Bag All You Need: Learning a Generalizable Bagging Strategy for Heterogeneous Objects

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Abstract—We introduce a practical robotics solution for the task of heterogeneous bagging, requiring the placement of multiple rigid and deformable objects into a deformable bag. This is a difficult task as it features complex interactions between multiple highly deformable objects under limited observability. To tackle these challenges, we propose a robotic system consisting of two learned policies: a rearrangement policy that learns to place multiple rigid objects and fold deformable objects in order to achieve desirable pre-bagging conditions, and a lifting policy to infer suitable grasp points for bi-manual bag lifting. We evaluate these learned policies on a real-world three-arm robot platform that achieves a 70% heterogeneous bagging success rate with novel objects. To facilitate future research and comparison, we also develop a novel heterogeneous bagging simulation benchmark that will be made publicly available.

I. INTRODUCTION

Imagine packing a bag for a picnic; we might first put several rigid objects (such as an apple and a water bottle) into the bag, fold deformable objects (such as a picnic mat and a T-shirt) and then place them on top of the bag opening. We must then lift the bag (another deformable object) in a way that these objects fall inside without spilling. Successful completion of this task requires both a comprehensive understanding of the objects’ physical properties and the capability to plan and integrate multiple manipulation skills. For instance, the robot’s actions must take into account:

- **Object geometry**: objects must be placed and oriented to fit into the bag opening.
- **Object material**: large deformable objects, such as blankets, must be folded or crumpled into a compact configuration prior to packing. This requires manipulation strategies that are conditioned on object material (*i.e.* rigid and deformable).
- **Inter-object dynamics**: the ultimate success of this task is determined jointly by object configurations and the robot’s grasp on the bag during lifting. Crucially, when objects are partially inside a bag (for example, a mat on top of the bag opening), different lifting positions will result in different outcomes. Therefore, a successful approach must decide when a desired pre-bagging condition is achieved and, if so, determine a good grasp location(s) to lift up the bag. Here, pre-bagging condition refers to when all objects are sufficiently inside the bag opening, and will fall into the bag with a proper lift.

Due to these difficulties, prior work focused either on only the lifting step of the process [1] or considered a simplified scenario of packing only rigid items [2], [3].

We seek to address these limitations and propose a system that tackles the complete bagging process for a diverse set of rigid and deformable objects — a task we refer to as heterogeneous bagging. Our proposed approach consists of two learnable policies: a rearrangement policy that uses sequential pick-and-place actions to rearrange or fold items (Fig. 1a) in order to achieve a suitable pre-bagging configuration and a lifting policy that determines where to grasp and lift up the bag once pre-bagging conditions are met (Fig. 1b,c). We show that estimating the satisfaction of these pre-bagging conditions (required to decide when to stop rearranging and begin lifting) can be jointly performed by the two policies.

To accomplish this task on real hardware, we develop a representative simulation environment and use it to train both policies. Then, to facilitate a better bridge for the inevitable sim2real gap, we train a self-supervised network that detects the bag opening from real-world depth images. These predictions are used as additional input to the rearrangement and lifting policies, allowing them to transfer more robustly from simulation, where they are trained, to the real world.

We evaluate the learned policies with a real-world three-arm robot system with novel objects. The system is equipped with two types of end-effectors: a suction gripper, responsible for...
object rearrangement, on one arm and a parallel-jaw gripper, used to perform the bag lifting portion of the task, on the other two arms. We find that our proposed approach achieves a 70% success rate for the heterogeneous bagging task.

The main contribution of this work is the development of the first real-world robot system for the task of heterogeneous bagging. To this end, we propose:

- A self-supervised bag opening detection algorithm from depth images, whose pixel-wise supervision is automatically obtained through color images. This detection result enables robust sim2real transfer for downstream policies.
- A learned rearrangement policy that strategically manipulates and reconfigures multiple rigid and deformable objects to satisfy required pre-bagging conditions.
- A learned lifting policy that determines valid pre-bagging configurations and infers suitable grasp points for a bi-manual bag lifting action.
- A novel simulation environment and benchmark for heterogeneous bagging. The benchmark will be publicly available to facilitate future research and enable a fair comparison between heterogeneous bagging approaches.

## II. Related Work

### Rigid object packing.
Owing to numerous potential real-world applications, the problem of packing rigid objects has been extensively studied [4], [5]. In the offline setting, where the set of items and packing order are predetermined, prior works have primarily focused on exact algorithms [6], heuristics and metaheuristics [7], [8]. In the online setting, where arbitrary items arrive sequentially and must be packed in the order they are received, deep reinforcement learning strategies [2], [3], and the NDOP/QOP algorithm for the nondeterministic order setting [9] have been used. However, all these approaches are limited to packing rigid, generally cuboidal, objects into rigid containers and are not suitable for deformable objects or non-rigid containers such as bags.

### Cloth and rope manipulation.
Early attempts at deformable object manipulation focused on methods for manipulating one-dimensional deformable objects such as ropes and cables [10]–[15] and two-dimensional deformable objects such as fabrics [16]–[20]. Data-driven techniques such as Reinforcement Learning and Imitation Learning have also been developed for cloth smoothing [21], [22], folding [23]–[25], and unfolding [26], [27]. While our approach is inspired by some of these prior works in fabric folding, we address a significantly harder task that involves 3D deformable objects such as bags and complex interactions between multiple deformable objects.

### Bag manipulation.
The manipulation of 3D deformable objects, such as bags, is an under-studied research area in robotics due to the inherent complexity and difficulty of the task. Initial work involved calculating the deformation characteristics of an object and determining the minimum lifting force through iterative lifting [28]. Recent relevant studies involve grasping randomly or at maximum width to lift a bag using a physical robot [1] or opening a deformable bag and maintaining the opened state using air-based blowing actions [29].

The most relevant work to our task is perhaps Seita et al. [15], where the task is to insert a rigid object into a deformable bag. But their approach is limited to handling a single rigid object placement and further simplifies the bag lifting task by attaching rigid beads around the bag opening. In contrast, our system can manipulate multiple objects (either rigid or deformable) and infer lift points for a fully-deformable bag directly from real-world RGB-D images, resulting in a more practical solution for real-world applications.

## III. Method

### A. Task and System Setup

We formulate the bagging task as follows: First, a bag is placed on a flat surface with its mouth open and facing upward. From this configuration, the robot perceives the bag and infers the bag opening (Fig. 2b). Note that this predicted bag opening remains constant throughout the episode. We then position all the objects randomly across the workspace (Fig. 2a). The robot manipulates and iteratively rearranges these objects to obtain a desirable pre-bagging configuration, estimates a pair of bag-lifting grasp points, and attempts to lift...
the bag. Finally, a bag-shaking primitive is executed to help the objects either drop inside the bag or fall out. We define success as no objects touching the surface of the workspace at the end of this sequence (i.e. all objects are inside the lifted bag). Refer to Fig. 2 for an overview of the pipeline.

Simulation benchmark. Our simulation environment is built on top of the PyFleX bindings to Nvidia FleX [26], [29]–[31]. We provide the functionality to load robot end-effectors, arbitrary cloth meshes, and arbitrary rigid objects. The simulated objects include our custom bag, primitive rigid geometries, a subset of the YCB dataset [32], [33]), rectangular cloths, and the CLOTH3D dataset [34] (Fig. 5). The internal stiffness is uniformly sampled from $[0.85 \text{kg/s}^2, 0.95 \text{kg/s}^2]$, bag dimensions from $[0.25 \text{m}, 0.40 \text{m}]$, and cloth dimensions from $[0.20 \text{m}, 0.60 \text{m}]$. The object HSV color is uniformly sampled from $[0.0, 1.0]$, $[0.1, 1.0]$, $[0.5, 1.0]$ and the observations are rendered using Blender 3D. To generate different initial configurations of the bag and cloths, they are randomly picked and dropped on the surface. We also ensure that the cloths are larger than the bag opening and the objects are not entirely inside the opening.

Our real-world setup consists of three UR5 robot arms, one with a suction gripper for object rearrangement and two with parallel-jaw grippers for bag lift. The suction gripper allows for targeted manipulation of only the top cloth layers, preventing accidental bag grasps during rearrangement. To perceive the workspace, the robots obtain a top-down RGB-D image from an Azure Kinect sensor.

B. Self-supervised Bag Opening Detection

A reliable bag opening detection is critical to the success of our approach. However, an algorithm trained in simulation would face difficulty generalizing to real-world images due to significant visual differences between the real-world and the simulated bag. Meanwhile, pixel-wise bag opening annotations in the real world are expensive to obtain.

To tackle the above challenges, we propose a self-supervised model that predicts the bag opening solely using depth information, while training the model with pixel-wise labels obtained from RGB images of bags with colored opening. This is illustrated in Fig. 4, where we color the opening of the training bag in the real world and use this color information to automatically obtain the segmentation labels. We use a filled bag opening mask (refer to (c) in Fig. 3 and Label in Fig. 4) as supervision to avoid the class imbalance issue. We then train a U-Net [35] based segmentation network with Dice Loss [36] to predict the filled bag opening mask from depth images. During inference (Fig. 4), the segmentation network takes a depth image as input and outputs the predicted filled bag opening mask. The system subsequently post-processes this prediction to obtain only the boundary of the bag opening mask. The predicted filled bag opening mask and the post-processed boundary of the bag opening mask are used as additional inputs to the rearrangement and the lifting policy, respectively. We utilize the intersection over union (IoU) metric over the filled bag opening mask to validate the performance of our bag opening detection model. The results indicate a 98% IoU for training bags (200 images for 3 bags each) and 95% IoU for test bags (25 images for 4 bags each), demonstrating that our model generalizes to novel and unseen test bags.

In simulation, we can use the initial bag configuration to obtain the ground truth opening masks, which are then input to the rearrangement and lifting policies. This shared bag opening representation allows downstream policies to perform direct sim2real transfer without any real-world finetuning.

C. Rearrangement Policy

A crucial part of the bagging task is to learn how to rearrange objects such that a good pre-bagging configuration is achieved; the object rearrangement policy is responsible for this. To achieve a valid pre-bagging configuration, the policy must learn how to place objects inside the bag opening while ensuring no object is neglected. Moreover, the policy needs to learn when to stop rearranging to avoid deteriorating a sufficiently good pre-bagging configuration and/or needlessly increasing the number of rearrangement steps.

Action parameterization and network. The rearrangement policy takes a top-down RGB image and the bag opening mask as input and outputs pick and place pixels, $P_{\text{pick}}$, $P_{\text{place}} \subseteq \mathbb{R}^2$, which can be depth-projected to get 3D locations.
We use the spatial action map policy formulation [26], [37]–[39] and parameterize pick-and-place with \( P_{\text{pick}} \) representing the maximum value pixel from the value network’s output, \( \theta \in \mathbb{R} \) for the planar rotation and \( w \in \mathbb{R} \) for the distance of \( P_{\text{place}} \) from \( P_{\text{pick}} \). The top-down color image and bag opening mask are concatenated \((H \times W \times 4)\) and used to generate a batch of rotated and scaled observations \((t \times H \times W \times 4)\). The network takes this batch as input and outputs a corresponding batch of predicted dense value maps \((t \times H \times W)\). The \( \text{argmax} \) of the value maps gives us \( P_{\text{pick}}, \) rotation \( \theta \) and scale \( w \) (Fig. 2e), which are then used to compute \( P_{\text{place}} \). The value of each pixel corresponds to the predicted reduction of volume of all the objects outside the bag opening and thus, we choose the pixel with the maximum value. In our experiments, we use 12 rotations in the range of \([-180°, 180°]\) and 8 scale factors in the range of \([1.00, 2.75]\) at 0.25 intervals (giving \( t = 96 \)). The value network is implemented as a U-Net.

**Supervision and training.** The policy is trained via a self-supervised epsilon-greedy exploration in simulation. During a training episode, a random task (refer to Section IV-A) is sampled and each rearrangement step is automatically labeled with the relative change in the volume of all the objects outside the bag opening: \( \Delta v/v = (vol_{\text{pre}} - vol_{\text{post}}) / \max\{vol_{\text{pre}}, vol_{\text{post}}\} \), where \( vol_{\text{pre}} \) and \( vol_{\text{post}} \) are the pre-action and post-action volumes. A reward of \(-0.5\) is given for pick points on the bag to ensure that \( P_{\text{pick}} \) is not on the bag during inference. Note that this supervision signal (i.e. object particles) is neither available nor required during real-world deployment. The robot manipulates objects with the rearrangement policy until no valid grasp is predicted (i.e. the highest value action is not on any object) or reaches the maximum interaction iterations (i.e. 10). The network is supervised via MSE loss between predicted and actual \( \Delta v/v \) and is trained using the Adam optimizer [40] with a learning rate of 1e-3 and a weight decay of 1e-6. The network is trained to convergence, which takes around 40K simulation steps or about 32 hours on 4 NVIDIA RTX3090s.

**D. Lifting Policy**

The final step of a bagging task is to lift the bag such that all objects fall inside. Accordingly, the lifting policy must predict a pair of points that are likely to be graspable and enable a successful lift. Secondly, it must determine when to take over from the rearrangement policy because a valid pre-bagging configuration has been achieved. Oftentimes, there is a significant nuance to this determination; for instance, a valid pre-bagging configuration may have a T-shirt’s sleeve extend beyond the bag opening but have its center of mass inside.

**Action parameterization and network.** The lifting policy takes a top-down RGB image and the bag opening mask as input and outputs a lifting score with the corresponding lift points, \( L_1, L_2 \in \mathbb{R}^2 \), which can be depth-projected to get 3D locations. To constrain the system to predict lift points on the estimated mouth of the bag, we formulate the action parameterization as \( \langle p_{\text{lift}}, \theta \rangle \), where \( p_{\text{lift}} \) is a pixel that lies on a line and \( \theta \in \mathbb{R} \) determines the slope of the line. The intersection of the line with the bag opening gives the two lift points, \( L_1, L_2 \) (Fig. 2e). To minimize collisions, we ensure that the distance between \( L_1 \) and \( L_2 \) does not exceed a given physical limit and is greater than the safe distance.

The concatenation of the top-down color image and bag opening mask is used to produce a batch of rotated observations \((t \times H \times W \times 4)\). This is input to the network and a corresponding batch of dense value maps \((t \times H \times W)\) is predicted. Each pixel in each value map contains the value of the action parameterized by that pixel’s location, providing \( p_{\text{lift}} \), and the rotation applied to the input observation, providing \( \theta \). The pixel value corresponds to the predicted probability of lifting success. At runtime, the robot selects the action with the highest predicted value. In our implementation, we use 12 rotations in the range of \( \theta \) to \([-90°, 90°]\) (giving \( t = 12 \)). The value network is implemented as a U-Net.

**Supervision and training.** The tasks for training the lifting network are generated from our trained rearrangement policy. Each lifting step is labeled as a 1 for success and 0 for failure, where success is defined as no object touching the surface of the workspace after a successful lift. The policy is trained similarly to the rearrangement policy but supervised via a binary cross-entropy loss. The training takes around 100K simulation steps or about 72 hours on 4 NVIDIA RTX3090s.

**E. Determining Lifting Conditions**

The robot uses the output of both policies to determine when desirable pre-bagging configurations are achieved, thereby allowing early-stopping rearrangement. This is beneficial since each policy is trained with different objectives: there are cases when the rearrangement policy predicts an action to further reduce the volume of objects outside the bag opening while the lifting policy predicts that the current configuration is sufficient for success. In this scenario, it is inefficient and unnecessary to continue rearranging items. At other times, the lifting policy may not be certain that the pre-bagging conditions are met, but the rearrangement policy infers that there is no action that can improve the configuration. In this case, the system should proceed with the lifting action.

At each step, the lifting score is evaluated to achieve this fused pre-bagging determination. If the lifting score is greater than a threshold, the rearrangement stops and the lift action is executed (Fig. 2). Otherwise, the rearrangement policy predicts an action, and if the action is to terminate, then the bag is lifted from the points corresponding to the highest score predicted previously by the lifting policy. We use a lift score threshold of 0.95 in simulation and 0.5 in real world to account for the lift-score network’s lower confidence in out-of-distribution inputs.

**IV. EVALUATION**

**A. Experiment Setup**

We use three metrics to evaluate system performance: 1) Success rate (SR): \( \text{successful \_episode} / \text{total \_episodes} \), where a successful episode is defined in Section III-A. 2) Average fraction of objects inside the bag (\( \text{AvgF} \)): The number of objects not touching the ground after lifting and shaking the bag divided by the total number of objects in that episode, averaged across all episodes. 3) Average episode length
(AvgL): The total number of rearrangement steps plus the lifting step in an episode, averaged across all episodes. We evaluate on the following task setups: two (1r1c, three (1r2c, 2r1c), four (1r3c, 2r2c, 3r1c), and five (2r3c, 3r2c) objects, where #r and #c denote the number of rigid objects and cloths.

Simulation tasks. During testing, we use a subset of YCB objects (different from training) and CLOTH3D [34] (Fig. 5). Each task has a bag that is kept open on the ground and 2-5 objects arranged in an arbitrary configuration in the workspace. Refer to Section III-A for details about task generation.

Real-world tasks. The testing objects are a subset of YCB, soft toys, T-shirts, pants, and rectangular cloths (Fig. 5). We run 5 different task configurations for the 2 objects case and 10 configurations for each of the 3-5 objects cases.

Baseline algorithms. Since there are no existing methods for the task of heterogeneous object bagging, we design strong heuristic baselines for comparison.

- **Heuristic rearrangement policy**: In both simulation and real-world, we design a strong rearrangement heuristic that picks objects from outside the bag opening and places them inside in a way that most likely reduces the volume of objects outside the bag. The heuristic selects a random point on the part of object mask that is non-overlapping with the filled bag opening mask and places it at the center of the bag opening. In real-world experiments, where the ground truth filled bag opening mask is unavailable, we use the bag mask instead, as shown in Fig. 6. The rearrangement is terminated and the bag is lifted when either no pick point is found or the episode length reaches 10.

- **Heuristic lifting policy**: We develop a strong lifting heuristic in accordance with the information available in each domain. In simulation, with the availability of ground truth bag opening, the heuristic randomly chooses two points on the boundary of the bag opening, with the constraint that the distance between them is greater than a threshold. In real-world experiments, due to the unavailability of a ground truth bag opening, the heuristic uses the maximum-width lifting strategy proposed by Seita et al. [1] (Fig. 6). Note that this heuristic policy does not determine when to stop rearranging.

### B. Experimental Results

**Benefits of learned rearrangement policy.** Comparing the second and the last rows in Table I shows the advantages of a learned rearrangement policy. We observe that as the number of objects increases, our method significantly outperforms the heuristic, signifying the importance of learning multi-object interactions for rearranging objects. Real-world experiments also showcase the effectiveness of the learned rearrangement policy. As can be seen in Table III, our policy performs consistently better than the heuristic. Having a rearrangement policy that learns which objects to rearrange and where to place them helps to achieve a good pre-bagging configuration. We also find that learning when to stop rearranging to avoid unnecessary steps or prevent further actions from deteriorating the pre-bagging configuration helps improve the performance of the system.

![Fig. 5. Train and Test Objects used in our experiments. The policy is always tested with novel objects not seen during training.](image)

![Fig. 6. Heuristic Rearrangement and Lifting Strategies in Real-world. The rearrangement pick point is chosen from the part of object mask that is non-overlapping with the bag mask (blue region) and the place point is the centre of the bag mask (red circle). The lift points are obtained from the maximum-width lifting strategy [1] (green circles).](image)

| **Learned** Rearr. Lift | **Train Tasks** | **Number of Objects** |
|------------------------|----------------|----------------------|
| ✓                      | ✓              | mixed                |
| ✓                      | ✓              | mixed                |
| ✓                      | ✓              | single-rigid         |
| ✓                      | ✓              | single-cloth         |
| ✓                      | ✓              | mixed                |

**Table II**

| **Average filled bag opening IoU** | **Number of Objects** |
|-----------------------------------|----------------------|
| 100% (ground-truth)               | 92.0                 |
| 95% (= real-world test bag IoU)   | 90.0                 |
| 93% (< real-world test bag IoU)   | 89.0                 |

**Benefits of learned lifting policy.** Comparing the third and the last rows in Table I illustrates the advantages of a learned lifting policy relative to the baseline (40%...
improvement). Despite being strong due to the availability of ground truth bag opening, the heuristic performs worse than our learned policy because it is unable to learn the critical relationship between lift points and object configurations. It is also incapable of determining when a desirable pre-bagging configuration is achieved and rearrangement can be halted. Our real-world experiments corroborate the effectiveness of a learned lifting policy as well (Table III).

Effects of different training tasks. In order to understand the impact of training task selection, we conducted experiments with two other training scenarios - a single rigid object in each configuration and a single cloth in each configuration. As depicted in Table I, the mixed training scenario performs the best, aligning with our intuition that training on a single object does not allow the policy to reason about multi-object interaction. Furthermore, the single-rigid policy performs worse than the single-cloth policy as it fails to learn appropriate folding strategies for cloths.

Sensitivity to bag opening. To examine the impact of accurate bag opening, we evaluated our method under two scenarios - a non-ablated version employing ground-truth bag opening as input, and an ablated version using a perturbed bag opening. The ablation technique involved randomly sampling bag opening vertices and transforming neighboring vertices using a Gaussian distribution centered on the selected points. Table II indicates that using ground-truth bag opening only marginally improves the performance of our learned policy in comparison to a perturbed bag opening with 95% filled bag opening IoU, equivalent to our real-world bag opening detection results from Section III-B. Furthermore, additional perturbation of the bag opening to 93% IoU has no substantial effect on the success rate.

Real-world experiments. We directly evaluate our simulation-trained rearrangement and lifting policies with real-world robots. To promote policy transfer from simulation to reality, we perform background substitution that is consistent with the simulation environment. We obtain the bag mask (for heuristic) and predict the bag opening (for ours) before any objects are placed. We also use object masks to remove predicted lift points that overlap with objects. Table III shows the performance, averaged over all test episodes, for each task category. Our policy outperforms the heuristic by as
much as 60% on the SR metric. Moreover, the significantly higher AvgF metric (84% vs 22% in the 5 objects case) indicates that our policy drops fewer objects outside the bag.

Fig. 7 illustrates examples of our system and the heuristic approaches operating in the real world. The first two rows demonstrate how heuristically placing all objects at the center of the bag can lead to failure. While our rearrangement policy learns to arrange each object relative to other objects inside the bag opening, the heuristic method places the apple on top of the soft toy, causing it to fall and roll outside the workspace (step 4, second row). This example also exhibits how our lifting policy learns that a partially protruding cloth can still be a valid pre-bagging configuration (green T-shirt). In the second example (the third and fourth rows), our policy successfully determines which object to rearrange so that a desired pre-bagging configuration is obtained. Despite the presence of three cloth objects partially outside the bag opening, our policy rearranges the pear (step 8, third row). In contrast, the heuristic keeps rearranging the cloth and overlooks the pear even though it is clearly outside the bag opening. The third example shows that even when the heuristic rearrangement policy is able to achieve a good pre-bagging configuration, learning from where to lift the bag is crucial. Our policy is able to infer the bag opening and predict optimal lift points, which lead to success, whereas the lift locations chosen by the heuristic lead to failure.

**Failure modes and limitations.** The most common failure case was during bag grasping (accounting for 50% of real-world failures). For instance, the robot would inadvertently grasp a cloth close to one of the predicted lift points and lift the cloth instead of the bag. Closing the loop between the rearrangement and the lifting policy to incentivize rearranging objects away from potential lift points might help resolve this issue. Another observed failure mode is suboptimal object rearrangement (accounting for 32% of real-world failures). For instance, a rigid object placed upon a pile of cloth is generally unstable. This failure is caused by the single-step training reward, causing the rearrangement policy to not explicitly consider object stability for future interactions.

Our method also makes certain assumptions that could be relaxed in future works: It assumes that the objects are placed in the scene only after the bag opening inference is performed. It also assumes that the bag is open and flat on a surface, potentially requiring an additional system [29], [41] to achieve this initial configuration.

### V. Conclusion

We propose and evaluate a real-world robotic system for the task of heterogeneous bagging which involves placing a diverse set of multiple rigid and deformable objects into a deformable bag. The system includes a self-supervised segmentation network trained to infer the bag opening, a rearrangement policy, and a lifting policy. We demonstrate the effectiveness of our method by comparing it against strong baselines on a set of real-world tasks. We hope that this work encourages others in the field to explore the challenging task of heterogeneous bagging and believe that the lessons learned in this setting have strong potential to transfer to other dexterous manipulation tasks involving the interaction of multiple highly deformable objects.

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