation of a primitive above the table can be estimated by external means such as an overhead depth camera or a force-feedback sensor of the robot arm. We define the output of our policy by distributions over 2D positions on the table plane and three possible orientations of primitives on the table. We represent such distributions as heatmaps $(h^{\text{pick}}, h^{\text{place}})$ corresponding to the source and target parameters of primitives. Our heatmaps are 4-channel images with one channel representing position distribution and three other channels representing orientation. The placing positions and orientations might depend on the picked primitive, hence, we predict pick and place action-heatmaps $(h^{\text{pick}}, h^{\text{place}})$ sequentially.

We render separate observations $(o^{\text{pick}}, o^{\text{place}})$ for pick and place action-heatmaps $(h^{\text{pick}}, h^{\text{place}})$ respectively. For each
For each picked object, we render the observation \( o_i \) the heatmap \( h \) heatmap prediction \( \pi \). We follow [39] and use a HourGlass CNN architecture for \( D \) dataset (see Fig. 3). We record all observation-heatmap pairs in the \( R \).

A. Implementation details

We control a 6-DoF UR5 robotic arm with a 3 finger Robotiq gripper. In simulation, we model the robot and its environment with the pybullet physics simulator [8]. Given the positions and orientations of primitives to be manipulated, we use standard path planning methods [32], [52] to implement the pick and place actions. The elevation of primitives above the table surface is obtained with a Microsoft Kinect-2 camera located above the table.

B. Tasks

Tower. The goal of the agent is to stack cubes in a specific order of colors (see Fig. 4). In the beginning of the task, green, yellow and red cubes of size 1 unit (1U) are randomly distributed on the surface of a table. The unit corresponds to a physical size of 4.5 cm. The lowest cube is always green, the rest of the tower is defined as alternating yellow and red cubes. We use the Tower task to compare HourGlass and ResNet architectures in Section IV-D.1. The spatial dimensions of HourGlass input and output are 256x256 and 64x64 pixels respectively. We train \( \pi_v \) using Adam and LR=2.5e-4 for 50 epochs. For both value and visual networks, we use datasets of size 200,000 value-state and heatmap-observation pairs correspondingly. To enable the transfer of policies to the real robot, we use sim2real [41] to augment synthetic depth maps during training. Color segmentation masks are augmented with Bernoulli noise. During rendering, we also randomize shapes of primitives by adding noise to spatial coordinates of points that define cube meshes. We use 500 episodes for evaluation in simulation and 20 trials on the real robot.

IV. EXPERIMENTS

In this section we evaluate our approach both in simulation and on the real robot. We start by describing implementation details of the method in Section IV-A and present tasks used for evaluation in Section IV-B. Section IV-C confirms the importance of learning the state-value function for efficient task solving. Section IV-D evaluates visual policies trained to solve tasks in the observation space. We validate our proposed network architecture and highlight the importance of the disassembling procedure. We evaluate our approach in simulation and on a real UR5 robot. Additional qualitative results are available in the Appendix and on the project webpage [1].

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Table I: Average amount and standard deviation of steps required to build an arch shape for our method, random exploration and MCTS. *The simulation steps used for training of our method are not included.

| Arch, state space | 3U | 4U | 5U |
|-------------------|----|----|----|
| Random            | 3.4e± 5.0e3 | 1.5e± 1.2e4 | 6.1e± 9.6e4 |
| MCTS [7]          | 6.3e± 4.7e2 | 7.0e± 6.2e3 | 1.6e± 2.4e4 |
| Ours (state policy)* | 4.0e± 0.7e0 | 5.7e± 0.7e0 | 6.9e± 1.8e0 |
| Oracle            | 4.0e± 0.7e0 | 5.7e± 0.7e0 | 6.4e± 1.0e0 |

Table II: Success rates of visual policies (in percent) trained to build tower instances of 3, 5 and 7 cubes. On the real robot, the policies are evaluated using 20 trials.

Our observations are depth images recorded with another Kinect-2 camera placed in front of the robot arm. Visual policies receive the depth image and color segmentation masks corresponding to the colors of primitives. While visual policies in simulation have average errors of less than 5mm, the sim2real gap increases this value up to 2-3cm on the real robot. Given that stacking multiple primitives requires high precision, we apply a correction procedure using the depth camera as explained in Appendix VI-A.

The neural network \( V_\theta \) for Value Function has five fully-connected layers with 128 hidden units, ReLU activations and Batch Normalization [26]. We train \( V_\eta \) for 20 iterations of 30 epochs each using Adam and LR=1e-3. The CNN \( \pi_\theta \) contains one HourGlass [39] module which we compare to ResNet [23] in Section IV-D.1. The spatial dimensions of HourGlass input and output are 256x256 and 64x64 pixels respectively. We train \( \pi_\theta \) using Adam and LR=2.5e-4 for 50 epochs. For both value and visual networks, we use datasets of size 200,000 value-state and heatmap-observation pairs correspondingly. To enable the transfer of policies to the real robot, we use sim2real [41] to augment synthetic depth maps during training. Color segmentation masks are augmented with Bernoulli noise. During rendering, we also randomize shapes of primitives by adding noise to spatial coordinates of points that define cube meshes. We use 500 episodes for evaluation in simulation and 20 trials on the real robot.

B. Tasks

Tower. The goal of the agent is to stack cubes in a specific order of colors (see Fig. 4). In the beginning of the task, green, yellow and red cubes of size 1 unit (1U) are randomly distributed on the surface of a table. The unit corresponds to a physical size of 4.5 cm. The lowest cube is always green, the rest of the tower is defined as alternating yellow and red cubes. We use the Tower task to compare HourGlass and ResNet architectures in Section IV-D.1.

Arch. The agent needs to use all primitives available on a table to build an arch (see Fig. 5). The construction primitives are cubes of size 1U and beams of length 2U and 3U. The

![Fig. 4: Visualization of predictions of visual policies using HourGlass (green blobs) and ResNet-18 (red crosses) architectures. The policies are trained to build towers and should start by placing a yellow cube on the green one. ResNet predicts the correct picking location when all the cubes have distinct colors (left). Once identical yellow cubes are introduced to the scene (right), ResNet fails to choose between them and predicts an averaged location. HourGlass locates all the cubes correctly in both cases.](image-url)
arch shape category is defined as two symmetrical pillars with a bar bridging them. For example, pillars of an arch could be constructed from a 3U beam, three cubes or one cube and a 2U beam. Initially, all primitives are randomly distributed on the surface of the table. The beams can have three axes-parallel orientations. The primitives can have any color that differ from the color of the table. The location of pillars on the table is pre-defined. There are 49, 16 and 4 instances for 5U, 4U and 3U arch shapes correspondingly. We use the Arch task to evaluate the generalization of our method to the shape category and to show advantages of unmaking procedure in Sections IV-C and IV-D.

| Arch, simulation | 3U | 4U | 5U |
|------------------|----|----|----|
| Single unmake trajectory | 98.6 | 92.8 | 69.6 |
| Multiple unmake trajectories | 99.0 | 98.8 | 95.6 |

TABLE III: Success rates of visual policies trained to build the arch shape category of different heights. The policies are trained on trajectories obtained by disassembling the same object once or multiple times.

| Arch, instance | 3U | 4U | 5U |
|----------------|----|----|----|
| Instance policies | 99.4 | 97.8 | 96.8 |
| Uni-height policies | 99.6 | 98.2 | 98.0 |
| Multi-height policy | 97.4 | 96.4 | 95.4 |

TABLE IV: Success rates of visual policies trained by disassembling only the input instance (top) and instances found by state policies. The state policies are trained on arches of the same height (middle) and arches of heights 3-5U (bottom). The policies assemble arches given a fixed set of primitives (left) or various configurations of primitives (right). While instance and uni-height policies need to be trained for each given arch height, a single multi-height policy can assemble arches of various heights.

C. Learning in state space

This section evaluates how efficient our approach in generalizing to 3D shapes in the state space. For evaluation, we use a simulated Arch task. Our approach receives a single shape instance as an input and learns a state-value function by unmaking this instance. Given the trained value function and the simulator, we obtain the state policy by iterating over all possible actions and taking the one that maximizes the value function prediction. This state policy is then used to discover new object instances. We iteratively repeat the state-value network training after unmaking the discovered instances during 20 iterations. We compare our approach to MCTS [7] and random exploration. Similarly to the state policy, both baselines choose an object for picking and its placing location on top of other objects. The baselines also choose the placing orientation among the three axis-parallel directions. For MCTS, we use a shape matching score which is defined by a percentage of how much the arch shape is completed with primitives.

We estimate an average amount of steps required by our method and the baselines to build an arch, and report results in Tab. I. We also report the minimum number of steps required to build an arch (Oracle). Note that the Oracle has a non-zero variance since arches can be composed from different numbers of primitives. While the efficiency of our approach is comparable to Oracle, baselines require orders of magnitude more steps to find a correct solution. For example, to build a 5U arch, MCTS and the random exploration require 1.6e4 and 6.1e4 steps respectively while our method solves the task in 6.9 steps on average. We expect our method to scale well to more complex tasks where the complexity of baselines will prohibit their use.

D. Evaluation of visual policies

This section evaluates visual policies trained to solve tasks given images as input. We validate the HourGlass architecture in Section IV-D.1, show benefits of the proposed unmaking approach over prior work in Section IV-D.2, evaluate generalization of our method to the shape category in Section IV-D.3 and present an evaluation on the real robot in Section IV-D.4.

1) Visual policies architecture: We compare our heatmap-based architecture to a ResNet-18 network that directly outputs source and target parameters of manipulated primitives. Our approach uses HourGlass [39] to predict a multi-modal distribution of picking and placing actions. The first heatmap corresponds to 2D locations on the robot workspace, the three additional heatmaps encode orientations of a primitive. ResNet-18 [23] predicts five values corresponding to 2D locations and three orientations of objects.

We train HourGlass and ResNet-18 networks to build towers of 3, 5 and 7 cubes of green, yellow and red colors. For ResNet-18, we adapt the learning rate to 1e-3 and the input image size to 224. Tab. II indicates that both HourGlass and ResNet policies achieve almost perfect accuracy for towers of 3 cubes (Fig. 4, left). Given more complex scenes with multiple primitives of the same color, ResNet fails due to its unimodal prediction. As illustrated in Fig. 4, it outputs a
mean location of relevant primitives. The HourGlass-based policy builds towers of 7 cubes with a failure rate of 6% where the errors are mainly caused by occlusions. On the real world Tower task with 7 cubes, the HourGlass-based policy succeeds in 18 trials out of 20. The two failure cases were caused by an occlusion and misidentifying a cube due to the sim2real gap. Empirically, we did not find any performance improvement when using multiple HourGlass modules.

2) Learning by unmaking: This section compares the proposed approach of unmaking assembled objects with prior work [58]. While our method disassembles objects in multiple ways, [58] proposes to use a single disassembly trajectory. Such disassembly trajectories consist of pairs of state and corresponding action. However, there could be multiple correct actions possible in a state as shown in Fig. 3. We address this by computing several disassembly paths and merging actions that correspond to states, where the only difference comes from positions of primitives located on the table surface.

We train visual policies on observation-heatmap pairs obtained with and without multiple unmake trajectories. Tab. III shows that using multiple unmake paths significantly improves the performance. The performance difference is 26% on the hardest task of building 5U arches. Using multiple unmake paths makes the policy learn multiple hypothesis of picking and placing locations. This property becomes critical when multiple identical objects are used or if there exist several shape instances where identical primitives are assembled in different configurations.

3) Learning to build a 3D category shapes: This section evaluates the generalization of our approach to a shape category. We train visual policies on trajectories of unmaking 3 sets of arch instances: (i) only the input instance, (ii) instances obtained by a state policy trained on arches of the same height, (iii) instances obtained by a state policy trained on arches of heights 3-5U. We refer to these policies as (i) instance, (ii) uni-height and (iii) multi-height. For instance and uni-height policies, we train separate networks to build arches of each height. For multi-height policy, the same network is used to build arches of varying heights.

We evaluate all the policies separately on the set of primitives corresponding to the input instance (Tab. IV, left) and on different sets corresponding to the entire category (Tab. IV, right). In the first case, all the policies assemble arches with less than 5% of failures. The results of uni–height policies are higher compared to the instance policies. We believe that this improvement is due to a higher variation of the category instances that can be seen as a form of data augmentation. However, the performance of the instance policies rapidly drops when they are exposed to unseen sets of primitives. The uni-height policies have 2-3% higher success rates than the multi-height policy. Their success rates on 5U arches are 95.6% and 94.0% correspondingly. However, we need to train only a single network for the multi-height policy which is then able to reason about available primitives on the table and decide which arch height to build.

4) Real robot evaluation: This section evaluates the performance of our method on the real world Arch task using two scenarios: (i) “normal” scenario that matches the simulation, (ii) “re-assembling” scenario. In the “normal” scenario the robot has to assemble arches from varying sets of primitives. Tab. V (left) shows that uni-height policies have similar performance to the multi-height policy in the standard scenario except for 3U arches. In the “re-assembling” scenario the task starts with an assembled arch and additional primitives on the table (see Fig. 6). The agent is expected to re-assemble the arch by using all available primitives on the table. Our method is able to automatically re-assemble
shapes without additional training due to the presence of random pick-place actions in the train set. Similarly to the value function dataset described in Section III-B, we record observation-actions pairs corresponding to the inverse of the one-step random actions that include examples of re-assembling. In the "re-assembling" scenario (Tab. V (right)) the multi-height policy has higher success rates for 4U and 5U arches. We illustrate the assembly of arches with the real UR5 robot arm in Figures 5, 6, 8 and on the project webpage [1]. Failure cases with incorrect assembly are typically caused by occlusions and the gap between simulated and real environments, see Fig. 10.

Finally, we test the generalization of our approach to new building primitives and compare it to the MCTS baseline. We use three different sets of primitives that resemble cuboids used during training. The sets contain (i) 2 jars and a pencil case (Fig. 5 last column, top), (ii) 4 cans and a juice box (Fig. 5 last column, bottom), (iii) 5 stones (Fig. 1 bottom). The input we provide to the MCTS baseline is the state of primitives in terms of their sizes and locations. Size and location are determined by clustering 3D points, which are obtained based on depth image coordinates above the table similarly to the prediction correction procedure used for our method (see Appendix VI-A). We estimate the spatial dimensions of primitives by fitting bounding boxes to depth points associated to each 3D cluster. Tab. VI shows that our method significantly outperforms the MCTS baseline with the performance gap of up to 45%. In all cases the failures of MCTS are caused by errors in the estimation of size and location of the primitives. Given the incorrect estimates, MCTS cannot find an assembly path to build a correct arch. In contrast, our method relies on position correction based on direct image input and does not require spatial estimation of the primitives. Both methods often fail on the third set of primitives with stones given the substantial difference of stones to cuboid primitives used during training. Qualitative results for additional sets of primitives are presented in Appendix VI-B and Fig. 9.

V. CONCLUSION

We proposed an approach to build 3D object shapes using a robotic arm and varying sets of primitives. Our method efficiently learns to solve the task in the state space and then uses the obtained solutions as supervision to train visual policies in the observation space. We demonstrate successful application of our method to the new task of assembling shape categories and show promising results on a real robot.

While the disassembling procedure explored in this work may not be directly applicable to all tasks, we note that it could generalize even to physically irreversible actions by learning appropriate backward models in state space. Future work will explore this direction for a wide range of tasks including cooking and other more complex assembling tasks.

REFERENCES

[1] Project webpage. http://pascal.inrialpes.fr/data2/3D-shapes/; 5, 8

[2] P. Agrawal, A. V. Nair, P. Abbeel, J. Malik, and S. Levine. Learning to poke by poking: Experiential learning of intuitive physics. In NIPS, 2016. 1

[3] M. Andrychowicz, D. Crow, A. Ray, J. Schneider, R. H. Fong, B. Welinder, B. McGrew, J. Tobin, P. Abbeel, and W. Zaremba. Hindsight experience replay. NIPS, 2017. 2

[4] B. D. Argall, S. Chernova, M. Veloso, and B. Browning. A survey of robot learning from demonstration. RAS, 57(5), May 2009. 2

[5] Z. Chen, D. Guo, T. Xiao, S. Xie, X. Chen, H. Yu, J. Gray, K. Srinet, H. Fan, J. Ma, C. Qi, S. Tulsiani, A. Szlam, and L. Zitnick. Order-Aware Generative Modeling Using the 3D-Craft Dataset. In ICCV, 2019. 1

[6] F. Codervilla, M. Müller, A. López, V. Kolunt, and A. Dosovitskiy. End-to-end driving via conditional imitation learning. ICRA, 2018. 1

[7] R. Coulom. Efficient selectivity and backup operators in monte-carlo tree search. In Computers and Games, 2006. 5, 6

[8] E. Courmons and Y. Bai. PyBullet, Python module for physics simulation, robotics and machine learning. 2016. 4, 5

[9] N. T. Dantam, Z. K. Kingston, S. Chaudhuri, and L. E. Kavraki. An incremental constraint-based framework for task and motion planning. IJRR, 37, 2018. 2

[10] Y. Duan, M. Andrychowicz, B. Stadie, J. Ho, J. Schneider, I. Sutskever, P. Abbeel, and W. Zaremba. One-shot imitation learning. NIPS, 2017. 1, 2

[11] F. Ebert, C. Finn, S. Dasari, A. Xie, A. X. Lee, and S. Levine. Visual Foresight: Model-Based Deep Reinforcement Learning for Vision-Based Robotic Control. arXiv, 2018. 1

[12] S. Edelkamp and J. Hoffmann. PDPLL2.2: The Language for the Classical Part of IPC-4. 2004. 2

[13] B. Espiau, F. Chaumette, and P. Rives. A new approach to visual servoing in robotics. IEEE Transactions on Robotics and Automation, 1992. 2

[14] R. Fikes and N. Nilsson. Strips: A new approach to the application of theorem proving to problem solving. Artificial Intelligence, 1971. 2

[15] C. Florensa, D. Held, M. Wulfmeier, M. Zhang, and P. Abbeel. Reverse curriculum generation for reinforcement learning. In CoRL, 2017. 2

[16] D. Gandhi, L. Pinto, and A. Gupta. Learning to fly by crashing. In IROS, 2017. 1

[17] C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling. Fprob: An efficient heuristic for task and motion planning. In Algorithmic Foundations of Robotics XI, pages 179–195. Springer, 2015. 2

[18] C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling. Fprob: Leveraging symbolic planning for efficient task and motion planning. IJRR, 37,104–136, 2018. 2

[19] C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling. Sampling-based methods for factored task and motion planning. IJRR, 37, 2018. 1

[20] A. Grabner, P. M. Roth, and V. Lepetit. 3D Pose Estimation and 3D Tracking of Moving Human Joints. In CVPR, 2016. 1

[21] S. Gu, E. Holly, T. Lillicrap, and S. Levine. Deep reinforcement learning for robotic manipulation. In ICML, 2016. 2

[22] K. He, M. Laihijanian, L. Kavraki, and M. Vardi. Towards manipulation planning with temporal logic specifications. In ICRA, 2015. 2

[23] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In CVPR, 2016. 2, 5, 6

[24] I.-A. Hosu and T. Rebedea. Playing atari games with deep reinforcement learning and human checkpoint replay. In ECAI Workshop on Evaluating General Purpose AI, 2016. 2

[25] D.-A. Huang, S. Nair, D. Xu, Y. Zhu, A. Garg, L. Fei-Fei, S. Savarese, and J. C. Niebles. Neural task graphs: Generalizing to unseen tasks from a single video demonstration. In CVPR, 2018. 1, 2

[26] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML, 2015. 5

[27] A. Irpan. Deep reinforcement learning doesn’t work yet, 2018. 1

[28] M. Jaderberg, V. Mnih, W. Czarnecki, T. Schaul, J. Z. Leibo, D. Silver, and K. Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. arXiv, 2016. 1

[29] M. Janner, S. Levine, W. T. Freeman, J. B. Tenenbaum, C. Finn, and J. Wu. Reasoning about physical interactions with object-oriented prediction and planning. In ICLR, 2019. 1, 2

[30] J. Kober, J. Bagnell, and J. Peters. Reinforcement learning in robotics: A survey. IJRR, 2013. 2

[31] T. Lampe and M. Riedmiller. Acquiring visual servoing reaching and grasping skills using neural reinforcement learning. IJCNN, 2013. 2

[32] S. LaValle. Planning Algorithms. Cambridge University, 2006. 5

[33] S. Levine, C. Finn, T. Darrell, and P. Abbeel. End-to-end training of deep visuomotor policies. JMLR, 2015. 1, 2
The goal of our method is to build a 3D object by selecting the right primitives and performing correct construction actions. While the learned policies typically plan correct actions, object locations predicted by the heatmaps in the real robot setup may miss the primitive by a few centimeters. Such errors could be addressed, for example, by learning additional policies for location prediction. Here we chose a simpler solution and make the correction of predicted locations using depth images. As illustrated in Figure 7, given a depth map, we first obtain object centroids by clustering points above the table surface. Next, we predict the spatial location for the next action by maximizing the heatmap produced by the policy. The predicted location is then corrected to the location of the nearest cluster centroid. The applied corrections are typically in the order of 2-3 centimeters.

**Fig. 7:** Correction procedure applied to the spatial maxima of predicted heatmaps. Left: object centroids (blue bars) are estimated by the spatial clustering of depth-map locations above the table surface. Right: The location of the heatmap maxima (red bar) is corrected to the location of the closest object centroid. Refer to Section VI-A for further explanations.

### A. Real robot implementation details

The goal of our method is to build a 3D object by selecting the right primitives and performing correct construction

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[33] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In CVPR, 2015. 5

[34] T. Lozano-P´erez and L. P. Kaelbling. A constraint-based method for solving sequential manipulation planning problems. In IROS, 2014. 2

[35] J. Mahler, J. Liang, S. Niyaz, M. Laskey, R. Doan, X. Liu, J. A. Ojea, and K. Y. Goldberg. Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics. RSS, 2017. 2

[36] A. Nair, B. McGrew, M. Andrychowicz, W. Zaremba, and P. Abbeel. Overcoming exploration in reinforcement learning with demonstrations. In ICRA, 2018. 1

[37] S. Nair, M. Babaeizadeh, C. Finn, S. Levine, and V. Kumar. Time reversal as self-supervision. ICRA, 2020. 2

[38] A. Newell, K. Yang, and J. Deng. Stacked hourglass networks for human pose estimation. In ECCV, 2016. 2, 5, 6

[39] A. Pashevich, D. Hafner, J. Davidson, R. Sukthankar, and C. Schmid. Modulated policy hierarchies. NIPS Deep RL workshop, 2018. 2

[40] A. Pashevich, R. Strudel, I. Kalevythki, I. Laptev, and C. Schmid. Learning to augment synthetic images for sim2real policy transfer. In IROS, 2019. 2, 3, 5

[41] C. Paxton, Y. Barnoy, K. Katyal, R. Arora, and G. D. Hager. Visual robot task planning. In ICRA, 2019. 2

[42] L. Pinto and A. Gupta. Superizing self-supervision: Learning to grasp from 50k tries and 700 robot hours. ICRA 2016. 2

[43] D. A. Pomerleau. Alvinn: An autonomous land vehicle in a neural network. In NIPS, 1989. 2, 4

[44] A. Popov, N. Heess, T. Lillicrap, R. Hafner, G. Barth-Maron, M. Vecerik, T. Lampe, Y. Tassa, T. Erez, and M. Riedmiller. Data-efficient deep reinforcement learning for dexterous manipulation. arXiv, 2017. 1, 2

[45] R. Rahmatizadeh, P. Abolghasemi, L. Bölöni, and S. Levine. Vision-based multi-task manipulation for inexpensive robots using end-to-end learning from demonstration. ICRA, 2018. 2

[46] S. Ren, K. He, R. Girshick, and J. Sun. Faster R-CNN: Towards Real-time Object Detection with Region Proposal Networks. In NIPS, 2015. 2

[47] M. A. Riedmiller, R. Hafner, T. Lampe, M. Neunert, J. Degrave, T. V. de Wiele, V. Mnih, N. Heess, and J. T. Springenberg. Learning by planning as self-supervised reward augmented tasks from scratch. MLR, 2018. 2

[48] F. Sadeghi and S. Levine. CAD2RL: Real Single-Image Flight Without a Single Real Flight. In ICRA, 2017. 2

[49] S. Srivastava, E. Fang, L. Riano, R. Chitnis, S. Russell, and P. Abbeel. Combined task and motion planning through an extensible planner-independent interface layer. In ICRA, 2014. 1, 2

[50] F. Suárez-Ruiz, X. Zhou, and Q.-C. Pham. Can robots assemble an ikea chair? Science Robotics, 3(17), 2018. 1, 2

[51] I. A. Şucaan, M. Moll, and L. E. Kavraki. The Open Motion Planning Library. Robotics & Automation Magazine, 19(4):72–82, 2012. 5

[52] S. Sukhbaatar, I. Kostrikov, A. Szlam, and R. Fergus. Intrinsic motivation and automatic curricula via asymmetric self-play. ICLR, 2017. 2

[53] J. Tobin, R. Fong, A. Ray, J. Schneider, W. Zaremba, and P. Abbeel. Domain randomization for transferring deep neural networks from simulation to the real world. IROS, 2017. 2

[54] M. Toussaint. Logic-geometric programming: An optimization-based approach to combined task and motion planning. IJACI, 2015. 1, 2

[55] A. Wang, T. Kurutach, K. Liu, P. Abbeel, and A. Tamar. Learning robotic manipulation through visual planning and acting. arXiv, 2019. 1

[56] A. Wang, T. Kurutach, K. Liu, P. Abbeel, and A. Tamar. Learning robotic manipulation through visual planning and acting. arXiv, 2019. 1

[57] S.-E. Wei, V. Ramakrishna, T. Kanade, and Y. Sheikh. Convolutional pose machines. In CVPR, 2016. 5

[58] K. Zakka, A. Zeng, J. Lee, and S. Song. Form2Fit: Learning Shape Priors for Generalizable Assembly from Disassembly. arXiv, 2019. 2, 7

[59] A. Zeng, S. Song, J. Lee, A. Rodríguez, and T. A. Funkhouser. Tossingbot: Learning to throw arbitrary objects with residual physics. RSS, 2019. 1, 2

[60] T. Zhang, Z. McCarthy, O. Jow, D. Lee, K. Goldberg, and P. Abbeel. Deep imitation learning for complex manipulation tasks from virtual reality teleoperation. ICRA, 2017. 2

### VI. APPENDIX

**A. Real robot implementation details**

The goal of our method is to build a 3D object by selecting the right primitives and performing correct construction actions. While the learned policies typically plan correct actions, object locations predicted by the heatmaps in the real robot setup may miss the primitive by a few centimeters. Such errors could be addressed, for example, by learning additional policies for location prediction. Here we chose a simpler solution and make the correction of predicted locations using depth images. As illustrated in Figure 7, given a depth map, we first obtain object centroids by clustering points above the table surface. Next, we predict the spatial location for the next action by maximizing the heatmap produced by the policy. The predicted location is then corrected to the location of the nearest cluster centroid. The applied corrections are typically in the order of 2-3 centimeters.

Figures 8-10 demonstrate application of our method to the construction of arches on a real robot. Figure 8 presents the construction of arches from blocks. The blocks are initially arranged in random positions and orientations. The policy changes positions and orientations of blocks, leading to the successful construction of arches of different sizes. Figure 9 demonstrates arch constructions from new primitives that have not been observed during training. We emphasize that our learned visual policies directly control the robot without intermediate geometric reconstruction of the world state. Nevertheless, the policy can handle diverse object shapes. The robustness to new shapes could be further improved by using various shapes for policy training in simulation. Finally, Figure 10 illustrates few failure cases originating from incorrectly estimated pick and place locations as well as from a failure to grasp a soft object (a shoe).
Fig. 8: Successful construction of arches from blocks with a real robot. Note the rotation movements performed by the robot to change the orientation of certain blocks.
Fig. 9: Construction of arches from new primitives that have not been observed during training. Despite the fact that our visual policy has been trained only with block-shaped primitives and only in simulation, it is able to generalize to new diverse primitives and to construct arches in a real robot setup.
Fig. 10: Failure cases for arch construction with a real robot. The failures originate from the wrong choice of a primitive (top example), wrong choice of the target location (middle example), and a failure to grasp a soft object (bottom example).