# 3D-AWARE DISENTANGLED REPRESENTATION FOR COMPOSITIONAL REINFORCEMENT LEARNING

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## **ABSTRACT**

Vision-based reinforcement learning can benefit from object-centric scene representation, which factorizes the visual observation into individual objects and their attributes, such as color, shape, size, and position. While such object-centric representations can extract components that generalize well for various multi-object manipulation tasks, they are prone to issues with occlusions and 3D ambiguity of object properties due to their reliance on single-view 2D image features. Furthermore, the entanglement between object configurations and camera poses complicates the object-centric disentanglement in 3D, leading to poor 3D reasoning by the agent in vision-based reinforcement learning applications. To address the lack of 3D awareness and the object-camera entanglement problem, we propose an enhanced 3D object-centric representation that utilizes multi-view 3D features and enforces more explicit 3D-aware disentanglement. The enhancement is based on the integration of the recent success of multi-view Transformer and the shared concept memory among the object-centric representations. The representation, therefore, can stably identify and track 3D trajectories of individual objects along with their semantic and physical properties, exhibiting excellent interpretability and controllability. Then, our proposed block transformer policy effectively performs novel tasks by assembling desired properties adaptive to the new goal states. We demonstrate that our 3D-aware block representation is scalable to compose diverse novel scenes and enjoys superior performance in out-of-distribution tasks with multi-object manipulations compared to existing methods.

## 1 Introduction

Vision-based reinforcement learning utilizes images as an input modality, enabling a flexible, human-like perception for robotic tasks, compared to specific sensory or motor configurations. However, the unstructured nature of raw observations further challenges the inherent inefficiency in reinforcement learning (RL). As the visual observations from various viewpoints result from a complex interplay between color, lighting, geometry and their non-linear projection, the images do not easily map to a coherent composition of meaningful attributes, which challenges their generalizability and controllability. While a visual perception module can benefit from recent advancements in computer vision literature, the feature-level abstractions are often high-dimensional and are no longer interpretable by humans.

Systematic factorization of visual observation can lead to generalizable perceptual reasoning, one of the desired benefits of vision-based RL (Yoon et al., 2023). Object-centric representations promote component-wise analysis, where individual objects are detached from the background. Furthermore, learning factor-level representations like Neural Systematic Binder (Singh et al., 2022) deduces the spatial locations and visual attributes, such as colors and shapes, from which humans can interpret without additional training. Thus, there have been studies that exploit object-centric representation as a state representation for agent control (Driess et al., 2023; Haramati et al., 2024; Min & Kim, 2025), which have been shown to improve both the task solving performance of vision-based RL agent and the efficiency of the training sample.

However, there remain two key challenges that prevent the agent from fully utilizing object-centric representations: 1) insufficient 3D-awareness and 2) imprecise object description. First, the insufficient 3D-awareness stems from missing multi-view attention and 2D UV-grid-based decoding.

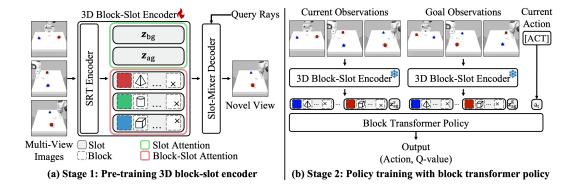


Figure 1: **Overall structure of our method:** Our proposed pipeline consists of two steps: representation learning and policy training. (a) **Pre-training 3D block-slot encoder**: The object slots are further decomposed into blocks of attributes. Then, the slot-mixer decoder mixes the object-centric representation to generate images at a query view. (b) **Policy training with block transformer policy**: We utilize the 3D block-slot encoder to extract a structured representation for the current observation and the goal image. The decomposed latent embedding serves as the input and the goal tokens, respectively, for our block transformer of the policy architecture.

Second, due to the unsupervised learning process, the object variables remain ambiguous in terms of the agent's manipulability.

To address these challenges, we propose a novel end-to-end neural network architecture called 3D block-slot representation, providing a 3D-aware and interpretable state estimation to facilitate vision-based RL tasks. Specifically, we adapt the *block-slot* concept from the attribute-level structural factorization (Singh et al., 2022) to facilitate explicit yet unsupervised object-centric decomposition. Further, to achieve 3D-awareness, we lift the decomposed attributes into 3D space using a light-field decoder (Sajjadi et al., 2022a;b; Smith et al., 2022; Yu et al., 2021; Stelzner et al., 2021; Qi et al., 2023; Luo et al., 2024; Liu et al., 2024), enabling camera view-object 3D position disentanglement. Building on our proposed representation, we introduce a block transformer policy that significantly improves the agent's generalization to novel object configurations. By recognizing matching properties between the current and goal states, the policy effectively reduces the search space for goal-conditioned planning.

To sum up, our main contributions are as follows:

- We propose a novel 3D block-slot attention mechanism that enables the construction of view-independent 3D structured representations by disentangling object attributes such as shape, color, size, and position.
- In the 3D block-slot attention, we design a novel slot attention scheme that applies blockslot attention to object slots, while using vanilla slot attention for background and agent slots, enabling consistent and disentangled representations across different scene components.
- We develop a block transformer policy that performs block-wise cross-attention between current and goal states, enabling precise goal conditioning on object attributes.
- Our experiments on attribute-level object manipulation confirm that the 3D block-slot representation is effective for structured and generalizable goal-conditioned RL.

#### 2 Method

We extract a 3D-aware representation that is decomposed into interpretable components with blocks, such that it can efficiently generalize to various goal-driven tasks with vision-based RL. We first describe the encoder architecture with disentangled components (Section 2.1) followed by the transformer policy architecture (Section 2.2). The overall architecture is summarized in Figure 1.

#### 2.1 3D BLOCK-SLOT REPRESENTATION

Our latent embedding encodes a consistent, disentangled representation that can match visual observations in an arbitrary viewpoint, thus being robust to occlusion or perspective distortion. We build upon the 3D object scene representation transformer (OSRT) (Sajjadi et al., 2022a), which disentangles individual instances and further identifies the active and passive components in fulfilling robotic tasks. The additional block-slot attention module (Singh et al., 2022) builds a strong structure with decomposed factors that are associated with various attributes of the objects.

## 2.1.1 Preliminary: 3D Object-Centric Learning

We adopt a transformer-based SRT encoder  $(E_{\theta})$  (Sajjadi et al., 2022b) to aggregate multi-view observations  $\{\mathbf{I}_i \in \mathbb{R}^{H \times W \times 3}\}$  and generate a scene-level latent representation  $\mathbf{F} \in \mathbb{R}^{L \times D}$ :

$$\mathbf{F} = E_{\theta}(\{\mathbf{I}_i\}). \tag{1}$$

The slot attention mechanism (Locatello et al., 2020) is applied to the scene feature  $\mathbf{F}$ , producing a set of slots  $\{\mathbf{z}_n \in \mathbb{R}^D\}_{n=1}^N$ , where each slot represents an individual object. Specifically, the mechanism observes the image latent embedding  $\mathbf{F}$  to produce an attention readout matrix  $\mathbf{U} \in \mathbb{R}^{N \times D_{\text{slot}}}$ , where each row  $\mathbf{u}_n \in \mathbb{R}^{D_{\text{slot}}}$  of the matrix  $\mathbf{U}$  stores values to update  $\mathbf{z}_n$  of the slot matrix  $\mathbf{Z} \in \mathbb{R}^{N \times D_{\text{slot}}}$ . Our framework augments the slot attention mechanism to reflect our additional factorization, which is described in Section 2.1.3.

The decoder employs the Slot Mixer (Sajjadi et al., 2022a), which is a 3D-aware light-field decoder that can identify the spatial extents of objects and account for occlusion. Given a query ray  $\mathbf{r} = (\mathbf{o}, \mathbf{d})$ , the Slot Mixer generates a feature  $\mathbf{x}$  that aggregates features from the object slots. We compute normalized dot-product similarity between  $\mathbf{x}$  and  $\mathbf{Z}$  using the learned linear projections  $W_Q$  and  $W_K$ , and then use this similarity to compute a weighted mean of the slot matrix  $\mathbf{Z}$ :

$$\mathbf{w} = \operatorname{softmax}((W_k \mathbf{Z}^\top)^\top (W_a \mathbf{x})), \quad \bar{\mathbf{z}} = \mathbf{w}^\top \mathbf{Z}.$$
 (2)

From the aggregated slot features  $\bar{\mathbf{z}}$ , an MLP decoder predicts the RGB value  $C(\mathbf{r})$  of the query ray  $\mathbf{r}$ . The entire network is trained with an  $L_2$  reconstruction loss for novel view synthesis, which matches the synthesized images with the ground-truth images  $\{\mathbf{I}_i^{\text{gt}}\}$ 

$$\mathcal{L}_{\text{recon}} = \underset{\theta}{\text{arg min }} \mathbb{E}_{\mathbf{r} \sim \mathbf{I}_{i}^{\text{gt}}} \left\| C(\mathbf{r}) - \mathbf{I}_{i}^{\text{gt}}(\mathbf{r}) \right\|_{2}^{2}.$$
(3)

# 2.1.2 DECOMPOSITION OF BACKGROUND, FOREGROUND AND AGENTS

Out of the disentangled 3D entities, we clearly identify the active and passive elements to provide the necessary evidence to learn intuitive physics in robotic tasks. Instead of handling the latent vectors  $\{\mathbf{z}_n\}$  as a permutation-invariant set, we explicitly assign specific indices to the background slots  $\mathbf{z}_{bg}$  and agent slots  $\mathbf{z}_{ag}$ . The remaining slots are considered as foreground slots  $\{\mathbf{z}_{o_n}\}_{n=1}^{N-2}$  which correspond to active objects, and we maintain permutation invariance among object slots. Our training dataset contains the background mask  $\mathbf{m}_{bg}^{\text{gt}}$  and agent mask  $\mathbf{m}_{ag}^{\text{gt}}$  within image regions from the simulator, which can also be obtained by detecting agents or objects with foundation models. We design an auxiliary loss that calculates the  $L_2$  loss between the provided masks and the slot weights  $\mathbf{w}$  of the corresponding slots, effectively assigning embeddings for the background and agent to the dedicated slots:

$$\mathcal{L}_{\text{bg}} = \left\| \mathbf{w}_{bg} - \mathbf{m}_{bg}^{\text{gt}} \right\|_{2}^{2}, \quad \mathcal{L}_{\text{ag}} = \left\| \mathbf{w}_{ag} - \mathbf{m}_{ag}^{\text{gt}} \right\|_{2}^{2}. \tag{4}$$

Our total loss combines reconstruction and auxiliary mask loss terms

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{recon}} + \lambda_{bg} \mathcal{L}_{\text{bg}} + \lambda_{ag} \mathcal{L}_{\text{ag}}.$$
 (5)

We can therefore visually observe the physical consequences of various robot interactions and distinguish the actions of robots from other movements. Along with the 3D reasoning, the decomposition can stabilize the training of the robot action policy.

#### 2.1.3 3D BLOCK-SLOT ATTENTION

While the slot-based representation interprets the scene into disentangled entities in 3D, the representation is trained only to reconstruct the observed scenes and is limited in generalization. Objects exhibit different properties, such as shape, size, position, or color, which can be categorized and interpreted as a combination of partially shared characteristics. If we can define an extensive set of task goals by combining object attributes, the trained policy can generalize to novel manipulation targets, earning even more sample efficiency.

We propose a novel mechanism called 3D block-slot attention, which further disentangles the object slots  $\mathbf{z}_n \in \mathbb{R}^{D_{\mathrm{slot}}}$  into the concatenation of M blocks of different attributes  $\{\mathbf{z}_{n,m} \in \mathbb{R}^{D_{\mathrm{block}}}\}_{m=1}^{M}$  from a latent vector  $\mathbf{F}$  extracted by SRT encoder, such that  $D_{\mathrm{slot}} = MD_{\mathrm{block}}$ . Since background and agent do not share concepts (e.g., shape, size, position, or color) in the same compositional manner as objects, we adapt the block-slot attention mechanism (Singh et al., 2022) only to the object slots and retain the vanilla slot-attention mechanism for the background and agent slots. By fixing the indices of the agent and background as described in Section 2.1.2, we can design the update mechanism that appropriately mixes block-slot attention and slot attention across all N slots  $\mathbf{Z} = \{\mathbf{z}_{bg}, \mathbf{z}_{ag}, \mathbf{z}_{o_1}, \dots, \mathbf{z}_{o_{N-2}}\}$ .

The block-slot attention learns visual concepts by extracting features from images and embedding them into blocks. It extends the slot-attention mechanism with an additional factor binding step, which operates at the block level. To enable this update, each slot update  $\mathbf{u}_n$  is equally divided into M segments  $\mathbf{u}_{n,m} \in R^{D_{\text{block}}}$ . Each block  $\mathbf{z}_{n,m} \in R^{D_{\text{block}}}$  is then updated independently using  $\mathbf{u}_{n,m}$  with a GRU (Cho et al., 2014), followed by an MLP

$$\mathbf{z}_{n,m} = \text{GRU}_{\phi_m}(\mathbf{z}_{n,m}, \mathbf{u}_{n,m}) \quad \Rightarrow \quad \mathbf{z}_{n,m} + = \text{MLP}_{\phi_m}(\text{LN}(\mathbf{z}_{n,m})).$$
 (6)

To make each block retrieve its corresponding representation, we use a concept memory  $\mathbf{C}_m \in \mathbb{R}^{K \times d}$  which serves as a learnable soft information bottleneck. The concept memory  $\mathbf{C}_m$  consists of K latent prototype vectors associated with the particular factor m, which allows each block to perform dot-product attention over the concept memory.

After disentanglement, we can further identify the attributes assigned to specific blocks with additional analysis. For example, if we perform K-means clustering on blocks or swap blocks of different objects, and interpret the semantics of factorized attributes. We observe that the individual blocks represent semantic attributes, such as colors, shapes, sizes, and positions of objects, which are utilized to generalize the policy into novel combinations of scenes.

For non-object slots,  $\mathbf{z}_{bg}$  and  $\mathbf{z}_{ag}$ , we apply vanilla slot-attention updates using their corresponding update vectors  $\mathbf{u}_{bg}$ ,  $\mathbf{u}_{ag} \in R^{D_{\text{slot}}}$ , each processed with GRU and MLP independently

$$\mathbf{z}_{n'} = \mathsf{GRU}_{\phi_{n'}}(\mathbf{z}_{n'}, \mathbf{u}_{n'}) \quad \Rightarrow \quad \mathbf{z}_{n'} + = \mathsf{MLP}_{\phi_{n'}}(\mathsf{LN}(\mathbf{z}_{n'})), \quad \text{where } n' \in \{bg, ag\}. \tag{7}$$

#### 2.2 BLOCK TRANSFORMER POLICY

We propose a block transformer policy that utilizes interpretable attributes in the 3D block-slot representations to efficiently train an agent for a goal-conditioned RL (GCRL) task. We first extract the decomposed slot embeddings using the pre-trained 3D block-slot encoder to represent the current state  $s \in \mathcal{S}$  and the goal  $g \in \mathcal{G}$  for an RL task. Given the multi-view images for the current state  $\{\mathbf{I}_i^s\}$ , the pre-trained 3D block-slot encoder extracts the N slots of latent embedding  $\mathbf{Z}^s = \{\mathbf{z}_{bg}^s, \mathbf{z}_{ag}^s, \mathbf{z}_{o_1}^s, \dots, \mathbf{z}_{o_{N-2}}^s\}$ , where the object slots  $\{\mathbf{z}_{o_i}^s\}$  are further decomposed into M blocks. Similarly, the goal images  $\{\mathbf{I}_i^g\}$ , provide the latent embedding for the goal state  $\mathbf{Z}^g = \{\mathbf{z}_{bg}^g, \mathbf{z}_{ag}^g, \mathbf{z}_{o_1}^g, \dots, \mathbf{z}_{o_{N-2}}^g\}$ . The goal-conditioned policy  $\pi^*(s,g)$  maps these structured representations to actions in  $\mathcal A$  to maximize the reward:

$$\mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^{t} r_{t}\right], \quad \text{where } r_{t} = r(s_{t}, a_{t}, g)$$
(8)

where  $\gamma \in [0,1)$  is the discount factor,  $r: \mathcal{S} \times \mathcal{G} \to \mathbb{R}$  is the reward function designed to minimize the discrepancy between the current and the goal state. By leveraging block-level attributes and agent information in the structured latent embedding, the policy can accurately interpret alignment against the desired goal. Consequently, the policy is efficient in training and achieves stable performance

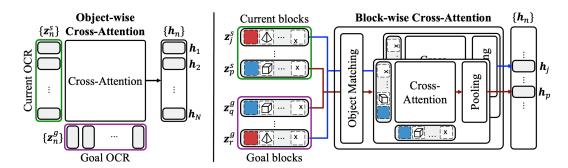


Figure 2: Comparison between object-wise cross-attention and block-wise cross-attention: When computing cross-attention between the current and the goal states of the scene, our block transformer policy utilizes a novel structure of decomposed *blocks*, rather than objects. (a) Object-wise cross-attention is applied between the set of permutation-invariant slots, without distinguishing objects, agents, and background. (b) Block-wise cross-attention operates between blocks, which are consistently decomposed attributes within object slots. By observing the attributes directly, we can stably match corresponding objects in the current and goal representations, and efficiently apply cross-attention to the blocks of desired objects.

compared to policies employing permutation-invariant OCR (Haramati et al., 2024; Zadaianchuk et al., 2020).

Our block transformer policy employs block-wise cross-attention, instead of object-wise cross-attention, such that the agent focuses on manipulating target objects with correct attributes, as described in Figure 2. We can interpret and combine factorized attributes within the blocks to scrutinize critical relations for the desired policy, which significantly enhances the performance. Suppose the task is to relocate objects with the matched attributes into the goal position. In that case, we first match objects within the current state and the goal by comparing their semantic attributes, while ignoring their positions. Then, we compute block-wise cross-attention between the matched objects. The matched object slot in the current state  $\mathbf{z}_{o_n}^s \in \mathbb{R}^{M \times D_{\text{block}}}$  serves as the query, and the corresponding object latent in the goal state  $\mathbf{z}_{o_{n'}}^g \in \mathbb{R}^{M \times D_{\text{block}}}$  acts as the keys and values. Then we pool the resulting attention features  $\{\mathbf{h}_{n,m}\}_{m=1}^M$  within the object's blocks:

$$\mathbf{H}_n = \operatorname{CrossAttn}(\mathbf{z}_{o_n}^s, \mathbf{z}_{o_{n'}}^g), \quad \mathbf{h}_n = \operatorname{PoolAttn}(\mathbf{H}_n).$$
 (9)

As the latent structure correctly disentangles components with factorized attributes, the resulting attention feature successfully encodes the pairwise relationship between matched objects in the current and goal states.

In addition to the features extracted from matched objects  $\mathbf{h}_n$ , the policy incorporates the agent slot features of both the current state  $\mathbf{z}_{ag}^s$  and goal state  $\mathbf{z}_{ag}^g$ , and the current action  $\mathbf{a}_t$ . Utilizing the agent representation, which is the entity that produces the action, is expected to improve the sample efficiency of vision-based RL (Pore et al., 2024). Additionally, the performance of the policy improves when the attention-based policy network handles the action input separately (Haramati et al., 2024). A self-attention module (Vaswani et al., 2017) aggregates the information to output P, followed by an MLP, which predicts the final output composed of action for the actor and the Q-values for the critic (Figure 1(b)):

$$\mathbf{P} = \text{SelfAttn}([\mathbf{h}_1, \dots, \mathbf{h}_{N-2}, \mathbf{z}_{ag}^s, \mathbf{z}_{bg}^g, \mathbf{a}_t]), \quad \text{Output} = \text{MLP}(\text{AttnPool}(P)). \tag{10}$$

An extended architectural description of this policy network is provided in Appendix A.1

## 3 RELATED WORK

**3D object-centric learning.** Several recent works have expanded object-centric learning from 2D to 3D representations. They train implicit representations with rendering losses in novel views, inspired by advances in novel view synthesis. OSRT (Sajjadi et al., 2022a) and COLF (Smith et al., 2022) employ an efficient light-field decoder and can quickly decompose complex static scenes. On

the other hand, a slot attention module can adapt formulations in neural radiance field, and be trained to reduce rendering losses (Yu et al., 2021; Stelzner et al., 2021; Qi et al., 2023; Luo et al., 2024; Liu et al., 2024). However, all these methods are trained on static scenes without interaction or mutual occlusion, and cannot accurately reason about physical context in dynamic scenes. Our approach additionally provides a highly structured latent representation, enabling systematic reasoning.

Object-Centric Learning for Structured Representation. Structured representation methods factor object representations into interpretable attributes (e.g., color, shape, position), which can be composed to produce different combinations of the scenes. SysBinder (Singh et al., 2022) introduces a "block-slot" design to learn such factors in an unsupervised manner. Dreamweaver (Baek et al., 2025) discovers both static and dynamic primitives (e.g., motion direction, speed) for compositional world models in video data. Deep Latent Particles (DLP) (Daniel & Tamar, 2022) and DLPv2 (Daniel & Tamar, 2023) represent scenes as probabilistic particles that encode position and appearance. Including other approaches that factorize object-centric representations (Kosiorek et al., 2018; Stanić & Schmidhuber, 2019; Jiang et al., 2019; Crawford & Pineau, 2019), these approaches often lack explicit 3D reasoning, limiting their robustness to occlusion, viewpoint changes, and real-world interaction.

Object-Centric Reinforcement Learning. Object-centric representations in RL enable policies that generalize across diverse scenes with fewer samples. POCR (Shi et al., 2024) integrates "what" (semantic) and "where" (mask) embeddings, improving zero-shot and imitation learning performance in cluttered manipulation tasks. Entity-Centric RL (ECRL) (Haramati et al., 2024) employs DLPv2 perception (Daniel & Tamar, 2023) together with an Entity Interaction Transformer (EIT)—an attention mechanism-based policy architecture—but struggles to recombine attributes with novel objects. PaLM-E (Driess et al., 2023) grounds language models in slot-based scene representations for embodied reasoning, though it falters on unseen property combinations. Additional works (Qi et al., 2024; Watters et al., 2019; Wu et al., 2022; Yoon et al., 2023; Zadaianchuk et al., 2020; 2022; Zhou et al., 2022) enhance RL with structured perception, yet most methods still fail on compositional variations of shape, size, and color, highlighting the need for richer, disentangled, and 3D-aware representations.

## 4 EXPERIMENTS

### 4.1 3D BLOCK-SLOT REPRESENTATION

We first analyze our scene representation, which captures a 3D-aware scene representation with factorized components. For the 3D-awareness, we evaluate the quality of generated novel-view images with PSNR. The object decomposition is evaluated with ForeGround Adjusted Rand Index (FG-ARI) (Hubert & Arabie, 1985; Rand, 1971; Sajjadi et al., 2022a). The additional factorization in block-wise attributes is evaluated in three perspectives: Disentanglement (D), Completeness (C), and Informativeness (I), as proposed in Singh et al. (2022). These values are extracted by training a gradient boost tree algorithm (Locatello et al., 2019) to map the ground-truth factor to the learned representation.

**Datasets.** We evaluate the performance of scene representation using two datasets: Clevr3D and IsaacGym3D. Clevr3D builds upon the CLEVR dataset (Johnson et al., 2017; Stelzner et al., 2021; Girdhar & Ramanan, 2019), a widely used dataset for object-centric representations. We employ the data generation pipeline (Li et al., 2020; 2021; Lin et al., 2020) to construct Clevr3D, which comprises multi-view observations of multiple objects exhibiting rich combinations of attributes. Each scene consists of a white background and a set of randomly positioned objects, with diverse attributes. Object attributes include three types of shapes (cube, cylinder, sphere), two types of sizes (small, large), and eighteen colors combined with materials (matte, glossy). The cameras are placed randomly on the surface of a hemisphere, capturing six different viewpoints of each scene.

The IsaacGym3D dataset contains more realistic scenarios, in which a robot manipulates objects with randomized actions on a white table. Objects in the scene are randomly assigned one of three types of shapes (cube, cylinder, cone), two types of sizes (small, large), and nine types of colors. They are placed at arbitrary (x, y) positions within the boundaries of the table. The cameras are

Dataset	Method	PNSR	FG-ARI	D	С	I
Clevr3D	OSRT Ours	<b>31.57</b> 31.11	0.365 <b>0.942</b>	0.140 <b>0.867</b>	0.083 <b>0.789</b>	0.452 <b>0.844</b>
IsaacGym3D	OSRT Ours	<b>27.35</b> 26.55	0.321 <b>0.619</b>	0.403 <b>0.659</b>	0.222 <b>0.550</b>	0.769 <b>0.938</b>

Table 1: **3D** awareness with novel-view synthesis and decomposition performance: Our method outperforms OSRT across FG-ARI, disentanglement (D), completeness (C), and informativeness (I), while achieving comparable PSNR. The results indicate that our approach improves object decomposition and effectively disentangles information into latent vectors, while maintaining 3D-aware representation.

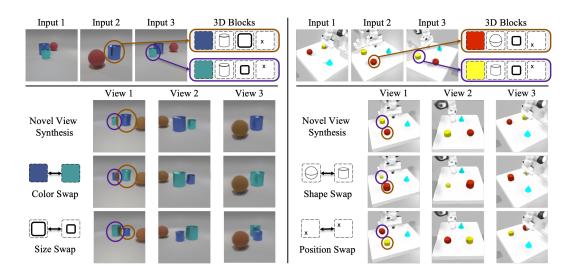


Figure 3: **Novel view synthesis after block manipulation:** After obtaining the structured latent representation of the scene (top), we can manipulate block-wise attributes to create a novel combination of properties in the 3D representations, which can be consistently synthesized in novel view images (bottom). The left images show the results after swapping the color and size blocks in a Clevr3D scene, while the right images are synthesized after swapping the shape and 3D position blocks in the IsaacGym3D dataset.

randomly placed on the surface of a hemisphere to capture diverse perspectives of the environment, resulting in a challenging setting for interpreting agent behavior.

**Results.** We compare the performance of our 3D block-slot representation against OSRT (Sajjadi et al., 2022a), which produces a 3D object-centric representation. They incorporate a similar encoder and decoder architecture, but treat individual components with permutation-invariant slots. In contrast, our approach distinguishes between foreground objects, agents, and backgrounds, and separately handles factorized blocks with block-slot attention. The quantitative results are shown in Table 1. Our results achieve comparable novel-view synthesis results (PSNR) but clearly outperform in distinguishing different components (FG-ARI). The additional factor-binding step enhances the ability to disentangle different attributes in the latent vectors, as indicated by D, C, and I scores, measured using the DCI framework proposed in (Singh et al., 2022) On the other hand, the 3D slot produced by OSRT misses such a structure and fails to assign consistent information to a dedicated location.

In Appendix B.1, we further visualize the information embedded in each block by clustering it based on the values contained within the block. After the interpretable properties, such as color, size, shape, and position, are clearly separated into different blocks, we can utilize the structured representation to manipulate attributes and create a novel combination of the 3D scene. Figure 3 demonstrates exemplary results of novel-view synthesis after swapping blocks between two objects.

With the 3D information, we can even emulate realistic occlusion effects. As demonstrated in Section 4.2, such generative capability highly enhances the performance of solving RL tasks. We further provide additional qualitative visualizations, including novel view synthesis, object decomposition, and disentanglement analysis in Appendix B.1.

## 4.2 GOAL-CONDITIONED REINFORCEMENT LEARNING

We exploit the structured representation with the block-transformer policy to perform goal-conditioned RL. The agent must push the objects to the desired positions based on the given goal images. The ground-truth reward is the mean of the negative  $L_2$  distance between each object's achieved goal position and its desired goal position. We define *success* as a condition when all N objects are within a threshold R distance from their respective desired goal. The average return is the immediate ground-truth rewards over T timesteps.

We set the RL environment for tabletop object manipulation using the IsaacGym simulator (Makoviychuk et al., 2021). We use the same environmental configuration of IssacGym3D dataset in Section 4.1, where cameras are fixed to capture the front, left, and right views of a Franka Panda robot arm pushing objects on a white table (Haramati et al., 2024) (see Figure 1, right). In each episode, objects are randomly respawned on the table with random shapes (cube, cone, cylinder) and colors. We adopt an off-policy RL algorithm, TD3 (Fujimoto et al., 2018) with hindsight experience replay (Andrychowicz et al., 2017). The policy architecture is usable with other on-policy or off-policy algorithms, providing flexibility for various state properties. Appendix A.3 provides additional information on the RL environment configuration.

**Baselines.** We evaluate the performance of three structured scene representations with two policy architectures, including ours. Before training the policy, we first pre-train the scene representation model using the IsaacGym3D dataset. In addition to 3D latent vectors of OSRT in Section 4.1, we also compare against DLPv2 (Daniel & Tamar, 2023), one of the best-performing 2D object-centric representations in goal-conditioned RL. It provides a set of disentangled latent vectors in the form of P foreground particles extracted from a single image  $I \in \mathbb{R}^{H \times W \times 3}$ . The 2D representations are trained with a separate dataset composed of single-view images. OSRT extracts a set of 3D object-centric latent vector set,  $\{\mathbf{z}_n\}$ , from multi-view images of a scene  $\{\mathbf{I}_i \in \mathbb{R}^{H \times W \times 3}\}$ . Implementation details of the pre-training procedures for the baselines are provided in Appendix A.2

The pre-trained visual encoder extracts structured latent embeddings of the current and goal states, which serve as the input to the policy architecture. In addition to the proposed Block Transformer (BT) policy, we adopt the Entity Interaction Transformer (EIT) (Haramati et al., 2024) as a baseline, which is a state-of-the-art object-centric policy for goal-conditioned RL.

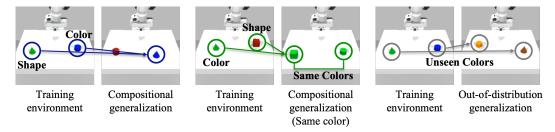


Figure 4: **Evaluation scenarios for compositional and out-of-distribution generalization:** Composition generalization environments consist of objects with properties during training, but novel in their combinations. Out of such unseen combinations, we separately evaluate cases with objects of the same color when the factorization of attributes is unsuccessful. Out-of-distribution environments use objects with colors that were not present in the training set.

**Results.** Our agent observes environments in three categories: in-distribution evaluation (ID), compositional generalization (CG), and out-of-distribution generalization (OOD). The ID refers to the scenes with objects that were observed during training. In contrast, CG and OOD are designed to analyze the generalization performance of the representation in unseen environments, as depicted in Figure 4. CG uses novel combinations of shapes and colors - the individual factors are encountered during policy training, but not in the same combinations within the same object. OOD includes

Representation w/ Policy		DLPv2 w/ EIT	OSRT w/ EIT	Ours w/ EIT	Ours w/ BT
Success Rate	ID	$0.984 \pm 0.005$	$0.980 \pm 0.011$	$0.984 \pm 0.005$	$0.967 \pm 0.017$
	CG	$0.747 \pm 0.030$	$0.758 \pm 0.021$	$0.773 \pm 0.048$	$0.895 \pm 0.011$
	CG (same color)	$0.388 \pm 0.064$	$0.414 \pm 0.167$	$0.682 \pm 0.118$	<b>0.837</b> ± 0.035
	OOD	$0.422 \pm 0.170$	$0.700 \pm 0.160$	$0.582 \pm 0.270$	<b>0.828</b> ± 0.099
Avg Return	ID	$-0.189 \pm 0.001$	<b>-0.175</b> ± 0.013	$-0.184 \pm 0.014$	$-0.218 \pm 0.003$
	CG	$-0.365 \pm 0.027$	$-0.372 \pm 0.002$	$-0.382 \pm 0.041$	<b>-0.310</b> ± 0.016
	CG (same color)	$-0.594 \pm 0.018$	$-0.635 \pm 0.068$	$-0.494 \pm 0.096$	<b>-0.388</b> ± 0.016
	OOD	$-0.587 \pm 0.090$	$-0.414 \pm 0.139$	$-0.591 \pm 0.306$	<b>-0.338</b> ± 0.064

Table 2: **Performance of goal-conditioned RL:** Our proposed 3D block-slot representation, combined with a block transformer (BT) policy, can effectively interpret goal conditions and exhibit superior performance in various scenarios. We compare the performance of goal-conditioned RL tasks employing different object-centric representations and policy architectures in four settings: ID (indistribution evaluation), CG (composition generalization), CG-same (compositional generalization with same colored objects), and OOD (out-of-distribution generalization). Results are calculated on 400 randomly sampled goals per seed.

instances of attributes that were not encountered during policy training. From the OOD cases, we can check how effectively the agent can adapt to zero-shot environments.

Table 2 contains an evaluation of performing goal-conditioned RL tasks with various scene representations and policy architectures. In our model, the agent generalizes well to novel factor compositions, achieving performance comparable to that in the in-distribution evaluation. In contrast, baseline models experience a significant performance drop compared to ID.

Among many failure cases in CG scenarios, we have noticed that sharing the same factor between two objects can severely confuse the instances in the scene. CG (same color) tackles these particularly challenging cases, where the agent must manipulate two objects of the same color. Notably, 3D block-slot representations are highly effective compared to unstructured or 2D representations, as they capture rich visual features within blocks and distinguish same-colored objects, even though such configurations were not seen during training. BT further enhances performance by carefully matching the desired instances with the correct attributes, a task that cannot be achieved with entitywise attention in EIT. The combination of 3D block-slot representations with the block transformer achieves results comparable to those of ID.

For this evaluation of OOD scenarios, we randomly spawned objects with six unseen colors or a sphere shape, all of which were absent in the training distribution. The results show that our model generalizes better than the other baseline methods in the OOD setting. We report additional RL evaluation results and analysis in Appendix B.2.

## 5 Conclusion

We propose a 3D block-slot representation, a 3D-aware structured representation that integrates 3D object-centric learning with attribute factorization. We successfully decompose background, foreground, and agent, and can disentangle object factors not only in synthetic static scenes but also in simulated robot environments. The block transformer policy effectively applies structured latent sets to the RL framework, leveraging both the advantages of factor-level input and object-level computation. Compared to prior methods using pre-trained object-centric representations, our policy network improves the performance of compositional generalization and out-of-distribution generalization. The results indicate that the factorized latent structure can be directly used in the policy network, demonstrating superior generalization. In future work, this approach can be extended to more complex environments. Furthermore, the 3D block-slot representations, which encode semantics akin to language tokens, have the potential to bridge the gap between 3D perception and Vision-Language-Action (VLA) frameworks.

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### APPENDIX

## A IMPLEMENTATION DETAILS

#### A.1 BLOCK TRANSFORMER POLICY.

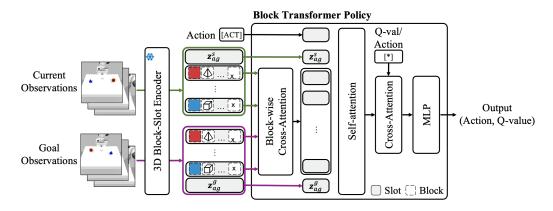


Figure 5: **Structure of block transformer policy:** The block transformer policy processes 3D block-slot representations using block-wise cross-attention, self-attention, and cross-attention with a pooling token, followed by an MLP to generate the final output.

In this section, we describe the architecture and implementation details of our block transformer policy, including its attention modules and how it integrates information from 3D block-slot representations.

The block transformer policy consists of block-wise cross-attention, self-attention and cross-attention modules, followed by an MLP as described in 2.2. We use only foreground blocks  $\{\mathbf{z}_{n,m}\}$  and agent slots  $\mathbf{z}_{ag}^{s}$ ,  $\mathbf{z}_{ag}^{g}$ , as background information tends to be noisy in robotic object manipulation tasks. The self-attention module takes as input the output of block-wise cross attention  $\{\mathbf{h}_{n}\}$ , linearly projected action information, and the slots extracted from current and goal observations, in order to model the interaction between agent information and object attributes. The output of self-attention module is then processed through a cross-attention mechanism with a pooling query token, followed by an MLP, to produce the final policy output.

## A.2 PRE-TRAINING REPRESENTATIONS

In this section, we describe the pre-trained representations used in our experiments-DLPv2, OSRT, and our proposed 3D block-slot representations-and introduce the Clevr3D and IsaacGym3D datasets used for training and evaluation. We first describe the datasets collected for pre-training, and then provide details of the 2D and 3D object-centric model.

**Dataset.** To investigate the capability of our 3D block-slot attention, we use datasets that represent multi-object scenes and robotic environments. First, we consider the CLEVR dataset, which has been widely used to evaluate decomposition & factorization quality. Clevr3D extends CLEVR (Johnson et al., 2017) by randomizing camera positions instead of using fixed viewpoints. Each scene contains three randomly placed objects with attributes independently sampled for shape, size, color and position. Object attributes include three types of shapes (cube, cylinder, sphere), two sizes (small, large), and eighteen colors resulting from combinations of nine base colors with two materials (glossy, matte). The dataset includes 20,000 training scenes (each with six views) and 1,000 test scenes.

In contrast, IsaacGym3D restricts the camera to the front side of the hemisphere, with viewpoints ranging from  $-90^{\circ}$  to  $90^{\circ}$ , because the rear views are not necessary for training in the robot manipulation environments. Each scene includes three objects with randomized attributes: shape (cube, cone, cylinder), size (small, large), and color (identical to Clevr3D). The dataset contains 30,000 training scenes and 200 test scenes. For 2D object-centric learning, we additionally collect two fixed views-front and right views-for each scene.

**Baseline: OSRT.** We train OSRT (Sajjadi et al., 2022a) as the 3D object-centric learning baseline in our experiments. Given multi-view observations  $\{\mathbf{I}_i \in \mathbb{R}^{H \times W \times 3}\}$ , the SRT encoder aggregates features into a scene-level latent representation  $\mathbf{F} \in \mathbb{R}^{L \times D}$ . Using the  $\mathbf{F}$ , the vanilla slot attention module is employed to produce a set of slots  $\{\mathbf{z}_n \in \mathbb{R}^D\}_{n=1}^N$ . The Slot Mixer decoder then predicts RGB values for a given query ray, as described in Section 2.1. The model is trained with 4 slots of 64 dimensions for Clevr3D, and 6 slots of 64 dimensions for IsaacGym3D. We set hyperparameters listed in Table 5. The model size is intentionally kept small (64-dimensional slots), as larger models-such as those with 1536-dimensional slots-incur significant computational cost and slow inference speed, which is not suitable for vision-based RL.

	Hyperparameter -	Clevr3D		IsaacGym3D	
Module		OSRT	Ours	OSRT	Ours
	Batch size	40	40	40	40
General	Training steps	1.5M	1.5M	1.5M	1.5M
	Learning rate	0.0001	0.0001	0.0001	0.0001
Slot attention Block-slot attention	Number of slots	4	4	4	4
	Slot size	64	64	64	64
	Number of blocks	N/A	8	N/A	8
	Block size	N/A	8	N/A	8
	Number of prototypes	N/A	20	N/A	16
	MLP hidden dimension	512	512	512	512

Table 3: Hyperparameters of OSRT and 3D block-slot attention used in our experiments.

**Baseline: DLPv2.** We train DLPv2 (Daniel & Tamar, 2023) as the 2D object-centric learning baseline in our experiments. We follow the modification of DLPv2 by ECRL (Haramati et al., 2024), which sets the background particle features to have a dimensionality of 1, and discards them during RL training. DLPv2 extracts P particles  $\mathbf{z}$  from a single image  $I \in \mathbb{R}^{H \times W \times 3}$ , where  $\mathbf{z} = (z_p, z_s, z_d, z_t, z_f) \in \mathbb{R}^{6+m}$ . Each latent component- $z_p \in \mathbb{R}^2$ ,  $z_s \in \mathbb{R}^2$ ,  $z_d \in \mathbb{R}$ ,  $z_t \in \mathbb{R}$  and  $z_f \in \mathbb{R}^m$ -represents the particle's position, scale, depth, transparency and latent feature of visual appearance, respectively. We use the hyperparameters listed in Table 4.

# A.3 REINFORCEMENT LEARNING

In this section, we describe the reinforcement learning setup in our experiments, including the reward function, evaluation metrics, and implementation details of reinforcement learning.

Hyperparameter	DLP
Epochs	60
Batch Size	64
learning rate	0.0002
Reconstruction Loss	MSE
Prior Patch Size	16
Posterior KP P	24
Prior KP Proposals $L$	32
Prior Patch Size	16
Glimpse Size $S$	32
Feature Dim m	4
Background Feature Dim $m_{bg}$	1
$\beta_{KL}$	0.1

Table 4: Hyperparameters of DLPv2 used in our experiments.

**Reward.** The reward is computed from the ground-truth state of the environment and is referred to as the ground-truth reward. It is defined as the mean negative  $L_2$  distance between each object and its corresponding goal position on the table:

$$r_{gt,t} = -\frac{1}{N_o} \sum_{i=1}^{N_o} \left\| g_i^d - g_i^a \right\|_2 \tag{11}$$

where each of  $r_{gt,t}$ ,  $N_o$ ,  $g_i^d$ , and  $g_i^a$  denotes the immediate ground-truth reward at time t, the number of objects, ith object's desired goal, and ith object's achieved goal, respectively.

**Evaluation metrics.** We adopt five evaluation metrics to evaluate the performance of reinforcement learning, following Haramati et al. (2024). Success indicates whether all objects have reached within a given distance threshold from their respective goals. Success fraction measures the proportion of individual objects that satisfy the same distance condition. Average return is the mean

cumulative reward over the episode. Maximum object distance refers to the furthest distance between any object and its target at the end of episode, and average object distance is the mean of all such distances across objects. The formal definitions are as follows:

Success: 
$$\mathbb{I}\left(\sum_{i=1}^{N_o} \mathbb{I}(\left\|g_i^d - g_i^a\right\|_2 < R) = N_o\right), \tag{12}$$

Success fraction: 
$$\frac{1}{N_o} \sum_{i=1}^{N_o} \mathbb{I}(\left\|g_i^d - g_i^a\right\|_2 < R), \tag{13}$$

Average return: 
$$\frac{1}{T} \sum_{t=1}^{T} r_t$$
, (14)

Maximum object distance: 
$$\max_{i} \{ \|g_i^d - g_i^a\|_2 \},$$
 (15)

Average object distance : 
$$\frac{1}{N_o} \sum_{i=1}^{N_o} \left\| g_i^d - g_i^a \right\|_2. \tag{16}$$

Here, T denotes the number of timesteps in an episode,  $r_t$  is the reward at timestep t, and R is the distance threshold used to determine success.

**Implementation of RL.** Our reinforcement learning implementation is based on the ECRL (Haramati et al., 2024), built upon Stable-Baseline3 (Raffin et al., 2021), using TD3 (Fujimoto et al., 2018) and HER (Andrychowicz et al., 2017). For exploration, we employ both  $\varepsilon$ -greedy strategies and Gaussian action noise, following the approach of Zhou et al. (2022). All models are optimized using the Adam optimizer.

Hyperparameter	EIT & BT
Batch size	512
Learning rate	5e-4
$\gamma$	0.98
au	0.05
Exploration action noise	0.2
Exploration $\varepsilon$	0.3
HER ratio	0.3
Number of episodes collected per training loop	16

Table 5: Hyperparameters of RL used in our experiments.

# B ADDITIONAL RESULTS

#### B.1 QUALITATIVE ANALYSIS OF 3D BLOCK-SLOT REPRESENTATIONS

In this section, we present additional qualitative results to evaluate the effectiveness of our 3D block-slot representation. We include visual comparisons of novel view synthesis and object decomposition between our method and OSRT on the Clevr3D and IsaacGym3D datasets. We also show additional examples of block manipulation through block swapping to demonstrate controllability of the blocks. Furthermore, we analyze factor disentanglement using feature importance matrices and clustering visualizations, which highlight how different blocks encode semantically meaningful components of the scene.

**Novel view synthesis and object decomposition.** We present qualitative comparisons of novel view synthesis results produced by OSRT and our method on the Clevr3D and IsaacGym3D datasets. By leveraging multi-view observations, our method remains robust under occlusions and accurately reconstructs the scene. In particular, our per-slot reconstructions demonstrate more consistent decomposition of background and individual objects across views. Additionally, the robot agent is reliably assigned to a fixed slot index, effectively capturing the agent's presence and action-related information.

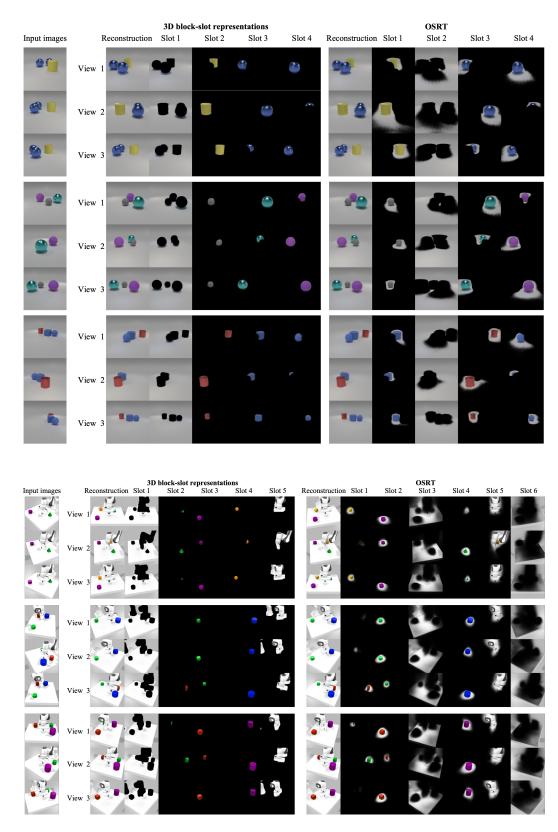
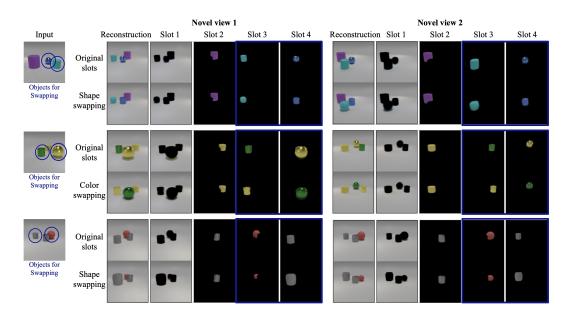


Figure 6: **Novel view synthesis and decomposition:** Our method achieves comparable novel view synthesis quality to OSRT while providing significantly better separation of foreground objects, background and agent components on the Clevr3D and IsaacGym3D datasets.

**Block manipulation and novel view synthesis.** We provide additional visualizations of novel view synthesis through block manipulation, as shown in Figure 3. In each scene, two objects are selected, and the specific blocks corresponding to their attributes are swapped. The model then synthesizes novel views based on the modified slot representations. In both Clevr3D and Isaac-Gym3D, our method successfully generates novel views with swapped blocks, while preserving the consistency of the remaining blocks.



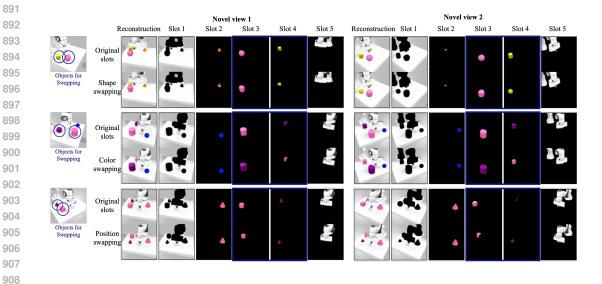


Figure 7: Additional samples of block manipulation and novel view synthesis: We show additional examples of block swapping, where blue-circled objects indicate the slots selected for attribute exchange.

**K-means clustering of blocks.** By extending k-means clustering from 2D to 3D block-slot representations, we identify meaningful clusters of blocks. Given multi-view observations  $\{I_i\}$ , the 3D block-slot attention mechanism produces 3D block representations  $\{\mathbf{z}_{n,m}\}$ . Unlike the 2D slot attention mechanism, our model aggregates multi-view information into latent vectors and thus cannot directly produce attention maps from the encoder outputs. Therefore, we obtain the corresponding

object images  $\{y_n\}$  using the slot weights w from Slot Mixer decoder applied to a novel view. Using 1,050 objects in 350 scenes, each containing three independently randomized objects, we collect a set of pairs  $\{(\mathbf{z}_{n,m},\mathbf{y}_n)\}$ . K-means clustering of the blocks (with K=10) reveals the underlying structure of the representation helps indentify which blocks encode specific object attributes.. In block 6 of the Clevr3D dataset, cluster 1 corresponds to cylindrical objects, while cluster 3 corresponds to spherical objects. These results suggest that block 6 encodes shape-related attributes.

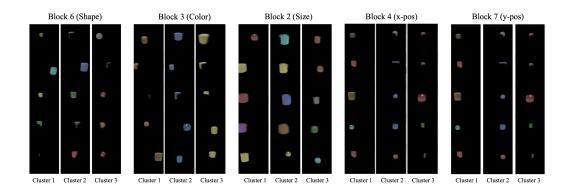


Figure 8: **K-means clustering of 3D block representations:** Clustering results indicate that different blocks capture distinct object attributes. For example, block 6 clustered by shape, block 3 by color, block 2 by size, block 4 by x-position, and block 5 by y-position.

**Feature importance matrix.** We visualize the feature importance matrices for our method and OSRT. As described in Section 4.1, we train a gradient boost tree to predict each ground-truth object attribute from the learned blocks, in order to evaluate how well the blocks capture and disentangle object attributes. Using the trained model, we extract the feature importance matrix, where each row corresponds to a ground-truth object factor, and each column represents a latent unit-either a slot in OSRT or a block in our method. The results show that our model learns more disentangled representations, with different blocks specializing in distinct object attributes across both the Clevr3D and IsaacGym3D datasets. In contrast, the slot-based representations from OSRT show more entangled feature importance patterns, indicating less structured encoding of object attributes.

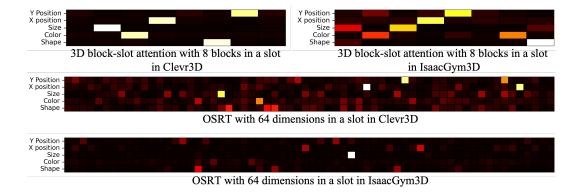


Figure 9: **Feature importance matrix:** Feature importances for predicting ground-truth object attributes from latent representations. Our method shows clear attribute-specific encoding in each block, while OSRT's 3D slot representations are less disentangled.

#### B.2 ADDITIONAL RL RESULTS

In this section, we present additional reinforcement learning results to complement the main experiments. We include agent rollout visualization, additional evaluation metrics, and learning curves. These results provide a more comprehensive understanding of our policy's performance and generalization capabilities.

**Rollouts of an agent across evaluation scenarios.** We assess the generalization capability of our model across four different environment setups: in-distribution evaluation, compositional generalization, compositional generalization of same-color objects, and out-of-distribution generalization. As reported in Table 2, our method demonstrates strong performance across all scenarios. The visualized rollouts show that the agent successfully completes the task in all evaluation scenarios, further demonstrating the robustness and generalization ability of our policy.

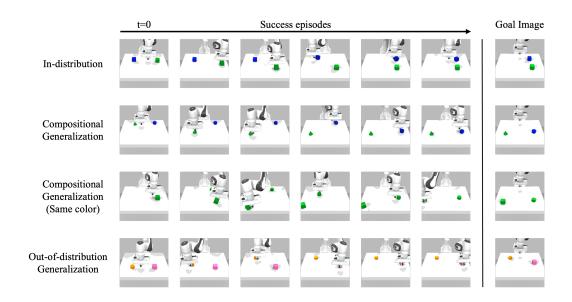


Figure 10: **Agent behavior in evaluation tasks:** Visualized rollouts demonstrate that the agent completes the task successfully across all evaluation scenarios, including in-distribution, compositional, and out-of-distribution settings.

Additional evaluation metrics. We evaluate the performance of four methods that combine pretrained representations with reinforcement learning policies. Following (Haramati et al., 2024), we adopt five evaluation metrics: success rate, success fraction, average return, maximum object distance, and average object distance. The results of success rate and average return are reported in Table 2, while the remaining metrics are shown in Table 6. Success fraction measures the proportion of individual objects that reach their respective goal positions. Maximum and average object distances are computed based on the Euclidean distances between each object and its assigned goal. As shown in Table 6, our method consistently outperforms all baselines across the additional metrics as well. Specifically, it achieves higher success fraction and lower object distance errors, indicating more precise and consistent goal-reaching behavior. These results further support the effectiveness of our policy and its strong generalization capability across different evaluation settings. Formal definitions of these metrics are provided in Appendix A.3

Representation w/ Policy		DLPv2 w/ EIT	OSRT w/ EIT	Ours w/ EIT	Ours w/ BT
Success Fraction	ID	<b>0.991</b> ± 0.003	$0.988 \pm 0.008$	$0.990 \pm 0.003$	$0.979 \pm 0.013$
	CG	$0.843 \pm 0.016$	$0.843 \pm 0.003$	$0.833 \pm 0.037$	<b>0.913</b> ± 0.010
	CG (same color)	$0.628\pm0.038$	$0.598 \pm 0.073$	$0.750 \pm 0.091$	<b>0.866</b> ± 0.027
	OOD	$0.654 \pm 0.113$	$0.812 \pm 0.107$	$0.720 \pm 0.192$	<b>0.888</b> ± 0.061
Max Obj Dist	ID	$0.026 \pm 0.001$	<b>0.021</b> ± 0.003	$0.022 \pm 0.001$	$0.030 \pm 0.003$
	CG	$0.084 \pm 0.010$	$0.083 \pm 0.005$	$0.083 \pm 0.016$	<b>0.049</b> ± 0.005
	CG (same color)	$0.167 \pm 0.012$	$0.172 \pm 0.037$	$0.108 \pm 0.034$	<b>0.066</b> ± 0.004
	OOD	$0.164 \pm 0.034$	$0.102 \pm 0.053$	$0.164 \pm 0.113$	<b>0.059</b> ± 0.019
Avg Obj Dist	ID	$0.018 \pm 0.001$	<b>0.016</b> ± 0.002	$0.017 \pm 0.002$	$0.023 \pm 0.002$
	CG	$0.054 \pm 0.005$	$0.054 \pm 0.002$	$0.056 \pm 0.009$	<b>0.039</b> ± 0.003
	CG (same color)	$0.103 \pm 0.006$	$0.114 \pm 0.017$	$0.081 \pm 0.021$	$0.052 \pm 0.003$
	OOD	$0.100 \pm 0.021$	$0.064 \pm 0.031$	$0.105 \pm 0.072$	$0.042 \pm 0.013$

Table 6: Additional evaluation metrics for the IsaacGym push task: We report results across four settings: ID (in-distribution evaluation), CG (composition generalization), CG-same (compositional generalization with same colored objects), and OOD (out-of-distribution generalization). Each metric is averaged over 400 randomly sampled goals per seed.

Visualization of GCRL training. We employed four methods that combine pre-trained vision models with control policies in our setup. We visualize both the success rate and the average reward over training timesteps. Among these methods, the combination of 3D block-slot representations with an object-centric policy achieves the highest sample efficiency. This suggests that the structured 3D block representations are more effective for learning robotic manipulation tasks than unstructured 3D object-centric representations or 2D object-centric representations. In addition, our block-level transformer, while slightly less sample-efficient, demonstrates superior generalization performance in environments where the object-centric policy fails.

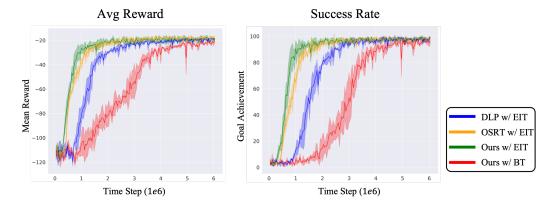


Figure 11: Success rate and average reward during GCRL training: Comparison of four methods using different pre-trained representations and policies. The 3D block-slot representation with object-centric policy achieves the fastest learning, and the block-level transformer shows stronger generalization in long-horizon tasks.

# C LLM USAGE

We use a large language model (LLM) to detect and correct grammatical errors and awkward phrasing.