Abstract

Scene Rearrangement Planning (SRP) is an interior task proposed recently. The previous work defines the action space of this task with hand-crafted coarse-grained actions that are inflexible to be used for transforming scene arrangement and intractable to be deployed in practice. Additionally, this new task lacks realistic indoor scene rearrangement data to feed popular data-hungry learning approaches and meet the needs of quantitative evaluation. To address these problems, we propose a fine-grained action definition for SRP and introduce a large-scale scene rearrangement dataset. We also propose a novel learning paradigm to efficiently train an agent through self-playing, without any prior knowledge. The agent trained via our paradigm achieves superior performance on the introduced dataset compared to the baseline agents. We provide a detailed analysis of the design of our approach in our experiments.

1 Introduction

Rearrangement is a task of bringing a physical environment into a specific goal state, leading to practical applications such as setting tables, packing objects, and rearranging furniture. To automate this task, an agent is called upon to perform actions such as analysis, planning, and moving objects. There has been a rich body of studies on rearrangement planning in robotics, for example, devising a robotic arm to rearrange objects on a tabletop through grasping, picking, or nonprehensile actions [Labbé et al., 2020; Yuan et al., 2019; Koval et al., 2015].

Recently, an emerging task of automatic Scene Rearrangement Planning (SRP), filling the gap between scene synthesis and layout realization, draws attention from researchers [Wang et al., 2020; Xiong et al., 2020; Batra et al., 2020]. In SRP, given an initial scene layout and a target scene layout, the goal is to find a feasible move plan by which an agent can move furniture and transform an initial layout to a target layout. Compared with the conventional tabletop rearrangement task, SRP is more complicated because SRP needs to consider the factors of object poses, object shapes, and terrain constraints, which are usually simplified in a tabletop setting to make the problem tractable. On the other hand, the decision sequence of SRP is often longer due to the large scale and complexity of scenes, making the move planning task more challenging.

Although some efforts have been spent on the study of accomplishing SRP tasks, some critical problems are not solved yet. First, the definition of the action space is highly constrained. The actions are designed either to meet specific moving mechanism or to be abstract and high-level to shorten the length of the decision sequence. With such coarse-grained or highly constrained action definitions, there are many unreachable states, which may result in no solution for some cases. Second, the quantitative evaluation of the agents is limited on a few real scenes. The evaluation protocol is not convincing enough to be followed by future work since it covers a limited amount of situations.

To address these problems, in this paper, we propose a fine-grained action space definition so that an agent can come up with furniture moving plans with an arbitrary path in scenes. Thus, an agent can more likely find an optimal and flexible solution to transform an initial scene to its target state. More concretely, we define 6 atomic actions which include four directions of translation and two directions of rotation to enable flexible and tractable manipulations of furniture objects.

Training an agent under the atomic action space is chal-
lenging because the use of atomic actions results in longer decision sequences in general. To tackle this problem, we propose a novel Parallelized Expert-Assisted Reinforcement Learning (PEARL) framework to efficiently train an agent through self-playing, leveraging the power of dual policy iteration and reinforcement learning. In addition, to enable the training of data-hungry learning approaches and quantitative evaluation, we construct a large-scale dataset based on 3D-FRONT [Fu et al., 2020] which contains 19,062 pairs of diverse furnished rooms.

Figure 1 shows an overview of the proposed PEARL framework. Under this framework, a search-based expert is constructed to sample more valuable state-action pairs, which alleviate the problem of sparse rewards in the training process. The expert can evolve based on the apprentice policy in each iteration. During the training of apprentice, we take a strategy of reinforcement learning. That is, the apprentice is reinforced by the rewards from the environment and learns from the expert selectively rather than imitating the expert actions directly. The PEARL framework accelerates the learning of the agent and makes the agent converge to a better policy.

The contributions of our work can be summarized as follows:

- We propose a more general SRP setting with a flexible and tractable action space definition. We also propose a novel PEARL framework to efficiently train an agent through self-playing without manual annotation and prior knowledge.
- We introduce a large-scale indoor scene dataset for SRP, which contains a diverse variety of realistic, furnished room layouts to support the training of data-driven approaches and quantitative evaluation.
- We demonstrate the superior performance of the proposed approach and analyze the effectiveness of each designed component on the introduced SRP dataset.

2 Related Work

Indoor Scene Synthesis. The indoor scene synthesis problem has attracted research attention for years. It inspired research on automatic interior design and planning serial tasks. With an given empty room, the main goal of scene synthesis is to coherently predict the pose and position of the furniture objects to form a realistic layout. Some early works are based on statistical relationships [Merrell et al., 2011] and rules [Yu et al., 2011]. The scene layouts are generated through optimization. Other early works focus on data-driven approaches for scene synthesis, whereas those approaches are limited by the scale of training data and available learning methods at that time.

Recent data-driven approaches leverage the power of Deep Learning to learn from the bigger scene dataset such as SUNCG [Song et al., 2017]. Some works model the spatial relations between furniture shapes by graphical models [Henderson et al., 2017; Fu et al., 2020]. Some works use generative approaches [Zhang et al., 2020; Ritchie et al., 2019] to model the distribution of interior layouts and generate new layouts by sampling. Some other works adopt sequential approach to place furniture objects iteratively [Li et al., 2019]. With the proposed generative methods, researchers can easily construct large scale scene dataset through automatic generation and manual verification, e.g., 3D-FRONT dataset [Fu et al., 2020]. These advances of indoor scene synthesis methods and datasets support further exploration in scene rearrangement planning.

Rearrangement Planning. Given a certain initial and target configuration of a pre-specified object set, the Rearrangement Planning problem refers to generating a feasible action sequence to transform the initial configuration to the target configuration. This topic has been studied by robotics researchers while most efforts focus on solving a tabletop rearrangement task by a robotic arm. The manipulation of the objects can be divided into two classes: prehensile actions like grasping, picking up and putting down [Labbé et al., 2020], and nonprehensile actions like pushing.

Many prior works adopt nonprehensile actions since this kind of manipulations are easier to execute by a robotic arm in practice. In this direction, the solution of rearrangement planning is to find a sequence of collision-free move path to push the object to its target position. Some robotics works [Haustein et al., 2019; Song and Boularias, 2019; King et al., 2016; Koval et al., 2015] solve multi-object rearrangement planning in two stages: a local move planning stage and a global strategy searching stage, whereas our approach adopts a universal policy to directly control the move of objects without isolated planning stages.

Recent graphics work [Wang et al., 2020] contributes to the Scene Rearrangement Planning (SRP) problem. Compared to the tabletop setting in robotics, scene rearrangement planning is of substantially higher complexity. For instance, the shapes of objects in a tabletop setting are usually regular (e.g., cubes, cylinders). Obstacles and boundaries are usually absent or sparse under a tabletop setting. In contrast, in realistic indoor scenes, the furniture pieces vary a lot in shape and dimensions in general; obstacles and boundaries (e.g., walls, pillars) are typically present. Despite such complexities, [Wang et al., 2020] solve SRP by selecting pre-defined paths to move the objects. Such a coarse-grained action definition is inflexible and intractable to perform in realistic, complex situations. Different from the prior SRP setting on the action space, our work adopts a nonprehensile action space in the problem setting to make the solution more tractable.

Dual Policy Iteration. Dual Policy Iteration (DPI) [Sun et al., 2019] algorithms like Expert Iteration (ExIt) [Anthony et al., 2017] and AlphaZero [Silver et al., 2017] have shown impressive performance on solving decision making problems. This new class of algorithms maintains two polices: a fast learnable policy (e.g., a neural network) performs quick rollouts, and a slow policy (e.g., a Tree Search algorithm) searches the valuable states and plans several steps ahead. Those two polices are combined to provide superior demonstrations for the learning of the fast policy, while the updated fast policy enhances the performance of the combination in return.

In Expert Iteration, the demonstrations from the combined
strong policy are used to supervise the training of the learnable policy. This supervision is achieved in the form of Imitation Learning (IL). Different from Expert Iteration, our approach trains the policy through Reinforcement Learning, which improves the generalizability of the learnable policy and reduces the learning bias caused by copying actions of a sub-optimal expert policy.

3 Preliminaries

3.1 Markov Decision Process

Sequential decision making procedure is often considered in a Markov Decision Process (MDP). A discounted infinite-horizon MDP is defined as a tuple $\langle S, A, P, R, \gamma \rangle$ [Puterman, 1994], where $S$ is the space of states, $A$ is the space of actions; $P$ is the transition function; $P(s'|s, a)$ is the probability of transforming $s$ to $s'$ by taking action $a$; $s'$ is also written as $P(s'|a)$; $R$ is the reward function; $R(s, a)$ represents the reward received from the environment by taking action $a$ at the state $s$; and $\gamma$ is the discount factor. A distribution over the valid actions $a$ given the state $s$ is called a policy, denoted as $\pi(a|s)$. The value function $V^\pi(s)$ is the expectation of accumulated discounted reward by following $\pi$ starting in state $s$, i.e.,

$$V^\pi(s) = E_{\pi}^s \left( \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right), \quad s_0 = s. \tag{1}$$

The optimal policy $\pi^*$ ought to maximize this expectation. Formally, we have $\pi^* = \arg \max_{\pi} V^\pi(s)$.

3.2 Monte Carlo Tree Search

Monte Carlo Tree Search (MCTS) [Kocsis and Szepesvári, 2006; Guo et al., 2014] is a useful strategy to address the challenge of selecting/learning policies for MDP. It is used to estimate the value of states through repeated Monte Carlo sampling and simulations. Each node in the search tree corresponds to a state $s$. The root node represents the current state. The edge from $s_1$ to $s_2$ represents the execution of action $a$ by which $s_1$ can be transformed to $s_2$.

In MCTS, four phases are repeated to grow the search tree: a) selection; b) expansion; c) rollout; and d) backpropagation. In the selection phase, a feasible unexpanded edge in the tree is selected according to a tree policy. The commonly used tree policy is the Upper Confidence bounds for Trees (UCT) [Auer et al., 2002], i.e.,

$$\text{UCT}(s, a) = \frac{r(s, a)}{n(s, a)} + C \sqrt{\log n(s) \frac{1}{n(s, a)}}, \tag{2}$$

where $r(s, a)$ is a prior function that gives suggestion on search. A canonical choice of this function returns a probability of taking action $a$ at state $t$. It could be estimated by simulations or a learnable function [Silver et al., 2017], e.g., neural network. $n(s, a)$ is the counter function which returns the visiting times of this edge; $n(s)$ is the counter function for the node corresponding to state $s$; $C$ is the tradeoff parameter to tune the influence of the terms. In the expansion phase, a new node corresponds to state $s' \in \{x | P(x | s, a)\}$, which is expanded from the selected edge. Then, in the rollout phase, a quick simulation under the rollout policy is performed from the state $s'$ until a terminal condition is satisfied. The results of simulation are used as the estimate of the node. Finally, in the backpropagation phase, the information of nodes, including the visited times $n(s)$, $n(s, a)$ and the estimated value $V(s)$, is updated bottom-up through the tree until it reaches the root node.

When the tree is built, $a^* = \arg \max_{a} E(s_R, a)$ is the action selected by MCTS, where $s_R$ is the state of the root node and $E(s, a) = R(s, a) + \gamma V(P(s, a))$.

3.3 Expert Iteration

The success of employing Deep Reinforcement Learning (DRL) in playing Atari games [Mnih et al., 2015] brings a great impact to the field. Various Deep Reinforcement Learning paradigms were proposed to solve MDP and achieved remarkable performance. However, those methods suffer from sparse rewards when facing challenging tasks, commonly resulting in slow convergence and local minima. Those drawbacks can be alleviated by introducing Imitation Learning (IL). In IL, an agent is taught to mimic the actions from experts. Experts can arise from observing humans completing a task and a labeled dataset can be constructed. Nevertheless, acquiring human demonstrations is expensive. The agent trained in static data also has difficulty in generalizing to novel observations.

Expert Iteration provides a method to create an expert which is able to evolve. The expert is composed of a boosting framework and a fast vanilla policy (e.g., neural network). The canonical choice of the boosting framework is a tree search algorithm (e.g., MCTS) which explores the possible states and exploits the gathered information to generate a strong move sequence. The vanilla policy can bias the searching towards more promising states and provide a quick estimation for the explored state. The vanilla policy is also known as the apprentice policy because it can imitate the actions taken by the built expert to accelerate the training. The expert can be improved by embedding the updated apprentice policy.

4 Method

4.1 Problem Definition

The Scene Rearrangement Planning (SRP) can be modeled as a MDP. The goal of SRP is to transform the current layout of the scene to the target layout. An agent can achieve this goal by learning a policy to make decisions and maximize the accumulated discounted reward during moving.

State Representation. The state in SRP is the scene layout, which includes the shapes, positions and orientations of the movable objects, and the impassable districts, e.g., walls. Following [Wang et al., 2020], we use the top-down view to characterize the scene layout since most movable objects lay on the floor plane. The objects and impassable districts are projected on the floor plane, the projection is bounded in a square and discretized into a $N \times N$ grid representation. Suppose a scene has $K$ objects, the state of the scene layout is defined as a binary tensor $l, l \in \{0, 1\}^{N \times N \times (K+1)}$. The first two dimensions of the matrix are the spatial dimensions and
the third dimension is the object dimension. For the $k^{th}$ object, a cell $l_{i,j,k}$ stores whether the location $(i,j)$ is occupied by the object $k$. The additional channel of the third dimension is for denoting the occupancy of the impassable districts. The state $s_t$ at time step $t$ is the concatenation of the scene layout $l_t$ and the target scene layout $l_T$ along the third dimension\(^1\), $s_t \in \{0,1\}^{N \times N \times (2K+1)}$.

**Action Space.** The action for SRP is defined as a pair $(o,p)$, $o \in O, p \in P$, where $O$ is the set of objects and $P$ is the set of possible actions which the object can be manipulated by. Previous work [Wang et al., 2020] defined $P$ as a set of constrained paths to move along, i.e. moving straightly along the up, down, left or right direction until the object reaches an obstacle (e.g., another object or a wall), and moving along a feasible path searched from the object’s current position to its target position. Such definition shortens the length of the decision sequence to limit the complexity of the solution space, making their approach more focused on moving order planning. This definition has two strong assumptions: 1) the simulation during path searching is accurate; and 2) the execution of path following is accurate. However, both of the assumptions are not promised in practice because the information gathered by sensors and execution of actions are susceptible to noises. Performing the sophisticated generated actions may result in a failure.

In robotics, more atomic action spaces are preferred since they are more tractable. Some robotic works [Yuan et al., 2019; Song and Bouliaras, 2019] adopt nonprehensile actions (e.g., push) in the rearrangement problem. Such action definition can be more easily achieved through a real mechanical arm. In this spirit, we define 6 simple nonprehensile actions to transform the positions and orientations of the objects. The first 4 actions are moving an object towards **up**, **down**, **left** or **right** direction by 1 unit. The last two actions are rotating an object clockwise or anti-clockwise by 15 degrees.

**Reward Shaping.** When an action is executed, the environment returns a reward value immediately. Our reward term definitions are shown in Table 1. There are 4 kinds of reward term in our reward shaping. **Distance** returns the change of distance after an action. Note that the distance includes the Manhattan distance between the current and target coordinates and the discretized distance between the orientation states. **Arrival** returns 4 if the current object arrives at its target state after an action. **Leave** returns $-4$ if the current object leaves its target state after an action. **Success** returns a big positive value 50 if all objects reached their target states. At each time step, after an action is executed, the triggered reward terms are summed up as the immediate reward value.

| Reward | \(\pm 1\) | 4 |
|--------|----------|---|
| Success| 50       | -4|

Table 1: Rewards used in SRP

\(^1\)\(l_t\) and \(l_T\) share the same impassable district channel.

### 4.2 PEARL

To solve the challenging problem, we propose a novel variation of the expert iteration framework to train the agent efficiently. The boosting framework is a MCTS algorithm. Our agent plays the role of apprentice, which is composed of a policy network \(\pi_\theta\) to predict the action distribution as well as a value network \(v_\phi\) to predict the future value. \(\theta\) and \(\phi\) are parameters of the neural networks.

The expert iteration has two stages in each iteration: 1) Improving stage and 2) Learning stage. In the improving stage, the apprentice is used to build the expert and the expert creates a playing record for the current episode. To construct the expert, the networks are used in the selection and simulation phases of MCTS. Specifically, in the selection phase, we use the policy network and the value network to suggest a more promising action to explore. The formulation of action score can be derived from Eq. 2.

\[
\text{UCT}_{\text{NN}}(s, a) = \frac{\pi_\theta(a|s)}{n(s,a)} + C\sqrt{\frac{\log n(s)}{n(s,a)}},
\]

In the simulation phase, the value of an expanded tree node is evaluated by the value network. In the learning stage, the policy network and the value network are trained in a reinforced fashion. In contrast to simply imitating expert actions in expert iteration, the learning of the apprentice in our method is reinforced by the rewards from the environment, which means that the apprentice is encouraged or discouraged to take the expert action accordingly. The learning is similar to Advantage Actor-Critic (A2C) [Mnih et al., 2016], where the policy network plays the role of actor and the value network is the critic. Since MCTS selects the action by the value of the action that the agent can take at the root node, it provides both an expert action and an expert estimate of the state value. The expert estimate of a state value is $V(s; \theta, \phi) = \max_a R(s,a) + \gamma V(P(s,a); \theta, \phi)$. Then the loss of the policy network is:

\[
\mathcal{L}_p = -\sum_{t=0} A(s_t, a_t) \log (\pi_\theta(a_t|s_t)),
\]

where $A(s_t, a_t)$ is the advantage defined as:

\[
A(s_t, a_t) = \sum_{i=0}^k \gamma^i R(s_{t+i}, a_{t+i}) + \gamma^k V(s_{t+k}; \theta, \phi) - v_\phi(s_t).
\]

The value network tries to mimic the state value estimated by the expert. The loss of the value network is:

\[
\mathcal{L}_v = \sum_{t=0}||v_\phi(s_t) - V(s_t; \theta, \phi)||_2.
\]

In this way, our method can potentially reduce the bias of learning target on the optimal policy compared to imitation learning for expert iteration.

### 4.3 Training

We train the networks in a parallelized online synchronous manner, where a group of data processes synchronize with
the latest network parameters and collect the experiences to support the training of the network in the optimization process. Since the fast convergence is a well-known advantage of imitation learning, similar to [Wang et al., 2019], we trade-off the imitation signal and reinforcement signal to speed up the training.

It is worth noting that the improving stage is extremely time-consuming compared to the learning stage because of the large simulations in the improving stage. Actually, in the learning stage, it is a waste if the apprentice learns from the selected action and observation records for only once. To improve data utilization, we adopt Prioritized Experience Replay (PER) [Schaul et al., 2016] in network training.

Prioritized Experience Replay. Experience Replay [Lin, 1992] is widely used in online reinforcement learning. To satisfy the i.i.d. assumption for stochastic gradient-based algorithm, the collected experiences are stored in a replay buffer and randomly sampled to feed the network. Conventional experience replay samples the experiences uniformly while PER samples the experiences with a priority to take a significance of the experience into account. PER has been demonstrated to achieve great performance improvement on many tasks (e.g., Atari games). In our network training, we prioritize the experiences with the critic error because the critic error suggests the difference between the value estimated and the value in reality. The high critic error is often caused by novel situations. It reinforces the agent to learn from those valuable experiences. We also utilize PER in all baseline agents training.

5 Implementation

Network Architecture. We modify the network architecture from [Wang et al., 2020] to build the actor, which is a CNN encoder appended with a fully connected (FC) layer. The feature size of the FC layer is 512. The critic shares the same CNN encoder with the actor and has an individual FC layer. The input of the two networks is the current state \( s \). The output of the actor is a 150-d tensor which represents the predicted probability of actions. It works for at most 20 objects in a scene. The output of the critic is a scalar, which refers to the estimated value of the current state.

Reproducibility. Our network is implemented in PyTorch. The batch size is 200. The number of the data processes is 8. The rounds of tree search for each decision making is 50. In network training, the maximum allowed action steps in each episode is 100. In testing, an episode is regarded as failing if it is not finished within 200 steps. The size of the replay buffer is 10,000. The optimizer used in the network training is ADAM. The learning rate is set to \( 10^{-4} \). The utilities including the virtual environment and the tree search algorithm are implemented in C++. The full model is trained on 4 NVIDIA RTX 3090 GPUs with 24GB memory in each card. For reproducibility, our implementation will be released.

6 Experiments

6.1 Data

We demonstrate our approach on 3D-FRONT [Fu et al., 2020], a large-scale indoor scene dataset, where the rooms layout are professionally designed and populated with high-quality 3D models. The interior designs of the rooms are transferred from expert creations. This dataset contains 6,813 distinct houses and 19,062 furnished rooms. It is proposed to support indoor scene tasks like 3D scene understanding, indoor scene synthesis, semantic segmentations, etc. The diverse variety of furnished rooms and the abundant labels satisfy the demand of the SRP task. In SRP, the complexity of planning highly depends on the number of objects in the scene. The rooms in 3D-FRONT have 6.1 objects in average. More than 99% rooms in the dataset have a number of objects ranging from 1 to 20. The statistics of the number of objects in each room is shown in Fig. 2. We split the dataset
into the training and test sets. 5\% of the data (953 rooms) are randomly sampled as the test set and the rest (18,109 rooms) belong to the training set.

We use the designed layout as the target layout and randomly sample a feasible layout with the same objects as the initial layout. To ensure that the layout pair can be transformed from each other, we sample an initial layout by rounds of random walks starting from the target layout. In each round, a random object is selected to perform a random feasible move. Each initial layout is generated by performing 1,000 rounds of random walks. The configurations of the layouts are extracted from the top-down silhouette of the scene. We first bound the view of the scene to the center of a square. Then the objects are rendered individually and the top-down silhouettes are discretized to extract the shape and position for each object. The same process is also adopted to extract the information of impassable districts. The resolution of the discretization is $64 \times 64$.

### 6.2 Quantitative Experiment

**Metrics.** To evaluate the performance of the agent, we define 2 metrics, i.e., $\textit{Success Rate}$ ↑, and $\textit{Length}$ ↓, for SRP. Success Rate (SR) is the rate of attaining the target layout. It illustrates the agent’s general ability of finishing the task. It is the primary metric in our experiment. Length refers to the average length of action sequence. It reflects the efficiency of the action sequence. For the failed cases, the length of action sequence is the maximum allowed action step (200 in testing).

**Baseline Agents.** We compare the agent trained by our approach with the following baseline agents:

- **RL:** An agent trained with standard A2C. ε-greedy strategy is adopted. The actor is used as the agent in inference.
- **Expert Iteration:** An agent trained with Expert Iteration. The apprentice actor is used as the agent in inference.

For a fair comparison, the networks used in our approach, RL, and Expert Iteration share the same architecture. PER strategy is utilized in the training of those agents.

**Comparison.** The comparison between the agents on test sets are shown in Table 2. The checkpoints of the learnable agents are selected by SR on test sets. The first three lines are the performance of single neural networks. The apprentice agent trained by Expert Iteration beats the one trained by RL, which shows the effectiveness of expert actions in training. The apprentice agent trained by our approach outperforming all baseline agents in all metrics. We also evaluate the expert equipped with different apprentices. As shown in the last two lines of Table 2, the expert of our approach achieves a high SR of 73.5\% and consistently outperforms the expert of Expert Iteration.

To analyze the training behavior of the agents, we plot the curve of SR and Length during training. As shown in Figure 4, the x-axis is the number of episodes the agent experienced, the y-axes are SR and Length respectively. Compared to RL, the class of expert-assisted algorithms (i.e., Expert Iteration, and PEARL) learn very fast, which illustrates the high efficiency of the actions sampled by expert. Though the performance of our approach grows slower than Expert Iteration at the beginning, it finally achieves higher success rate than Expert Iteration. It shows that the actor trained in a reinforced manner converges to a better policy compared to directly imitating expert actions.

### 7 Conclusion

In this paper, we propose a more general SRP task setting with a flexible atomic action space definition. To tackle the challenging problem setting, we propose a novel training paradigm, PEARL, which leverages the power of dual policy iteration and reinforcement learning. A large-scale SRP dataset is introduced for training and evaluating SRP agents. Based on the dataset, we conduct experiments to validate the proposed approach. The results show that the agent trained by the proposed learning approach achieves outstanding performance compared to the baseline agents.

Our approach automates the generation of a move plan for scene rearrangement and facilitates the realization of scene designs, leading to potential applications such as warehouse automation, home rearrangement robots, and smart homes with movable furniture.

 Currently, in our problem setting and introduced dataset, we only consider the rearrangement task on a 2D plane. The furniture objects can only move and rotate on the floor plane. We do not consider scenarios with multiple floors nor scenarios with more terrain constraints. Enriching the SRP task dataset and increasing the variety of scenes could empower the agent to deal with more complicated scenarios.

We devise a move planning approach to automate scene rearrangement. Future works may integrate object-level, robot action space considerations for plan execution with high-level move planning. Incorporating factors related to robot movement constraints into the rewards is a promising extension.
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