



# SPA: 3D SPATIAL-AWARENESS ENABLES EFFECTIVE EMBODIED REPRESENTATION

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## ABSTRACT

In this paper, we introduce SPA, a novel representation learning framework that emphasizes the importance of 3D spatial awareness in embodied AI. Our approach leverages differentiable neural rendering on multi-view images to endow a vanilla Vision Transformer (ViT) with intrinsic spatial understanding. We present the most comprehensive evaluation of embodied representation learning to date, covering 268 tasks across 8 simulators with diverse policies in both single-task and language-conditioned multi-task scenarios. The results are compelling: SPA consistently outperforms more than 10 state-of-the-art representation methods, including those specifically designed for embodied AI, vision-centric tasks, and multi-modal applications, while using less training data. Furthermore, we conduct a series of real-world experiments to confirm its effectiveness in practical scenarios. These results highlight the critical role of 3D spatial awareness for embodied representation learning. Our strongest model takes more than 6000 GPU hours to train and we are committed to open-sourcing all code and model weights to foster future research in embodied representation learning. Project Page: <https://haoyizhu.github.io/spa/>.

## 1 INTRODUCTION

Vision systems have made remarkable progress in understanding 2D images (He et al., 2020; Chen et al., 2020a; He et al., 2022; Feichtenhofer et al., 2022; Tong et al., 2022; Yang et al., 2023; Oquab et al., 2023; Radford et al., 2021; Fang et al., 2023b; Chen et al., 2024). However, achieving true visual intelligence necessitates a comprehensive understanding of the 3D world. This is crucial for embodied AI, where agents must perceive, reason, and interact with complex 3D environments.

Existing visual representation learning methods for embodied AI (Nair et al., 2022; Radosavovic et al., 2023; Majumdar et al., 2023; Karamcheti et al., 2023; Shang et al., 2024; Yang et al., 2024b) largely rely on paradigms from 2D vision, predominantly employing contrastive-based or masked autoencoder (MAE)-based approaches. However, they often struggle to fully capture the spatial relationships and 3D structures inherent in the physical world. This limitation arises from their primary emphasis on 2D semantic understanding, which, though valuable, is still insufficient for the sophisticated spatial reasoning required in embodied AI tasks, where agents need to navigate environments, manipulate objects, and make decisions using their 3D spatial awareness.

In this paper, we introduce SPA, a general 3D spatial-aware representation learning framework for embodied AI. SPA leverages neural rendering (Mildenhall et al., 2021) as the pre-training pre-text task on multi-view images. Unlike explicit 3D representations like point clouds or meshes—which prior work (Wang et al., 2024b;a; Ze et al., 2024; Zhu et al., 2024) has shown to outperform pure 2D inputs in robot learning—multi-view images are easier to process and more readily available, making them ideal for large-scale training, such as from internet videos. Specifically, given a vanilla 2D image backbone, *e.g.* a Vision Transformer (ViT) (Dosovitskiy et al., 2021), we first extract multi-view feature maps from the input images. Using known camera poses, we then construct a feature volume from these feature maps and sample rays to apply differentiable neural rendering. This process generates multi-view RGB-D images and semantic maps for supervision without labels, enabling the pre-training of a 2D image backbone to enhance 3D spatial awareness.

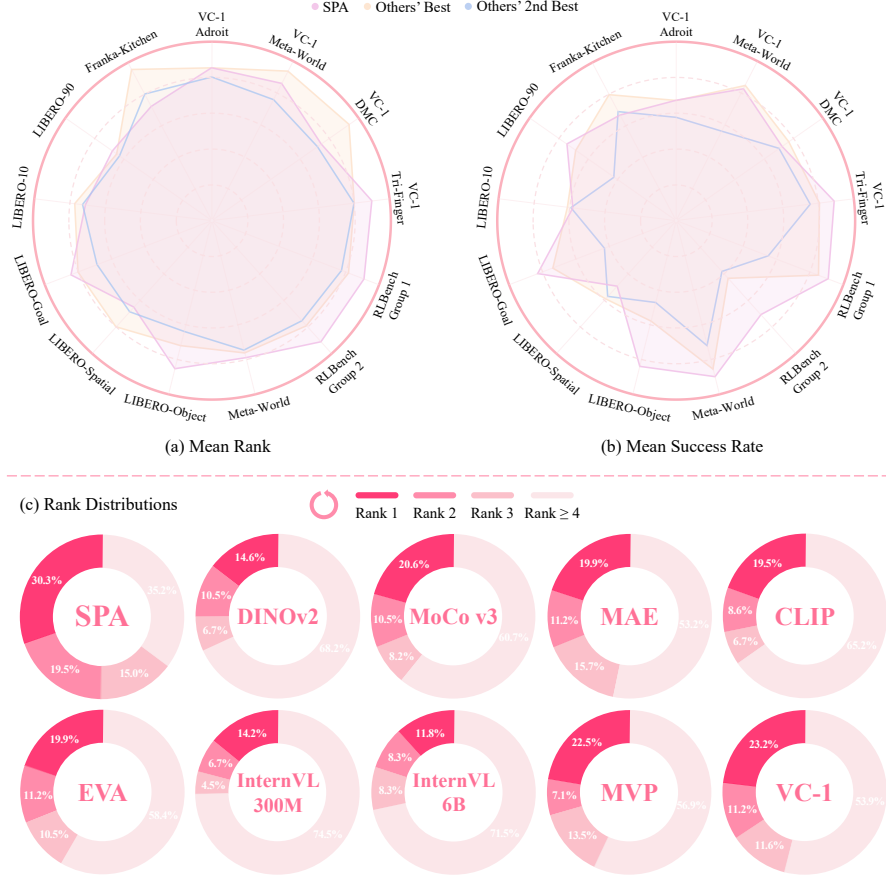


Figure 1: **Performance comparison across representations.** Above: (a) Mean rank and (b) mean success rate on benchmarks. Lines represent the performance of SPA, best, and second best performance on each benchmark. Bottom: Rank distributions for 268 individual tasks, showing proportions from rank 1 to rank  $\geq 4$  counterclockwise. Our model demonstrates superior overall performance.

To thoroughly validate our assumption and method, we collect 268 embodied tasks across 8 simulators using various policy methods. To our knowledge, this represents **the largest scale of embodied evaluation to date**. Previous work, such as R3M (Nair et al., 2022) and VC-1 (Majumdar et al., 2023), evaluated fewer than 20 tasks, potentially leading to incomplete or biased conclusions. Our evaluation spans both single-task and language-conditioned multi-task learning. We compare over 10 state-of-the-art representation learning methods, categorized as embodied-specific (Nair et al., 2022; Majumdar et al., 2023; Radosavovic et al., 2023), vision-centric (Oquab et al., 2023; Chen et al., 2021; He et al., 2022), and multi-modal (Radford et al., 2021; Fang et al., 2023b; Chen et al., 2024). Our method consistently outperforms others, underscoring the importance of 3D spatial awareness for embodied AI. Notably, multi-modal models like CLIP (Radford et al., 2021), consistently perform poorly. This holds even the vision-language model scales the ViT to 6B parameters (Chen et al., 2024). Through a camera pose estimation task and feature map visualization, we demonstrate that SPA has learned superior 3D spatial understanding. Further, we find that 3D awareness shows a positive correlation with embodied performance. Finally, we conduct several real-world tasks, where SPA also demonstrates superior performance. Our contribution can be summarized as follows.

- We propose a significant *spatial hypothesis*: 3D spatial awareness is crucial for embodied representation learning. Our experiments provide clear evidence for the hypothesis.
- We introduce SPA, a novel paradigm for representation learning in embodied AI. It enhances a vanilla Vision Transformer (ViT) with 3D awareness using differentiable neural rendering as the pre-text task on multi-view images.
- We conduct the largest evaluation benchmark for embodied representation learning, significantly larger than previous studies. It involves 268 tasks, 8 simulators, and over 10 SOTA methods with diverse downstream policies and task settings.

- Through extensive experiments in both simulators and real-world settings, SPA outperforms more than 10 SOTA representation learning methods, demonstrating its effectiveness.

## 2 METHODOLOGY

In this section, we first describe our process for handling multi-view image inputs and feature extraction in Sec. 2.1. Subsequently, we construct an explicit feature volume from these multi-view features, detailed in Sec. 2.2. Finally, we explain the image rendering from the feature volume and loss functions for network optimization in Sec. 2.3 and Sec. 2.4. Our pipeline is visualized in Fig. 2.

### 2.1 INPUT PROCESS AND FEATURE EXTRACTION

Given a set of multi-view images  $\mathbf{I} = \{I_1, I_2, \dots, I_N\}$ , where each  $I_i \in \mathbb{R}^{3 \times H \times W}$  and  $N \in \mathbb{Z}^+$ , we utilize a 2D image backbone  $F$ , such as a ViT. The images are processed separately through  $F$ , yielding latent features  $\mathbf{L} = \{l_1, l_2, \dots, l_N\}$ , where each  $l_i = F(I_i) \in \mathbb{R}^{L \times C}$ . Following MAE, we apply random masking to input images to enhance robustness, but without a ViT decoder and MAE’s pixel reconstruction objective. For each  $l_i$ , masked positions are filled with a mask token, and we concatenate the global class token with other patch tokens as read-out tokens similar to DPT (Ranftl et al., 2020). We then unpatchify them to obtain a latent feature map of size  $\frac{H}{P} \times \frac{W}{P}$ , where  $P$  is the ViT patch size. Finally, two simple upsampling layers transform this into a feature map  $M_i$  matching the input resolution. Each upsampling layer includes a convolution, a GELU (Hendrycks & Gimpel, 2016) activation, and a pixel shuffle layer (Shi et al., 2016) with an upscale factor of  $\sqrt{P}$ .

### 2.2 DYNAMIC VOLUME CONSTRUCTION

To enable multi-view interaction, we construct a 3D feature volume from multi-view feature maps,  $\mathbf{M}$ . Unlike the bird’s-eye view (BEV) construction in autonomous driving (Li et al., 2022), which usually relies on a fixed scene range around ego vehicle, our method dynamically adjusts the scene range based on the spatial extents of the environment to accommodate varying datasets. Specifically, the scene’s bounds are first estimated using available depth data, sparse points, or pre-defined rules. We then partition the scene into a volume of size  $X \times Y \times Z$ , with voxel size dynamically adjusted to capture either fine object details or larger environments. Voxel features,  $\tilde{\mathcal{V}}$ , are initialized with learnable positional embeddings. Each voxel is projected onto the multi-view feature maps using the known transformation matrix  $\mathbf{T}$ . Deformable attention (Zhu et al., 2021) is then applied, where the multi-view features act as keys and values, and the voxel features as queries. Finally, a 3D convolution refines the output volume features to obtain  $\mathcal{V}$ . The process can be formulated as:

$$\mathcal{V} = \text{Conv3D}(\text{DeformAttn}(\tilde{\mathcal{V}}, \mathbf{M}, \mathbf{T})). \quad (1)$$

### 2.3 DIFFERENTIABLE VOLUMETRIC RENDERING

After constructing the feature volume, we employ differentiable neural rendering (Mildenhall et al., 2021) to connect 2D and 3D domains. For better geometry representation, we utilize the implicit signed distance function (SDF) field modeling as in NeuS (Wang et al., 2021). The SDF represents the 3D distance from a query point to the nearest surface, implicitly capturing the 3D geometry.

Given a feature volume  $\mathcal{V}$ , we apply a shallow 3D CNN  $\phi$  to directly produce three outputs: an SDF feature volume  $\mathcal{S} \in \mathbb{R}^{X \times Y \times Z}$ , a spherical harmonic (SH) (Yu et al., 2021; Zhu et al., 2023a) coefficient field  $\mathcal{K} \in \mathbb{R}^{D \times X \times Y \times Z}$  (where  $D = 3 \cdot (l_{\max} + 1)^2$ ) for color rendering, and a semantic feature volume  $\mathcal{F} \in \mathbb{R}^{C_{\text{semantic}} \times X \times Y \times Z}$ :

$$\mathcal{S} \in \mathbb{R}^{X \times Y \times Z}, \quad \mathcal{K} \in \mathbb{R}^{D \times X \times Y \times Z}, \quad \mathcal{F} \in \mathbb{R}^{C_{\text{semantic}} \times X \times Y \times Z} = \phi(\mathcal{V}). \quad (2)$$

Unlike prior work (Huang et al., 2023; Zhu et al., 2023b; Yang et al., 2024a), which employs an MLP to compute the attributes of each sampled point individually, we directly apply a 3D CNN to  $\mathcal{V}$ . This eliminates the need for pointwise MLP computations, reducing redundant processing and enabling more efficient execution. Consequently, our approach leads to substantial improvements in both time and memory efficiency, especially when sampling a large number of points during rendering.

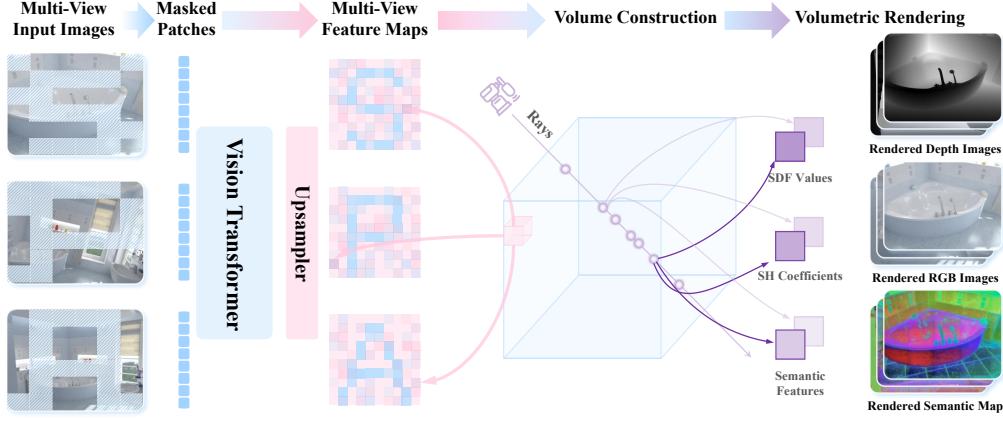


Figure 2: **Pipeline Overview.** Given multi-view images, we randomly mask patches and input the remaining into a Vision Transformer. The upsampled latent features generate multi-view feature maps, from which we construct a feature volume to derive SDF values, SH coefficients, and semantic features. We then render depth, RGB, and semantic maps for loss computation.

To render a 2D pixel  $i$ , we sample  $N$  ray points  $\{\mathbf{p}_j = \mathbf{o} + t_j \mathbf{d}_i \mid j = 1, \dots, N, t_j < t_{j+1}\}$  from ray  $\mathbf{r}_i$ , where  $\mathbf{o}$  is the camera origin and  $\mathbf{d}_i$  is the viewing direction. Attributes for each point are obtained via trilinear sampling:

$$s_j = \tau(\mathcal{S}, \mathbf{p}_j), \quad \mathbf{k}_j = \tau(\mathcal{K}, \mathbf{p}_j), \quad \mathbf{f}_j = \tau(\mathcal{F}, \mathbf{p}_j). \quad (3)$$

The SH vector  $\mathbf{k}_j = (k_l^m)_{0 \leq l \leq l_{\max}, -l \leq m \leq l}$ , where  $k_l^m \in \mathbb{R}$ , is used to compute view-dependent colors  $\hat{\mathbf{c}}_j$  by querying the SH basis functions  $Y_l^m : \mathbb{S}^2 \rightarrow \mathbb{R}$  based on the viewing direction  $\mathbf{d}_j$ :

$$\hat{\mathbf{c}}_j = \text{Sigmoid} \left( \sum_{l=0}^{l_{\max}} \sum_{m=-l}^l k_l^m Y_l^m(\mathbf{d}_j) \right). \quad (4)$$

Following the formulation in NeuS (Wang et al., 2021), the RGB color  $\hat{\mathbf{C}}_i$ , depth  $\hat{\mathbf{D}}_i$ , and semantic feature  $\hat{\mathbf{F}}_i$  for pixel  $i$  are computed by integrating the predicted values along the ray:

$$\hat{\mathbf{C}}_i = \sum_{j=1}^N w_j \hat{\mathbf{c}}_j, \quad \hat{\mathbf{D}}_i = \sum_{j=1}^N w_j t_j, \quad \hat{\mathbf{F}}_i = \sum_{j=1}^N w_j \hat{\mathbf{f}}_j, \quad (5)$$

where  $w_j = T_j \alpha_j$  is the occlusion-aware weight, with  $T_j = \prod_{k=1}^{j-1} (1 - \alpha_k)$  representing the accumulated transmittance and  $\alpha_j$  being the opacity value. Specifically,  $\alpha_j$  is computed as:

$$\alpha_j = \max \left( \frac{\sigma_s(s_j) - \sigma_s(s_{j+1})}{\sigma_s(s_j)}, 0 \right), \quad (6)$$

where  $\sigma_s(x) = (1 + e^{-sx})^{-1}$  is the sigmoid function modulated by a learnable parameter  $s$ .

## 2.4 LOSS FUNCTIONS

During pre-training, we randomly sample  $K$  pixels from multi-view inputs in each iteration. The rendering loss is calculated based on the differences between the input pixel values and the predicted values. For the semantic feature map, we use the feature map from AM-RADIO (Ranzinger et al., 2024) as supervision. Our framework has the capability to distill knowledge from multiple vision foundation models by adding multiple rendering heads. However, this paper does not explore that approach, as it is not the primary focus. The rendering loss is expressed as:

$$\mathcal{L}_{\text{render}} = \frac{1}{K} \sum_{i=1}^K \left( \lambda_{\text{color}} \cdot \|\mathbf{C}_i - \hat{\mathbf{C}}_i\| + \lambda_{\text{depth}} \cdot \|\mathbf{D}_i - \hat{\mathbf{D}}_i\| + \lambda_{\text{semantic}} \cdot \|\mathbf{F}_i - \hat{\mathbf{F}}_i\| \right). \quad (7)$$

Additionally, we incorporate the Eikonal regularization loss  $\mathcal{L}_{\text{eikonal}}$ , near-surface SDF supervision loss  $\mathcal{L}_{\text{sdf}}$ , and free space SDF loss  $\mathcal{L}_{\text{free}}$ , which are standard in neural surface reconstruction. Detailed definitions of these losses are provided in Appendix A. The total loss is defined as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{render}} + \lambda_{\text{eikonal}} \cdot \mathcal{L}_{\text{eikonal}} + \lambda_{\text{sdf}} \cdot \mathcal{L}_{\text{sdf}} + \lambda_{\text{free}} \cdot \mathcal{L}_{\text{free}}. \quad (8)$$



Figure 3: **Overview of our large-scale embodied evaluation.** We conduct the largest-scale evaluation of embodied representation learning to date. Our study encompasses 268 tasks across 8 simulators, including both single-task and language-conditioned multi-task settings. We evaluate diverse policy architectures and assess various state-of-the-art representation methods. This thorough evaluation allows us to provide a comprehensive and unbiased analysis of different representations.

### 3 LARGE-SCALE EMBODIED EVALUATION

Unlike the CV or NLP communities, where large-scale benchmarks are common, embodied representations have not been thoroughly assessed. The largest previous evaluation, VC-1 (Majumdar et al., 2023), includes only 17 tasks. This may lead to randomness and bias. Therefore, we have created **the largest embodied evaluation to date**, encompassing **268 tasks** across 8 simulators—**over 15 times larger** than VC-1’s evaluation. Additionally, unlike previous approaches (Majumdar et al., 2023; Nair et al., 2022; Radosavovic et al., 2023) that used a small MLP policy under single-task settings, our evaluation spans multiple policy types (*e.g.* MLP, diffusion, transformer) and includes both single-task and language-conditioned multi-task settings. This unprecedented scale and diversity ensure robust and convincing conclusions. During all evaluations, we adhere to standard practices by freezing the pre-trained representation model. Our detailed evaluation settings can be found in Appendix B. The overview of our evaluation is shown in Fig. 3.

We have included 3 *single-task benchmarks*:

- 1) **VC-1** (Majumdar et al., 2023) involves 4 selected simulators with 14 tasks in total: Adroit (AD) (Kumar, 2016), Meta-World (MW) (Yu et al., 2020), DMControl (DMC) (Tunyasuvunakool et al., 2020), and TriFinger (TF) (Wüthrich et al., 2020). We use a 3-layer MLP as the policy network.
- 2) **Franka Kitchen** (Gupta et al., 2019) involves 5 selected tasks. Each task spans two camera viewpoints and three random seeds. We utilize 25 demonstrations to train a 2-layer MLP policy.
- 3) **Meta-World** (Yu et al., 2020) involves 48 selected tasks of varying difficulty. We implemented the Diffusion Policy (Chi et al., 2023) on this benchmark and adhered to the setup in Ze et al. (2024) to generate 10 demonstrations for each single-task training, followed by evaluation through 20 rollouts.

We have also included 2 *language-conditioned multi-task benchmarks*:

- 1) **RLBench** (James et al., 2020) features 71 selected tasks that can be successfully executed. We divide the tasks into two groups according to their category defined by PolarNet (Chen et al., 2023). We employ RVT-2 (Goyal et al., 2024), the SOTA method on this benchmark, as our policy.
- 2) **LIBERO** (Liu et al., 2024) comprises 130 tasks across 5 suites: LIBERO-Spatial, LIBERO-Object, LIBERO-Goal, LIBERO-10, and LIBERO-90. We train a language-conditioned transformer policy provided by the original LIBERO on each suite with only 20 demonstrations per task.

### 4 TRAINING AND IMPLEMENTATION DETAILS

In this section, we present the step-by-step implementation and training of our SPA model. We first pre-train a ViT-base (ViT-B) backbone using a small dataset and evaluate this model on the VC-1 benchmark to examine the effects of hyperparameters (Sec. 4.1). We then compile several multi-view datasets, training ViT-B models on each to assess the impact of different datasets (Sec. 4.2). Finally, we integrate all factors and scale up both data and model size to train the strongest version of SPA using a ViT-large (ViT-L) backbone (Sec. 4.3). More details can be found in Appendix C.



#### 4.1 HYPERPARAMETER INVESTIGATION

We conduct hyperparameter tuning with a ViT-B model on ScanNet (Dai et al., 2017), and evaluate it on VC-1 benchmarks, as shown in Tab. 1. **1) Mask Ratio.** Our results indicate that a mask ratio of 0.5 is the most effective. **2) Loss Components.** As discussed in Sec. 2.4, our rendering loss consists of color, depth, and semantic components. We sequentially deactivate each and find that all three are valuable. However, deactivating the semantic loss has the least impact.

Table 1: **Influence of mask ratio and loss components.** C., D., and S. denote the color, depth, and semantic loss components, respectively.

Mask Ratio	Loss			VC-1 Benchmark				Mean S.R.
	C.	D.	S.	AD	MW	DMC	TF	
0.00	✓	✓	✓	53.3±4.6	88.5±5.7	57.5±2.6	74.1±0.6	70.36
0.25	✓	✓	✓	52.7±3.1	89.6±4.5	57.6±3.0	70.4±1.7	70.17
0.50	✓	✓	✓	53.3±4.2	88.8±1.6	60.1±3.1	72.6±0.7	<b>71.18</b>
0.75	✓	✓	✓	51.3±1.2	88.0±3.5	61.1±3.5	73.0±0.8	71.01
0.95	✓	✓	✓	51.3±1.2	85.6±4.0	62.5±5.3	73.1±0.2	70.67
0.50	✓	✗	✓	51.3±1.2	90.9±3.3	58.8±5.6	71.5±1.0	71.01
0.50	✗	✓	✓	52.0±2.0	89.3±3.3	53.9±4.3	70.9±1.3	68.71
0.50	✓	✓	✗	52.7±3.1	88.0±4.5	61.5±3.4	71.6±1.2	71.16

#### 4.2 DATASET INVESTIGATION

We collect several multi-view datasets. To investigate their effectiveness in SPA representation learning, we train a ViT-B model on one or two of the datasets, keeping the total training steps constant, and assess performance on the VC-1 benchmarks. For simplicity, semantic rendering is disabled. The datasets investigated are listed in the first column of Tab. 2. Most datasets provide ground-truth depth, which we use for supervision. As our findings above reveal that depth supervision is helpful, for datasets lacking ground-truth depth, we employ a depth estimation model. For instance, Droid (Khazatsky et al., 2024) only offers binocular images, so we apply CroCo-Stereo (Weinzaepfel et al., 2023) for dense depth estimation. Additionally, due to inaccurate camera poses in Droid, we treat its data as single-view inputs. The results are presented in Tab. 2, with further details in Appendix C. Our analysis reveals that some datasets can be detrimental. For example, although RH20T (Fang et al., 2023a) is a large-scale robotic dataset, its lack of visual diversity—stemming from data collected in the same lab—negatively impacts representation learning.

Table 2: **Influence of different datasets.** We present the performance results on the VC-1 benchmark. *Mean S.R.* refers to the mean success rate across all individual tasks.

Datasets	AD	MW	DMC	TF	Mean S.R.
ScanNet (Dai et al., 2017)	52.67±4.11	90.93±3.22	65.11±1.31	70.75±1.08	73.68
ScanNet++ (Yeshwanth et al., 2023)	56.00±2.83	89.87±4.20	62.24±4.51	71.28±0.38	72.51
Arkitscenes (Baruch et al., 2021)	50.67±5.73	89.87±4.59	60.51±2.55	66.54±0.13	70.45
Droid (Khazatsky et al., 2024)	53.33±5.25	90.40±4.90	60.99±3.72	73.28±0.61	72.16
Hypersim (Roberts et al., 2021)	52.67±4.11	88.80±3.27	60.84±2.06	72.29±0.47	71.29
Hypersim + ADT (Pan et al., 2023)	52.00±2.83	87.20±2.30	63.61±1.04	70.83±0.13	71.41
Hypersim + S3DIS (Armeni et al., 2017)	49.33±0.94	94.13±2.04	64.57±3.91	71.74±0.75	73.98
Hypersim + Structured3D (Zheng et al., 2020)	46.67±4.11	80.27±7.72	58.02±2.34	65.05±0.40	65.35
Hypersim + RH20T (Fang et al., 2023a)	47.33±1.89	86.93±4.99	57.01±4.35	64.28±0.46	67.35
Hypersim + ASE (Avetisyan et al., 2024)	47.33±4.11	87.73±3.39	60.62±4.14	68.59±0.30	69.54

#### 4.3 PUT ALL TOGETHER

Based on the previous analyses, we proceed to pre-train the final version of SPA. We use a mask ratio of 0.5 and enable all three rendering losses. Following Ponder (Huang et al., 2023), we set the weight for the RGB loss to 10, the weights for the depth and semantic losses to 1, and use  $\lambda_{\text{eikonal}} = 0.01$ ,  $\lambda_{\text{sdf}} = 10$ , and  $\lambda_{\text{free}} = 1$ . The volume size is  $128 \times 128 \times 32$ . For stable training, we apply the Exponential Moving Average (EMA) technique with a decay of 0.999. We use AdamW (Loshchilov et al., 2017) as the optimizer with a weight decay of 0.04 and a learning rate of  $8e^{-4}$ . OneCycle (Smith & Topin, 2019) learning rate scheduler is adopted. We utilize 80 NVIDIA A100-SXM4-80GB GPUs, each with a batch size of 2, and accumulate gradients over 8 batches, resulting in a total effective batch size of  $2 \times 8 \times 80 = 1280$ . Training is conducted over 2000 epochs, sampling each dataset to match the size of ADT per epoch. The datasets used for the final version include ScanNet, ScanNet++, ADT, S3DIS, Hypersim, and Droid.

## 5 EXPERIMENT RESULTS

In this section, we present the results of our large-scale evaluation. Our experiments are designed to address the following research questions:

Table 3: **Summary of different representation learning methods.** ‘#Param.’ is the total parameters of the encoder, while ‘#Frames’ indicates the total number of image frames used during pre-training.

Method	Vision-Centric			Multi-Modal				Embodied-Specific		
	MoCoV3 (Chen et al., 2020b)	MAE (He et al., 2022)	DINOv2 (Oquab et al., 2023)	CLIP (Radford et al., 2021)	EVA (Fang et al., 2023b)	InternViT-300M (Chen et al., 2024)	InternViT-6B (Chen et al., 2024)	MVP (Radosavovic et al., 2023)	VC-1 (Majumdar et al., 2023)	SPA (Ours)
Is Vanilla?	✓	✓	✗	✓	✓	✗	✗	✓	✓	✓
Input Size	224	224	224	224	224	448	224	256	224	224
Patch Size	16	16	14	14	14	14	14	16	16	16
#Param.	303M	303M	303M	303M	303M	303M	5.9B	303M	303M	303M
#Frames	1.28M	1.28M	1.2B	400M	14M	5.0B	5.0B	4.5M	5.6M	3.8M

Table 4: **Comparison of different representation learning methods.** ‘OOM’ indicates InternViT-6B encountered an out-of-memory error during evaluation. The best and second-best results are **bolded** and underlined respectively. The number in parentheses denotes the number of tasks.

Method		Vision-Centric			Multi-Modal				Embodied-Specific		
		MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT-300M	InternViT-6B	MVP	VC-1	SPA (Ours)
VC-1	AD (2)	58.7±7.0	58.0±2.0	47.3±3.1	48.7±3.1	58.0±6.0	53.3±3.1	60.0±9.2	53.3±4.2	54.0±4.0	<b>60.0±4.0</b>
	MW (5)	88.8±5.0	90.0±4.6	84.0±3.7	77.1±3.2	90.7±0.9	84.0±3.7	89.1±1.2	<b>93.6±5.2</b>	87.5±3.8	93.3±2.0
	DMC (5)	67.3±3.3	<b>74.4±1.8</b>	64.5±2.5	53.9±3.6	62.7±2.8	53.3±0.4	66.3±3.2	69.4±2.6	65.3±3.6	<u>71.1±5.0</u>
	TF (2)	67.9±0.2	73.0±0.5	68.5±0.4	56.1±1.6	67.2±0.2	65.2±1.6	70.7±0.9	<u>73.2±0.8</u>	70.9±1.1	<b>73.6±2.0</b>
RLBench	Group 1 (35)	73.7	78.3	78.2	76.8	75.2	74.1	OOM	76.2	<u>80.1</u>	<b>80.5</b>
	Group 2 (36)	54.2	<u>57.7</u>	56.1	55.7	57.0	54.9	OOM	56.3	55.7	<b>61.2</b>
Meta-World (48)		<b>69.3±1.5</b>	67.8±1.7	56.3±0.6	66.7±1.7	63.7±1.3	57.5±1.7	OOM	66.4±1.7	68.6±1.5	69.2±1.7
LIBERO	Object (10)	65.3±8.0	71.7±13.1	64.7±9.9	50.2±7.0	<u>73.2±6.0</u>	67.7±6.0	58.0±10.6	63.7±4.8	69.7±7.2	<b>76.7±5.3</b>
	Spatial (10)	40.5±0.9	57.2±2.9	36.3±11.8	32.2±0.6	<b>59.3±7.7</b>	48.3±6.4	42.0±10.3	58.0±6.2	50.5±7.5	50.0±3.8
	Goal (10)	49.2±8.1	54.3±6.0	22.2±2.3	30.3±3.2	56.8±2.9	58.8±4.5	33.2±2.0	<u>63.8±2.8</u>	57.5±6.6	<b>65.3±2.5</b>
	10 (10)	34.2±3.8	<b>41.2±4.5</b>	28.3±3.0	27.5±3.9	43.3±2.8	38.2±1.3	34.3±4.6	<u>39.0±0.9</u>	39.7±3.5	40.2±3.6
	90 (90)	30.0±1.4	29.9±2.0	27.5±2.2	29.4±2.0	31.3±2.3	23.8±1.8	27.1±2.1	<u>32.1±3.5</u>	30.6±3.3	<b>32.2±1.6</b>
Franka-Kitchen (5)		<b>48.3±4.7</b>	<u>42.7±2.6</u>	40.9±6.4	30.8±3.3	37.3±1.3	28.5±1.7	OOM	34.3±6.1	37.5±3.5	40.6±1.9
Mean S.R. ↑		81.67	<u>85.13</u>	75.18	77.10	83.84	75.41	30.65	84.85	84.69	<b>88.63</b>
Mean Rank ↓		4.51	<u>4.07</u>	5.61	5.17	4.37	5.92	7.57	4.24	4.13	<b>3.20</b>

**Q1:** How does SPA compare to other methods in our large-scale embodied evaluation?

**Q2:** What insights do we gain about various representation learning approaches from our evaluation?

**Q3:** Does SPA really learn enhanced 3D awareness that results in improved embodied representation?

**Q4:** Can SPA facilitate robot learning in real-world environments in a zero-shot manner?

## 5.1 OVERALL COMPARISONS (Q1, Q2)

**Evaluation Metrics.** We follow prior work (Majumdar et al., 2023; Zhu et al., 2024) in reporting two metrics: *Mean Success Rate (Mean S.R.)* and *Mean Rank*. Mean S.R. is the average success rate across all tasks, indicating overall performance, while Mean Rank reflects the average ranking of each method’s success rate across tasks, providing a measure of relative performance. Since RLBench has fixed train and test sets, we report a single result for this benchmark.

**Baselines.** We evaluate 9 state-of-the-art representation learning models, all using the same ViT-L backbone, categorized into vision-centric, multi-modal, and embodied-specific. This also includes a comparison with a 6B-parameter multi-modal model (Chen et al., 2024). Details of the models are summarized in Tab. 3. The results on each benchmark are shown in Tab. 4. For detailed results on each task and each random seed, please refer to Appendix D. We also have visualized the performance radar chart and the per-task rank distributions in Fig. 1.

**Finding 1:** We observe that SPA demonstrates superior performance in both mean success rate and mean rank. While no method ranks first across all individual benchmarks, consistent with the findings by Majumdar et al. (2023), SPA achieves the best or second-best mean success rate in **11 out of 13 benchmarks**. Additionally, it ranks in the top 3 for **over 65.5% of individual tasks**, surpassing the second and third highest percentages of 46.8% for MAE and 46.0% for VC-1, respectively. These trends demonstrate the robustness and superiority of SPA.

**Finding 2:** We observe that for vision-centric methods, superior performance on vision tasks does **not** necessarily translate to better embodied performance. Despite using 10 times more data, DINOv2 performs worse than MoCoV3 and MAE. Notably, MAE performs exceptionally well, likely due to its reconstruction objective, which enhances *2D spatial awareness*. Interestingly, methods like MVP and VC-1, which are MAE models pre-trained on human interaction data, show **no clear advantage**

Table 5: Additional comparisons of ViT-base models on VC-1 benchmarks.

Methods		DINOv2-B (Oquab et al., 2023)	MAE-B (He et al., 2022)	R3M-B (Nair et al., 2022)	VC-1-B (Majumdar et al., 2023)	STP-B (Yang et al., 2024b)	Voltron-B (Karamcheti et al., 2023)	Theia-B (Shang et al., 2024)	SPA-B (Ours)
Is Vanilla?		✗	✓	✓	✓	✓	✗	✓	✓
Embodied?		✗	✗	✓	✓	✓	✓	✓	✓
VC-1	AD	36.67±2.31	52.67±3.06	48.00±6.93	50.00±5.29	52.00±2.00	46.67±4.62	53.33±5.03	52.00±3.46
	MW	60.80±0.80	88.80±4.00	59.20±5.60	86.67±0.92	92.00±1.39	84.00±3.20	89.07±3.23	92.00±4.16
	DMC	35.19±4.87	62.39±4.97	49.57±4.85	60.92±0.70	61.40±2.86	56.36±2.01	64.98±3.42	64.21±3.52
	TF	54.50±1.16	70.78±0.17	56.18±7.00	72.33±0.69	67.96±0.95	74.26±1.57	69.41±0.60	73.06±0.51
Mean S.R.		47.31	71.63	54.37	70.19	71.92	69.50	<u>72.55</u>	<b>73.66</b>

Table 6: Zero-shot camera pose estimation. SPA demonstrates strong 3D awareness.

Error	MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT-300M	InternViT-6B	MVP	VC-1	SPA(Ours)
Trans. ( $\times e^{-2}$ )	2.29±0.07	2.15±0.07	6.55±0.07	4.21±0.37	5.49±0.24	4.62±0.14	5.39±0.41	2.15±0.12	2.02±0.07	<b>1.65±0.09</b>
Rot. ( $\times e^{-1}$ )	0.79±0.07	0.73±0.03	2.12±0.25	1.52±0.08	1.83±0.09	1.83±0.08	1.91±0.12	0.77±0.05	0.72±0.01	<b>0.61±0.01</b>

over ImageNet (Deng et al., 2009) pre-trained MAE. This suggests that while human activity data may seem more relevant, data diversity and thorough convergence are more critical.

**Finding 3:** Multimodal methods **generally perform poorly** in embodied evaluations, except EVA, which combines image-language contrastive techniques with MAE reconstruction. Furthermore, InternViT-6B, despite having significantly more model parameters, does not demonstrate superiority and even performs worse on some benchmarks compared to InternViT-300M. This indicates that current scaling properties of multimodal approaches do not effectively translate to embodied AI.

**Finding 4:** Focusing on a single benchmark can **lead to highly biased conclusions**. For instance, ImageNet pre-trained methods (e.g. MoCoV3 and MAE) perform exceptionally well on the Franka Kitchen benchmark, suggesting a minimal domain gap between ImageNet and Franka Kitchen observations. Moreover, despite being based on MAE, previous SOTA embodied representations like MVP and VC-1 do not consistently outperform the original ImageNet version. These observations underscore the importance of our large-scale embodied evaluation.

## 5.2 ADDITIONAL COMPARISONS (Q1)

We primarily compare with SOTA methods using the ViT-L backbone, which is commonly available and pre-trained on large-scale datasets. However, some embodied-specific models are only offered in ViT-B variants. Therefore, we provide additional comparisons with several ViT-B models in Tab. 5. Our ViT-B version, SPA-B, also outperforms other baselines. Furthermore, when compared to SPA-L on VC-1 benchmarks, the mean success rate increases by 4.16 (73.66  $\rightarrow$  77.82). This indicates that increasing the model size positively impacts SPA’s performance.

## 5.3 STUDY ON 3D AWARENESS OF SPA (Q3)

Firstly, we aim to provide clear evidence that the performance improvements of SPA are due to its 3D awareness. To demonstrate this, we conducted two additional ablation studies on the VC-1 benchmarks: 1) To determine whether the performance gain is due to SPA’s pre-training objectives or the datasets used, we continue pre-training the ImageNet pre-trained MAE-B (the most competitive method besides SPA) on the same datasets used by SPA-B, referring to this model as SPA-MAE. Hyperparameters, including mask ratio and batch size, are kept at their default settings, and both the ImageNet pre-trained encoder and decoder weights are initially loaded. 2) Since SPA uses the feature map of RADIO for semantic rendering supervision, we also evaluate the original RADIO (653M parameters) and its efficient version, E-RADIO (391M parameters). Results are presented in Tab. 7.

**Finding 5:** The 3D-aware pre-training objective significantly enhances SPA’s performance. It surpasses the single-image naive MAE with the same data. Notably, SPA learns superior representations compared to its semantic rendering teacher by a substantial margin.

Moreover, we provide both quantitative and qualitative evidence to demonstrate that SPA has acquired 3D awareness. For qualitative analysis, we visualize the zero-shot feature maps on mul-

Table 7: Additional ablations on VC-1.

Methods		SPA-B	SPA-MAE	RADIO	E-RADIO
VC-1	AD	52.00±3.46	55.33±3.06	55.33±3.06	56.67±2.31
	MW	92.00±4.16	90.67±6.00	72.00±9.23	83.47±4.11
	DMC	64.21±3.52	63.85±3.60	67.38±7.35	62.92±4.24
	TF	73.06±0.51	70.14±0.98	71.75±0.14	68.44±1.19
Mean S. R.		<b>73.66</b>	73.11	67.93	70.16



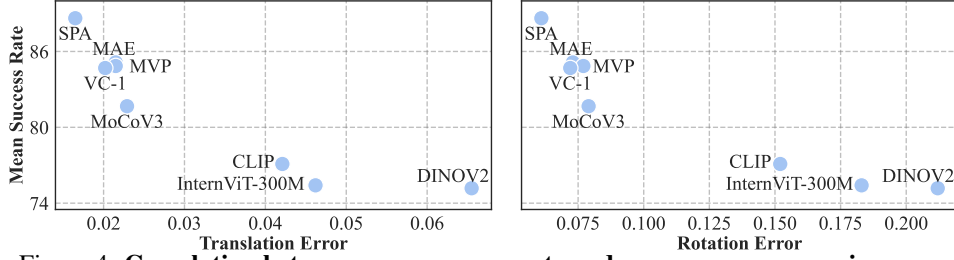


Figure 4: **Correlation between mean success rate and camera pose regression error.**

tiview images of different encoder outputs, as shown in Fig. 5. The images are taken from the unseen Arkitscenes dataset. For quantitative analysis, we evaluate the zero-shot 3D awareness of various methods using a camera pose estimation task on the NAVI dataset (Jampani et al., 2023). Specifically, given a pair of images from different viewpoints, we use a frozen encoder to extract features and concatenate them. A small MLP then regresses the relative camera pose and we report rotation and translation errors in Tab. 6. Details are in Appendix E. While El Banani et al. (2024) has explored 3D awareness of different vision models, their context differs. Their tasks can allow strong semantic models like DINOv2 to ‘cheat’. For example, multiview correspondence can be achieved through semantic matching, and the relative depth estimation task involves transforming normalized values into discrete bins, resembling a per-pixel classification task. Additionally, they emphasize fine-grained dense local context, whereas, embodied AI focuses more on sparse, global information (Nair et al., 2022). Thus, we believe camera pose estimation, which predicts a global ‘pose’ from observations, is more relevant to embodied AI, where a policy must predict a global ‘action’.

**Finding 6:** We observe that SPA outperforms all other methods in zero-shot camera pose estimation. It achieved an **18.3% improvement in translation** and a **15.3% reduction in rotation error** compared to the second-best model. Additionally, we identify a **clear positive correlation** between camera pose estimation and embodied evaluation performance, as demonstrated in Fig. 4. This finding supports our spatial hypothesis and may offer valuable insights for future research on embodied representation.

**Finding 7:** The feature map visualization provides clear evidence that SPA has learned multi-view consistent knowledge, demonstrating its 3D awareness. Additionally, the features produced by SPA are **cleaner and more coherent**. Though VC-1 also generates smooth features, they are *not consistent across viewpoints*. The feature maps from the multi-modal approach are highly noisy and lack details.

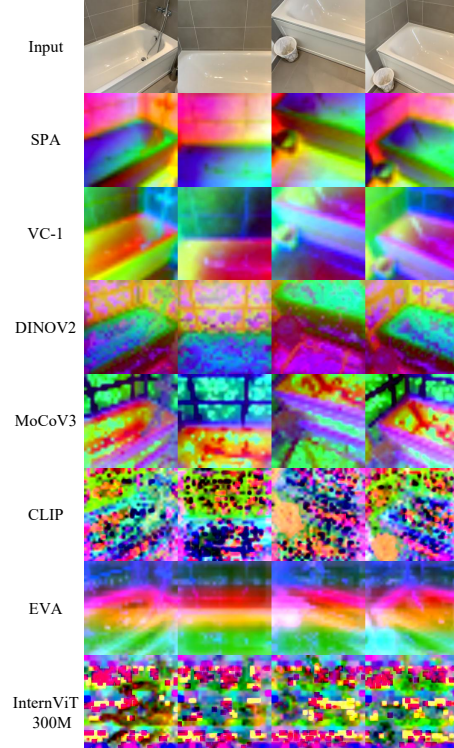


Figure 5: **Feature map visualization.**

#### 5.4 REAL-WORLD EXPERIMENTS (Q4)

We conduct several real-world experiments to further investigate the generalization ability of different representations. Specifically, we utilize the open-sourced Low-Cost Robot Arm (Koch, 2024) to learn real-world tasks from pixels, with only 50 demonstrations per task using different frozen pre-trained representations. The robot performed two single-arm tasks: (1) picking a cube, and (2) stacking a yellow cube on a pink cube, as well as one dual-arm task: folding a cloth in half. Refer to Fig. 6 for illustrations and Appendix F for more details. We evaluate each task with 25 rollouts, with

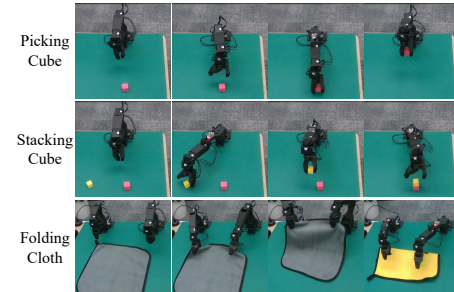


Figure 6: **Real-world task illustrations.** We evaluate each task with 25 rollouts, with

Table 8: Real-world experiment results.

Methods	MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT-300M	InternViT-6B	MVP	VC-1	SPA (Ours)
Picking Cube	28.00	64.00	20.00	28.00	56.00	32.00	52.00	36.00	40.00	64.00
Stacking Cube	16.00	32.00	4.00	16.00	8.00	8.00	36.00	20.00	16.00	48.00
Folding Cloth	48.00	64.00	32.00	24.00	28.00	48.00	44.00	64.00	60.00	84.00
Mean S.R.	30.67	53.33	18.67	22.67	30.67	29.33	44.00	40.00	38.67	<b>65.33</b>

the results presented in Tab. 8. SPA consistently performs better on real-world tasks, suggesting that SPA’s pre-trained representations can robustly adapt to real-world environments without finetuning.

## 6 RELATED WORK

**Representation Learning for Computer Vision.** Recent advances in computer vision have increasingly focused on unsupervised and self-supervised learning to utilize large amounts of unlabeled data. Techniques like contrastive learning (Chen et al., 2020a; 2021; 2020b; He et al., 2020), masked autoencoders (He et al., 2022; Feichtenhofer et al., 2022; Bachmann et al., 2022; Tong et al., 2022; Wang et al., 2023), and self-distillation (Caron et al., 2021; Oquab et al., 2023; Ranzinger et al., 2024) have shown that effective representations can be learned without supervision. Moreover, multi-modal pre-training approaches (Radford et al., 2021; Fang et al., 2023b; Chen et al., 2024) leverage language to learn more comprehensive representations. These developments have significantly improved transfer learning capabilities while also displaying zero-shot abilities.

**Representation Learning for Embodied AI.** Inspired by computer vision, recent work has applied methods such as contrastive learning (Nair et al., 2022; Yang et al., 2023) and masked autoencoders (Radosavovic et al., 2023; Majumdar et al., 2023; Karamcheti et al., 2023; Yang et al., 2024b) to embodied AI. However, these approaches often overlook the unique challenges of embodied tasks, focusing primarily on semantic knowledge. However, many of these methods primarily adapt techniques from computer vision and focus predominantly on learning semantic knowledge, often overlooking the unique requirements of embodied AI tasks. Prior studies (Zhu et al., 2024; Ze et al., 2024; Wang et al., 2024b;a) have highlighted the importance of 3D spatial structure for improving robotic learning, though point clouds are difficult to scale. Despite this, point clouds are challenging to obtain and encode, limiting their scalability. In this work, we propose a spatial hypothesis: while semantic understanding is crucial, 3D spatial awareness is even more important, and we demonstrate how a standard 2D backbone can integrate 3D spatial awareness.

**Neural Rendering.** Recent advances in 3D vision, particularly in neural rendering (Mildenhall et al., 2021), have enabled the encoding of scenes using neural networks, which support differentiable rendering and reconstruction. Alongside improvements in neural rendering techniques themselves (Wang et al., 2021; Zhu et al., 2023a; Gropp et al., 2020; Ortiz et al., 2022; Wang et al., 2022), the Ponder series (Huang et al., 2023; Zhu et al., 2023b; Yang et al., 2024a) was the first to apply differentiable neural rendering for representation learning. However, these works primarily focus on point cloud perception or autonomous driving scenarios Yang et al. (2024a); Wang et al. (2024c). To the best of our knowledge, our work is the first to apply neural rendering for embodied AI representation learning using a standard 2D backbone, marking a novel contribution to this area of research.

## 7 CONCLUSION AND LIMITATIONS

In this work, we propose that 3D spatial awareness is crucial for embodied AI and introduce SPA, a novel framework that pre-trains a standard ViT backbone with 3D spatial awareness. To validate our hypothesis, we conduct the largest-scale embodied evaluation to date, over 15 times larger than previous studies. Our experiments demonstrate the clear superiority of SPA and highlight the importance of 3D awareness. Despite strong results across simulated and real robotic tasks, limitations remain. Our evaluation is currently restricted to imitation learning (specifically behavior cloning), and exploring SPA’s performance in other settings, such as reinforcement learning, presents an exciting future direction. Additionally, SPA currently focuses on static multi-view scenes; extending it to dynamic, temporal scenarios could enhance its generality. Lastly, while we use the ViT encoder for fair comparison, the volume decoder’s multi-view interaction knowledge could be leveraged in policy learning, offering further potential for improvement.

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## A ADDITIONAL RENDERING LOSSES

Here we detail the three additional rendering losses we have applied in Sec. 2.4.

**Eikonal Regularization Loss.** The Eikonal regularization loss, denoted as  $\mathcal{L}_{\text{eikonal}}$ , is a widely used loss function for the regularization of signed distance functions (SDFs) (Gropp et al., 2020). It is defined as:

$$\mathcal{L}_{\text{eikonal}} = \frac{1}{N_r N_p} \sum_{i=1}^{N_r} \sum_{j=1}^{N_p} (\|\nabla s(\mathbf{p}_{i,j})\| - 1)^2, \quad (9)$$

where  $\nabla s(\mathbf{p}_{i,j})$  represents the gradient of the SDF  $s$  at the location  $\mathbf{p}_{i,j}$ . Since the SDF is a distance measure,  $\mathcal{L}_{\text{eikonal}}$  encourages the gradients to have unit norm at the query point.

**Near-Surface and Free Space Loss for SDF.** To improve SDF estimation, we incorporate additional approximate SDF supervision, similar to iSDF (Ortiz et al., 2022) and GO-Surf (Wang et al., 2022). Specifically, for near-surface points, the difference between rendered depth and ground-truth depth serves as pseudo-SDF ground-truth supervision. For points far from the surface, a free space loss is used to further regularize the SDF values.

To compute the approximate SDF supervision, we define an indicator  $b(z)$  for each sampled ray point with ray length  $z$  and corresponding ground-truth depth  $D$ :

$$b(z) = D - z. \quad (10)$$

The value  $b(z)$  can be considered a credible approximate SDF value when it is small. Let  $t$  be a user-defined threshold, set to 0.05 in our experiments. For sampled ray points satisfying  $b(z) \leq t$ , we apply the near-surface SDF loss to constrain the SDF prediction  $s(z_{i,j})$ :

$$\mathcal{L}_{\text{sdf}} = \frac{1}{N_r N_p} \sum_{i=1}^{N_r} \sum_{j=1}^{N_p} |s(z_{i,j}) - b(z_{i,j})|. \quad (11)$$

For the remaining sampled ray points, we utilize a free space loss:

$$\mathcal{L}_{\text{free}} = \frac{1}{N_r N_p} \sum_{i=1}^{N_r} \sum_{j=1}^{N_p} \max\left(0, e^{-\alpha \cdot s(z_{i,j})} - 1, s(z_{i,j}) - b(z_{i,j})\right), \quad (12)$$

where  $\alpha$  is set to 5, following Ortiz et al. (2022); Wang et al. (2022). Due to the presence of noisy depth images,  $\mathcal{L}_{\text{sdf}}$  and  $\mathcal{L}_{\text{free}}$  are applied only to rays with valid depth values.

In our experiments, we adopt a similar weighting scheme to GO-Surf (Wang et al., 2022), setting  $\lambda_C = 10.0$ ,  $\lambda_D = 1.0$ ,  $\lambda_{\text{sdf}} = 10.0$ , and  $\lambda_{\text{free}} = 1.0$ . We observe that the Eikonal term can lead to overly smooth reconstructions, so we use a small weight of 0.01 for the Eikonal loss.

## B EVALUATION SETUPS

Here we detail the setups of our large-scale evaluation in Sec. 3.

### B.1 SINGLE-TASK BENCHMARKS

**VC-1 (Majumdar et al., 2023).** This benchmark includes several simulators. We selected four: Adroit (Kumar, 2016), Meta-World (Yu et al., 2020), DMControl (Tunyasuvunakool et al., 2020), and TriFinger (Wüthrich et al., 2020). The Adroit subset focuses on dexterous manipulation with 2 tasks. The Meta-World subset addresses two-finger gripper manipulation with 5 tasks. The DMControl subset is for locomotion control, also with 5 tasks. The TriFinger subset targets three-finger manipulation with 2 tasks. For all tasks, we use a 3-layer MLP as the policy network for each single-task training, following the original implementation. Each task is trained with 100

demonstrations, except for 25 on Meta-World, and evaluated 50 times using the specific seeds 100, 200, and 300. The [CLS] token of a frozen pre-trained ViT is used as the observation feature. All hyper-parameters are kept the same with the original implementation.

**Franka Kitchen (Gupta et al., 2019).** Franka-Kitchen is a MuJoCo-modeled simulation environment with a Franka robot in a kitchen scene. Its action space is the 9-dimensional joint velocity with 7 DoF for the arm and 2 DoF for the gripper. Following previous works (Nair et al., 2022; Karamcheti et al., 2023), we evaluate five tasks: Sliding Door, Turning Light On, Opening Door, Turning Knob, and Opening Microwave. Each task spans two camera viewpoints and three random seeds. Similar to the evaluation scheme in VC-1, we utilize 25 demonstrations to train a policy model, which is a 2-layer MLP with hidden sizes [256, 256] preceded by a BatchNorm.

**Meta-World (Yu et al., 2020).** This benchmark comprises a series of tasks in which an agent directs a Sawyer robot arm to manipulate objects in a tabletop environment. We selected 48 tasks, encompassing easy, medium, and hard levels. We implemented the Diffusion Policy (Chi et al., 2023) on this benchmark and adhered to the setup in Ze et al. (2024) to generate 10 demonstrations for each single-task training, followed by evaluation through 20 rollouts. The average results across three fixed seeds (100, 200, 300) are reported. The [CLS] token from a frozen pre-trained ViT serves as the observation feature.

## B.2 LANGUAGE-CONDITIONED MULTI-TASK BENCHMARKS

**RLBench (James et al., 2020).** This benchmark is a prominent language-conditioned multi-task robot learning framework. PolarNet (Chen et al., 2023) has categorized all tasks into 9 groups. We selected 71 tasks from RLBench that can be successfully executed and split them into two groups uniformly on categories: Group 1 with 35 tasks and Group 2 with 36 tasks. Each task includes 100 training demonstrations and 25 testing rollouts. For each group, we train a language-conditioned multi-task agent. We employ RVT-2 (Goyal et al., 2024), the state-of-the-art (SOTA) method on this benchmark, as our policy. RVT-2 takes multiple images rendered from point clouds as inputs and uses a convolutional block to generate feature maps. We substitute the convolutional block with different pre-trained ViTs, unpatchifying the latent vectors concatenated with the global [CLS] token to obtain feature maps. All other architectures and hyperparameters remain consistent with the original RVT-2 implementation.

**LIBERO (Liu et al., 2024).** Built upon Robosuite (Zhu et al., 2020), LIBERO (Liu et al., 2024) generates a total of 130 language-conditioned tasks across five suites: LIBERO-Spatial, LIBERO-Object, LIBERO-Goal, LIBERO-10, and LIBERO-90. Each suite contains 10 tasks, except for LIBERO-90, which includes 90 tasks. We train a language-conditioned multi-task policy for each suite, adopting the transformer policy provided by LIBERO. The image encoders are modified from default CNNs to frozen pre-trained ViTs, utilizing the [CLS] token for feature extraction. To expedite policy training, we use only 20 demonstrations per task and forgo augmentations, allowing for pre-extraction of all image features during training. After training for 25 epochs, the checkpoints from the 20th and 25th are evaluated with 20 rollouts per task, and the best checkpoint’s performance is taken. Finally, the results are averaged on 3 random seeds.

## C MORE IMPLEMENTATION DETAILS

### C.1 DATASET DETAILS

The datasets used for SPA include ScanNet, ScanNet++, Hypersim, ADT, S3DIS, and Droid.

**ScanNet** consists of 1.89 million frames in total. Each epoch includes 1.5 times the dataset size. For each scene, a random starting frame is selected, followed by the sampling of 1 to 8 frames at random, with an interval of 8 frames between them.

**ScanNet++** comprises 0.11 million frames. Each epoch includes 5 times the dataset size. For each scene, a random starting frame is selected, followed by the sampling of 1 to 8 frames at random, with an interval of 5 frames between them.

**Hypersim** contains 0.03 million frames. Each epoch includes 8 times the dataset size. For each scene, we randomly select 1 to 8 continuous frames.

**ADT** consists of 0.0015M frames in total. Each epoch includes 1 times the dataset size. For each scene, 1 to 8 continuous frames are randomly selected.

**S3DIS** consists of 0.015 million frames. Each epoch includes 5 times the dataset size. For each scene, a random starting frame is selected, followed by the sampling of 1 to 8 frames at random, with an interval of 5 frames between them.

**Droid** contains a large number of videos, but due to the high similarity between frames, the videos are first downsampled by a factor of 15 during pre-processing, resulting in 1.78 million frames. Since Droid does not provide depth data, we utilize Croco-Stereo [Weinzaepfel et al. \(2023\)](#) to estimate dense depth maps for rendering supervision. Additionally, due to the significant noise in the camera pose data, only a single frame is sampled at a time during training.

During pre-training, we first resize the multi-view input images to slightly larger than  $224 \times 224$ , and then randomly crop them to a final size of  $224 \times 224$ . Random photometric distortions with a probability of 0.5 are applied for augmentation, including brightness ranging from 0.875 to 1.125, contrast ranging from 0.5 to 1.5, saturation ranging from 0.5 to 1.5, and hue ranging from -0.05 to 0.05. Frames with very small valid depth areas or scene boxes are filtered out.

For semantic rendering supervision, we observe that using larger image sizes improves the quality of feature maps generated by RADIO. Consequently, we resize the images to  $1024 \times 1024$  before feeding them into RADIO, which outputs a feature map of size  $64 \times 64$ . We then apply bilinear sampling to query the semantic feature labels for each pixel.

## C.2 PRE-TRAINING DETAILS

For stability during pre-training, we apply the Exponential Moving Average (EMA) with a decay rate of 0.999. The model is trained for 2000 epochs on 80 NVIDIA A100-80G GPUs, using a gradient clipping threshold of 1.0. Each GPU processes a batch size of 2, with 8 gradient accumulation steps, resulting in a total effective batch size of  $2 \times 80 \times 8 = 1280$ . We employ the AdamW optimizer with a weight decay of 0.04. The base learning rate is set to  $5 \times 10^{-6}$ , and the actual learning rate is scaled by a factor of 8 times the effective batch size. A OneCycle learning rate scheduler is used, with a percentage start of 0.05, a divide factor of 100, and a final divide factor of 1000.

To facilitate faster convergence and improve stability, we initialize the encoder with ImageNet pre-trained weights from the Masked Autoencoder (MAE), applying a learning rate layer decay of 0.8. This initialization does not affect the validity of our conclusions, as demonstrated by the ablation study of SPA-MAE in Sec. 5.3. The ViT encoder and upsampling layers are trained with FP16 precision, while the volume decoder is trained with FP32 precision.

We set the loss weights to  $\lambda_{\text{color}} = 10$ ,  $\lambda_{\text{depth}} = 1$ ,  $\lambda_{\text{semantic}} = 1$ ,  $\lambda_{\text{eikonal}} = 0.01$ ,  $\lambda_{\text{free}} = 1$ , and  $\lambda_{\text{sdf}} = 10$ . For the NeuS sampler, the initial number of samples is set to 72, with 24 importance samples. In each iteration, we randomly sample 512 pixels per view for rendering and supervision.

## D DETAILED RESULTS OF EACH TASK

We present the results of all individual tasks in Tab. 9, Tab. 10, Tab. 11, Tab. 12, Tab. 13, and Tab. 14.

## E CAMERA POSE ESTIMATION DETAILS

We adopt a setup similar to that of [El Banani et al. \(2024\)](#) for camera pose estimation using the NAVI dataset ([Jampani et al., 2023](#)). Given an image pair from different viewpoints, we first extract features from each image using a frozen, pre-trained Vision Transformer (ViT) encoder. Following standard protocols for embodied evaluation, we use the [CLS] token as the feature representation. The two [CLS] tokens are then concatenated and passed through a BatchNorm layer and a Multi-Layer Perceptron (MLP) to regress the camera pose. The MLP consists of four linear layers with three ReLU activations, using hidden sizes of 512, 256, and 128 units, and outputs a 7-dimensional pose vector. The first three dimensions represent the  $xyz$  translation, while the last four dimensions correspond to the rotation quaternions.



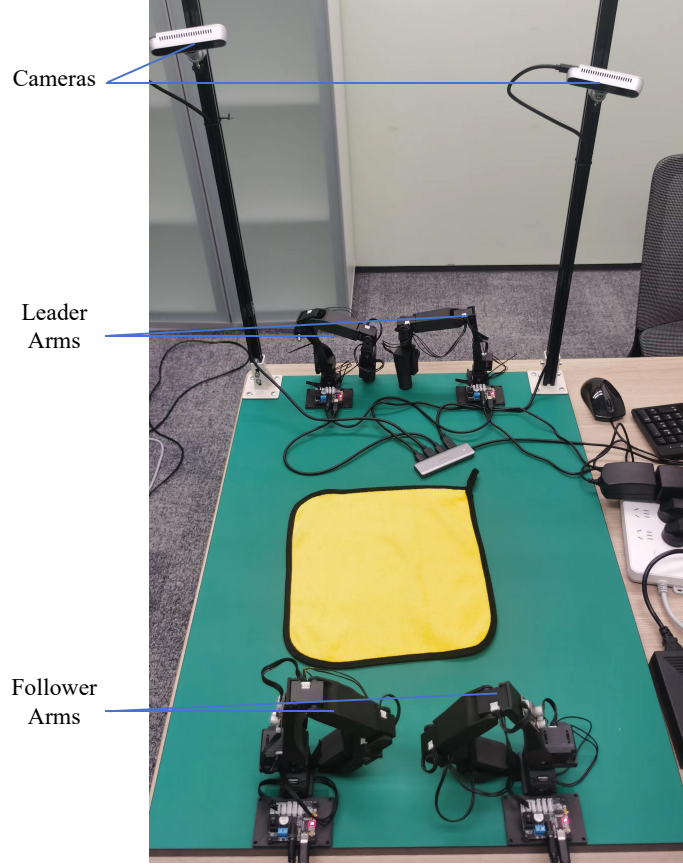


Figure 7: **Real-world hardware platform.**

We employ the Mean Squared Error (MSE) loss function and optimize the model using the AdamW optimizer with a OneCycle learning rate scheduler. The model is trained for 100 epochs with a base learning rate of  $1 \times 10^{-3}$  and a starting percentage of 0.1. For evaluation, we use Euclidean distance as the translation error metric and geodesic distance as the rotation error metric. The geodesic distance between two quaternions  $q_1$  and  $q_2$  is defined as:

$$\theta = 2 \cdot \arccos(|q_1 \cdot q_2|), \quad (13)$$

where  $q_1$  and  $q_2$  are normalized quaternions, and  $\cdot$  denotes the quaternion dot product. The Euclidean distance  $d$  between two translation vectors  $\mathbf{t}_1 = (x_1, y_1, z_1)$  and  $\mathbf{t}_2 = (x_2, y_2, z_2)$  is given by:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}. \quad (14)$$

## F REAL-WORLD EXPERIMENT DETAILS

Our real-world hardware setup is based on the open-source Low-Cost-Robot project (Koch, 2024). We utilize two Intel RealSense D415 cameras for image capture. A visualization of our platform is provided in Fig. 7. For teleoperation, policy training, and evaluation, we leverage the open-source RealRobot project (Contributors, 2024). The policy used is the ACT policy (Zhao et al., 2023).

For each task, we collect 50 demonstrations, and during evaluation, we conduct 25 rollouts, each with randomized object locations and orientations. The model is trained for 10,000 epochs using four NVIDIA A100 GPUs. We employ the AdamW optimizer with a learning rate of  $5 \times 10^{-5}$  and a weight decay of 0.05. Additionally, a OneCycle learning rate scheduler is used, with a starting percentage of 0.1, a division factor of 10, and a final division factor of 100.

Table 9: All results on Vc-1 benchmarks.

Benchmark		AD		MW				DMC				TF			
Methods	Seed	Relo- cate	Pen	Button Press Topdown	Drawer Open	Bin Picking	Ham- mer	Assem- bly	Walker Stand	Walker Walk	Reacher Easy	Cheetah Run	Finger Spin	Reach Cube	Move Cube
ViT-L Methods															
MoCoV3	100	40.00	92.00	88.00	100.00	88.00	100.00	88.00	84.88	57.59	92.29	56.28	70.49	84.37	61.20
	200	36.00	80.00	88.00	100.00	80.00	100.00	84.00	82.95	55.02	92.08	43.17	69.49	84.20	61.26
	300	28.00	76.00	84.00	100.00	68.00	92.00	72.00	81.42	53.59	91.96	41.27	68.23	84.09	64.24
MAE	100	36.00	84.00	84.00	100.00	88.00	100.00	100.00	951.27	680.69	976.50	482.47	703.30	85.46	59.46
	200	36.00	80.00	84.00	100.00	76.00	96.00	96.00	933.67	676.92	952.20	49.22	695.00	86.88	59.45
	300	32.00	80.00	68.00	100.00	72.00	98.00	88.00	873.53	659.41	895.60	501.91	691.80	85.26	61.69
DINOv2	100	32.00	68.00	68.00	100.00	84.00	100.00	88.00	87.01	56.52	94.50	26.98	70.87	86.16	50.84
	200	28.00	68.00	60.00	100.00	80.00	96.00	80.00	86.00	53.97	89.97	21.84	68.78	86.87	50.78
	300	28.00	60.00	60.00	100.00	80.00	92.00	72.00	82.41	51.69	88.36	21.34	67.41	86.05	50.17
CLIP	100	24.00	80.00	28.00	100.00	88.00	100.00	84.00	66.16	43.94	90.71	18.40	68.30	73.28	41.09
	200	24.00	72.00	24.00	100.00	84.00	100.00	80.00	64.04	34.51	88.26	16.52	66.68	75.11	33.45
	300	24.00	68.00	16.00	100.00	84.00	96.00	72.00	52.70	31.60	85.17	14.51	67.49	74.73	38.95
EVA	100	44.00	84.00	72.00	100.00	76.00	100.00	100.00	77.92	51.64	98.17	31.04	70.17	82.56	52.04
	200	40.00	76.00	84.00	100.00	72.00	100.00	100.00	77.63	50.81	86.66	19.37	67.43	81.72	52.07
	300	32.00	72.00	96.00	100.00	68.00	96.00	96.00	77.21	47.71	88.41	29.19	67.43	82.13	52.70
InternViT-300M	100	40.00	72.00	80.00	100.00	72.00	100.00	84.00	70.04	30.44	80.80	16.70	67.05	78.59	53.67
	200	28.00	72.00	68.00	100.00	76.00	96.00	84.00	67.63	31.55	82.33	19.39	67.57	77.07	55.21
	300	28.00	80.00	60.00	100.00	72.00	96.00	72.00	66.95	29.28	81.87	18.80	68.55	78.27	48.58
InternViT-6B	100	32.00	72.00	88.00	100.00	80.00	100.00	84.00	88.53	70.02	93.09	26.54	70.62	85.96	57.52
	200	40.00	76.00	84.00	100.00	76.00	100.00	80.00	85.28	60.09	90.86	22.84	69.04	86.30	54.11
	300	60.00	80.00	80.00	100.00	88.00	100.00	76.00	81.88	59.17	87.87	21.53	67.20	85.68	54.86
MVP	100	32.00	84.00	96.00	100.00	96.00	100.00	100.00	84.88	57.59	92.29	56.28	70.49	84.37	61.20
	200	28.00	76.00	92.00	100.00	84.00	100.00	96.00	82.95	55.02	92.08	43.17	69.49	84.20	61.26
	300	24.00	76.00	84.00	100.00	68.00	100.00	88.00	81.42	53.59	91.96	41.27	68.23	84.09	64.24
VC-1	100	32.00	84.00	84.00	100.00	76.00	96.00	96.00	82.36	55.33	98.09	35.31	72.60	83.36	58.00
	200	28.00	80.00	68.00	100.00	72.00	92.00	84.00	80.21	53.90	89.83	34.10	70.15	83.17	61.00
	300	24.00	76.00	76.00	100.00	96.00	88.00	84.00	68.62	50.13	87.89	31.18	70.11	82.75	57.16
SPA-L	100	40.00	88.00	76.00	100.00	92.00	100.00	100.00	94.19	66.34	95.57	52.53	73.95	87.37	56.68
	200	44.00	76.00	84.00	100.00	88.00	100.00	84.00	92.28	60.60	81.43	44.99	71.83	87.26	64.35
	300	36.00	76.00	96.00	100.00	88.00	96.00	96.00	87.87	51.75	83.86	39.10	70.91	87.62	58.02
ViT-B Methods and Others															
STP-B	100	20.00	80.00	88.00	100.00	84.00	100.00	96.00	77.02	45.34	87.97	40.01	72.72	80.41	54.66
	200	28.00	76.00	92.00	100.00	84.00	100.00	80.00	71.50	33.60	84.08	34.30	72.18	80.13	57.97
	300	32.00	76.00	88.00	100.00	72.00	100.00	96.00	71.44	42.86	79.67	39.17	69.12	80.65	53.95
R3M-B	100	20.00	92.00	52.00	96.00	32.00	88.00	48.00	668.49	301.54	842.90	256.56	678.00	75.08	45.66
	200	12.00	76.00	48.00	96.00	32.00	88.00	44.00	634.62	256.82	661.40	198.63	660.90	75.62	48.09
	300	12.00	76.00	32.00	88.00	28.00	76.00	40.00	633.39	211.90	585.50	188.15	657.30	74.54	45.59
Theia-B	100	32.00	76.00	88.00	100.00	80.00	96.00	96.00	72.90	43.97	82.09	37.02	70.50	84.55	55.62
	200	36.00	80.00	60.00	100.00	84.00	100.00	84.00	79.05	56.99	94.36	39.59	70.22	83.27	54.59
	300	24.00	72.00	80.00	100.00	72.00	96.00	100.00	79.64	54.39	82.89	39.09	72.00	84.01	54.43
Voltron-B	100	16.00	72.00	76.00	100.00	64.00	100.00	96.00	74.31	42.05	68.88	36.94	70.91	86.28	65.11
	200	32.00	72.00	76.00	100.00	60.00	96.00	88.00	71.57	38.17	67.53	31.01	70.17	86.61	62.39
	300	20.00	68.00	72.00	100.00	52.00	96.00	84.00	71.25	36.50	66.14	30.11	69.88	86.16	59.02
MAE-B	100	24.00	88.00	88.00	100.00	84.00	96.00	96.00	88.28	42.55	95.18	44.08	69.26	85.63	55.68
	200	28.00	76.00	84.00	100.00	84.00	88.00	88.00	77.13	38.49	88.22	32.75	69.02	85.14	56.81
	300	28.00	72.00	76.00	100.00	80.00	88.00	80.00	75.60	36.93	78.35	31.03	69.01	84.11	57.30
DINOv2-B	100	8.00	60.00	40.00	100.00	44.00	96.00	20.00	45.95	16.61	63.57	13.38	60.11	74.07	36.29
	200	8.00	68.00	40.00	100.00	64.00	88.00	16.00	37.96	15.81	51.44	12.59	59.56	74.18	32.14
	300	12.00	64.00	48.00	100.00	64.00	88.00	4.00	32.43	14.31	36.01	11.67	56.54	73.77	36.53
VC-1-B	100	20.00	76.00	76.00	100.00	76.00	100.00	76.00	72.35	43.14	92.77	27.31	68.67	84.19	62.00
	200	32.00	80.00	68.00	100.00	76.00	100.00	92.00	81.83	44.05	83.62	27.80	70.98	83.88	59.63
	300	24.00	68.00	80.00	100.00	80.00	88.00	88.00	83.01	41.25	77.60	28.53	70.89	84.76	59.51
RADIO	100	28.00	76.00	48.00	100.00	72.00	100.00	84.00	87.84	62.72	96.53	15.71	67.88	85.70	57.52
	200	36.00	76.00	44.00	100.00	72.00	96.00	52.00	80.26	57.39	95.93	15.26	67.51	85.67	57.81
	300	44.00	72.00	32.00	100.00	40.00	92.00	48.00	79.62	53.51	89.16	14.80	66.57	85.64	58.14
E-RADIO	100	32.00	84.00	64.00	100.00	84.00	96.00	96.00	71.47	53.41	93.01	50.19	70.75	87.17	46.97
	200	32.00	84.00	60.00	100.00	68.00	88.00	96.00	68.80	44.56	88.54	33.19	70.46	87.39	50.72
	300	28.00	80.00	60.00	100.00	72.00	88.00	80.00	65.96	33.56	98.14	32.64	69.18	87.09	51.31
SPA-B	100	20.00	84.00	84.00	100.00	88.00	100.00	100.00	80.50	45.08	91.38	48.90	71.16	86.04	59.03
	200	28.00	80.00	68.00	100.00	84.00	100.00	84.00	79.71	46.65	85.75	40.84	71.01	86.16	60.05
	300	24.00	80.00	88.00	100.00	92.00	100.00	92.00	74.70	48.97	81.60	34.92	71.16	85.16	61.94

Table 10: All results on Franka Kitchen.

Task	View	Seed	MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT-300M	MVP	VC-1	SPA
Task 1	Left	100	86.00	76.00	84.00	72.00	78.00	74.00	66.00	74.00	84.00
		200	78.00	78.00	74.00	72.00	76.00	72.00	58.00	74.00	92.00
		300	80.00	80.00	78.00	62.00	82.00	70.00	64.00	74.00	80.00
	Right	100	82.00	80.00	86.00	78.00	78.00	72.00	82.00	78.00	86.00
		200	88.00	62.00	90.00	70.00	86.00	86.00	86.00	84.00	72.00
		300	86.00	82.00	92.00	82.00	86.00	76.00	92.00	78.00	86.00
Task 2	Left	100	60.00	56.00	48.00	26.00	40.00	22.00	40.00	32.00	48.00
		200	64.00	60.00	46.00	44.00	40.00	32.00	32.00	42.00	60.00
		300	58.00	54.00	40.00	26.00	32.00	34.00	30.00	50.00	66.00
	Right	100	62.00	54.00	56.00	26.00	44.00	26.00	32.00	54.00	48.00
		200	64.00	54.00	60.00	36.00	40.00	24.00	28.00	56.00	42.00
		300	64.00	52.00	50.00	38.00	40.00	30.00	34.00	44.00	42.00
Task 3	Left	100	16.00	24.00	18.00	18.00	22.00	24.00	6.00	24.00	28.00
		200	28.00	20.00	14.00	18.00	20.00	16.00	6.00	30.00	38.00
		300	22.00	16.00	14.00	10.00	26.00	22.00	8.00	26.00	30.00
	Right	100	46.00	26.00	38.00	22.00	14.00	8.00	32.00	12.00	10.00
		200	48.00	22.00	38.00	24.00	18.00	4.00	32.00	12.00	12.00
		300	54.00	34.00	52.00	14.00	12.00	6.00	26.00	14.00	16.00
Task 4	Left	100	32.00	36.00	26.00	22.00	34.00	12.00	16.00	36.00	22.00
		200	30.00	30.00	32.00	14.00	20.00	8.00	14.00	24.00	10.00
		300	24.00	46.00	28.00	14.00	32.00	4.00	20.00	36.00	16.00
	Right	100	38.00	24.00	28.00	22.00	32.00	12.00	26.00	12.00	30.00
		200	42.00	24.00	24.00	24.00	24.00	12.00	30.00	8.00	38.00
		300	46.00	16.00	32.00	28.00	36.00	16.00	26.00	12.00	30.00
Task 5	Left	100	36.00	18.00	8.00	16.00	24.00	22.00	26.00	28.00	20.00
		200	30.00	24.00	8.00	10.00	24.00	16.00	20.00	22.00	16.00
		300	22.00	22.00	10.00	12.00	16.00	14.00	28.00	30.00	18.00
	Right	100	24.00	46.00	20.00	4.00	14.00	10.00	26.00	22.00	30.00
		200	24.00	30.00	16.00	8.00	18.00	18.00	22.00	22.00	26.00
		300	14.00	36.00	16.00	12.00	10.00	12.00	20.00	16.00	22.00

Table 11: All results on Meta-World.

Method	MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT-300M	MVP	VC-1	SPA
Seed	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300
ButtonPressWall	100 100 100	100 100 100	95 90 95	100 100 100	95 95 100	95 100 95	100 100 100	100 100 100	100 100 100
DoorClose	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100
DoorUnlock	70 65 80	70 65 85	35 35 30	60 50 60	85 85 90	80 65 75	75 70 85	80 75 90	80 75 80
DrawerClose	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100
DrawerOpen	80 70 85	85 65 75	60 40 60	90 80 80	60 55 75	70 75 75	95 75 85	85 85 80	90 60 75
FaucetClose	70 80 55	60 80 60	55 65 35	70 80 50	65 75 60	50 65 50	70 75 60	65 75 100	70 80 65
PlateSlide	90 95 100	95 100 100	65 70 80	85 95 80	100 100 100	85 95 90	100 100 100	100 95 100	95 95 95
PlateSlideBack	80 65 85	85 65 85	90 75 90	85 75 90	80 65 90	85 80 90	85 70 90	80 70 90	80 70 85
PlateSlideSide	85 90 95	95 90 95	90 85 85	80 85 95	100 95 100	90 95 90	80 90 95	100 95 90	90 90 95
WindowClose	100 100 100	100 100 100	70 90 100	100 100 95	95 100 100	100 100 100	100 100 100	100 100 100	100 100 100
Basketball	85 95 95	95 100 100	70 55 65	85 85 70	95 85 80	90 80 95	95 100 95	90 100 95	95 100 100
BinPicking	30 45 40	20 10 35	10 15 10	30 30 25	20 5 45	10 10 10	25 20 15	30 30 30	40 25 30
BoxClose	80 80 80	75 80 70	35 45 30	80 70 60	55 70 55	60 65 40	80 80 65	80 95 60	80 80 65
CoffeePush	45 50 40	40 55 30	30 25 15	45 40 55	45 35 40	45 30 25	25 45 25	30 45 55	35 40 30
Assembly	70 60 55	55 65 45	30 35 25	45 55 50	45 50 40	30 25 30	60 60 45	60 60 50	50 55 50
Disassemble	40 55 50	30 45 45	30 20 45	55 50 60	30 50 50	40 45 50	40 45 45	40 30 35	40 45 55
PushWall	25 35 30	20 30 40	40 30 45	35 30 35	25 35 30	15 15 25	30 35 35	55 55 60	30 40 45
ShelfPlace	35 35 20	25 45 20	30 30 35	30 35 30	25 20 15	15 15 15	25 25 15	25 15 15	15 35 15
DoorOpen	95 90 90	100 95 95	95 80 95	85 75 90	80 90 100	50 55 60	80 75 95	95 95 95	85 100 95
ButtonPress	75 85 85	85 100 100	80 95 85	55 70 75	80 90 90	85 90 80	85 90 95	80 90 85	100 95 100
SweepInto	45 45 40	55 55 45	50 50 40	45 45 40	45 25 30	35 25 30	45 50 40	55 50 50	50 50 45
DoorLock	100 85 85	90 100 100	95 90 85	85 85 75	95 100 95	80 90 95	85 100 95	100 100 90	80 95 85
ReachWall	70 70 80	75 85 70	85 80 85	90 90 80	65 75 85	60 55 55	75 65 75	75 80 80	75 80 70
Hammer	25 45 30	30 30 30	40 45 35	25 35 25	30 35 20	20 20 20	30 35 30	45 40 55	30 40 30
StickPush	95 95 100	80 90 95	90 90 90	75 85 85	90 85 100	60 80 85	90 95 90	85 85 95	90 90 85
ButtonPressTopdown	80 80 75	80 85 80	80 90 90	80 90 70	55 65 55	45 55 55	80 85 80	75 80 70	80 85 80
HandlePressSide	100 100 100	100 100 100	95 100 90	80 100 90	100 100 95	85 100 90	95 100 100	75 100 80	90 100 100
PlateSlideBackSide	100 100 100	100 95 95	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100	100 100 100
Sweep	50 80 70	35 60 60	65 85 95	60 85 75	35 50 55	15 60 35	35 70 65	35 65 65	30 65 55
ButtonPressTopdownWall	45 70 80	45 75 75	70 75 75	45 60 70	30 45 65	20 55 45	30 60 70	50 85 80	45 65 75
HandlePress	85 95 95	80 100 75	75 100 80	90 100 90	85 100 85	65 90 75	80 95 75	85 100 90	85 100 80
Push	25 30 30	25 30 30	30 25 40	25 15 30	30 25 20	25 20 20	25 20 25	40 30 25	30 15 35
CoffeePull	55 55 55	40 45 40	20 30 20	50 70 40	40 45 45	40 40 25	55 55 40	55 55 60	55 55 55
DialTurn	80 65 80	85 75 75	40 30 35	80 95 90	65 65 80	70 70 55	70 65 75	80 95 75	85 85 75
Reach	90 75 80	90 75 80	70 75 85	95 95 100	85 80 75	95 80 90	80 70 75	70 80 80	85 70 85
CoffeeButton	85 95 75	100 100 95	85 80 60	95 100 85	90 100 95	90 85 85	100 100 90	90 100 80	100 100 100
PickPlaceWall	45 35 65	40 25 45	15 10 20	35 40 50	20 25 35	30 25 25	25 35 40	35 20 45	40 35 55
StickPull	35 35 25	15 40 20	25 10 5	45 40 45	25 35 15	25 25 15	15 30 25	30 30 30	25 35 30
HandInsert	35 30 30	30 25 25	20 20 20	45 45 40	20 25 20	25 30 25	40 40 35	40 30 40	40 50 40
PegInsertSide	40 35 40	50 35 45	25 15 10	45 30 20	45 25 30	30 20 25	45 45 30	50 25 35	55 45 60
PickPlace	35 30 30	25 45 15	15 10 10	25 15 30	25 30 25	30 10 30	20 35 25	25 20 20	25 30 40
FaucetOpen	95 95 100	100 100 100	80 80 100	100 95 100	95 95 100	80 85 95	100 100 100	100 100 100	95 100 100
PushBack	65 70 60	40 55 40	15 15 25	30 45 25	35 35 45	15 35 25	40 45 45	45 55 25	35 55 50
LeverPull	70 80 80	80 70 75	15 30 35	55 85 80	70 65 70	60 55 55	65 80 65	65 80 70	85 70 80
HandlePull	85 85 80	85 80 85	45 55 40	75 75 80	80 60 65	45 70 65	80 90 80	70 85 75	100 90 90
Soccer	25 40 35	50 30 25	15 10 15	45 40 30	35 35 25	20 20 30	30 30 35	20 20 20	25 50 25
WindowOpen	65 80 80	55 80 85	60 50 65	50 65 60	65 80 75	55 75 75	60 70 70	60 70 75	55 85 65
PickOutOfHole	65 75 80	65 65 60	60 55 60	70 70 50	60 55 50	60 55 55	65 55 60	70 75 60	65 60 75

Table 12: All results on RL Bench.

Method	MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT 300M	MVP	VC-1	SPA
<i>Group 1</i>									
basketball in hoop	100	100	100	100	100	100	100	100	100
put rubbish in bin	100	100	96	96	96	100	96	100	100
meat off grill	100	100	100	100	100	100	100	100	100
meat on grill	80	76	76	68	80	72	68	76	80
slide block to target	0	84	96	24	4	0	100	100	4
reach and drag	100	96	88	100	96	100	96	100	100
take frame off hanger	88	88	92	88	84	84	88	88	96
water plants	64	60	28	64	60	44	52	60	68
hang frame on hanger	8	4	0	4	8	8	12	4	4
wipe desk	0	0	0	0	0	0	0	0	0
stack blocks	60	72	72	68	56	60	84	68	68
reach target	60	96	88	100	96	80	92	96	92
push button	100	100	100	100	100	100	100	100	100
lamp on	88	68	84	88	52	80	28	88	64
toilet seat down	100	100	100	100	100	100	96	96	100
close laptop lid	96	96	96	96	84	80	80	96	100
open box	12	12	20	4	16	4	0	12	16
open drawer	88	96	92	100	88	88	92	96	96
pick up cup	92	92	88	96	96	88	96	96	96
turn tap	88	84	84	96	88	92	96	100	100
take usb out of computer	100	100	100	100	100	100	100	88	100
play jenga	96	96	96	100	96	100	96	96	96
insert onto square peg	28	84	80	44	88	40	64	92	84
take umbrella out of umbrella stand	92	100	100	92	100	96	100	100	100
insert usb in computer	12	20	20	24	24	20	16	8	68
straighten rope	56	44	72	80	48	72	52	60	84
turn oven on	96	96	96	96	96	96	100	100	100
change clock	64	68	48	68	64	72	64	60	68
close microwave	100	100	100	100	100	100	100	100	100
close fridge	80	92	92	88	92	96	88	92	100
close grill	96	96	96	96	96	96	100	100	96
open grill	100	100	100	100	100	100	96	100	100
unplug charger	44	32	48	36	48	40	40	44	44
press switch	92	92	88	72	76	84	76	88	92
take money out safe	100	96	100	100	100	100	100	100	100
<i>Group 2</i>									
change channel	0	8	4	0	0	4	0	0	4
tv on	4	8	0	4	4	8	4	4	8
push buttons	12	4	4	0	0	0	0	12	4
stack wine	12	16	40	4	12	0	28	8	28
scoop with spatula	0	0	0	0	0	0	0	0	0
place hanger on rack	0	0	0	0	0	0	0	0	0
move hanger	0	0	0	0	0	0	0	0	0
sweep to dustpan	92	96	96	96	92	100	100	88	96
take plate off colored dish rack	96	100	96	92	84	96	88	92	96
screw nail	52	36	36	36	36	52	32	32	48
take shoes out of box	20	28	24	36	40	12	32	36	36
slide cabinet open and place cups	0	0	0	0	0	4	0	0	4
lamp off	100	96	96	100	96	96	100	100	100
pick and lift	88	96	92	96	92	80	96	96	96
take lid off saucepan	100	100	100	100	100	100	100	100	100
close drawer	100	100	100	100	96	100	100	100	100
close box	92	92	96	96	100	96	100	96	100
phone on base	100	100	100	100	100	96	100	100	100
toilet seat up	80	88	100	88	88	80	88	92	96
put books on bookshelf	12	24	24	28	28	20	20	28	16
beat the buzz	88	92	96	88	92	84	88	88	100
stack cups	40	56	52	52	48	56	64	68	64
put knife on chopping board	72	76	68	72	80	88	80	76	80
place shape in shape sorter	20	36	32	28	36	20	44	36	56
take toilet roll off stand	100	92	76	96	92	88	84	92	96
put umbrella in umbrella stand	8	0	12	12	0	4	12	8	12
setup checkers	76	80	68	68	88	92	92	80	80
open window	96	96	100	100	96	100	96	100	100
open wine bottle	80	100	88	92	92	88	96	88	88
open microwave	100	100	88	96	100	80	96	100	100
put money in safe	96	100	88	92	100	96	100	100	100
open door	100	96	96	96	96	96	84	96	96
close door	32	68	56	60	80	20	24	20	60
open fridge	44	52	48	44	36	64	52	32	64
open oven	8	4	12	8	4	20	4	4	16
plug charger in power supply	32	36	32	24	44	36	24	32	60



Table 13: All results on LIBERO-OBJECT, LIBERO-SPATIAL, LIBERO-GOAL, LIBERO-10.

	MoCoV3	MAE	DINOv2	CLIP	EVA	InternViT-300M	InternViT-6B	MVP	VC-1	SPA
Seed	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300	100 200 300
<i>LIBERO-OBJECT</i>										
0	0.65 0.60 0.65	0.65 0.45 0.55	0.65 0.80 0.85	0.80 0.75 0.65	1.00 0.70 0.95	0.80 0.65 0.60	0.70 0.85 0.50	0.80 0.90 0.65	0.80 0.50 0.60	0.90 0.95 0.95
1	0.35 0.35 0.55	0.90 0.75 0.80	0.30 0.50 0.75	0.40 0.30 0.05	0.65 0.30 0.70	0.15 0.40 0.20	0.60 0.25 0.45	0.05 0.80 0.60	0.40 0.65 0.45	0.65 0.70 0.45
2	0.90 0.85 0.95	0.90 0.40 0.95	0.85 0.50 0.90	0.70 0.80 0.75	0.85 0.75 0.75	0.90 0.85 0.80	0.85 0.45 0.85	0.80 0.85 0.90	1.00 0.95 0.95	0.90 0.95 0.80
3	0.55 0.70 0.65	0.90 0.15 0.90	0.30 0.65 0.90	0.25 0.45 0.60	0.80 0.80 0.90	0.75 0.70 0.40	1.00 0.50 0.55	0.70 0.65 0.85	0.95 0.75 0.60	0.70 0.90 0.90
4	0.65 0.85 0.85	0.80 0.90 0.75	0.75 0.55 0.75	0.35 0.75 0.65	0.95 0.75 1.00	0.90 1.00 0.85	0.90 0.70 0.80	0.80 0.75 0.70	0.90 0.85 0.90	0.90 1.00 0.95
5	0.50 0.70 0.80	0.70 0.35 0.60	0.55 0.75 0.60	0.25 0.70 0.45	0.75 0.75 0.65	0.85 0.60 0.75	0.60 0.35 0.50	0.55 0.40 0.80	0.65 0.70 0.70	0.25 0.15 0.65
6	0.35 0.50 0.65	0.60 0.65 0.65	0.55 0.70 0.70	0.35 0.55 0.60	0.40 0.35 0.25	0.65 0.60 0.55	0.30 0.10 0.35	0.25 0.50 0.65	0.50 0.50 0.30	0.50 0.70 0.80
7	0.75 0.75 0.80	0.90 0.40 0.75	0.55 0.30 0.70	0.40 0.35 0.40	0.55 0.75 0.70	0.80 0.40 0.60	0.60 0.65 0.70	0.60 0.45 0.65	0.80 0.75 0.50	0.80 0.75 0.65
8	0.50 0.95 0.90	1.00 0.95 1.00	0.50 0.35 0.50	0.45 0.45 0.35	1.00 0.75 0.85	0.70 0.65 0.75	0.50 0.40 0.75	0.65 0.55 0.70	0.80 0.90 0.50	0.85 0.95 0.90
9	0.45 0.50 0.40	0.60 0.65 0.95	0.80 0.90 0.95	0.50 0.70 0.30	0.85 0.75 0.75	0.85 0.95 0.65	0.90 0.60 0.15	0.65 0.60 0.30	0.70 0.70 0.65	0.60 0.95 0.90
<i>LIBERO-SPATIAL</i>										
0	0.35 0.55 0.45	0.45 0.40 0.70	0.65 0.50 0.60	0.25 0.20 0.35	0.70 0.75 0.65	0.55 0.65 0.55	0.55 0.50 0.30	0.75 0.75 0.60	0.35 0.55 0.60	0.45 0.50 0.35
1	0.65 0.70 0.70	0.80 0.80 0.50	0.55 0.30 0.35	0.75 0.75 0.70	0.55 0.70 0.25	0.35 0.50 0.50	1.00 1.00 0.90	0.60 0.40 0.60	0.45 0.65 0.80	0.65 0.65 0.85
2	0.55 0.50 0.50	0.35 0.60 0.40	0.20 0.05 0.55	0.10 0.00 0.40	0.70 0.80 0.50	0.70 0.75 0.60	0.75 0.60 0.20	0.85 0.55 0.75	0.45 0.45 0.70	0.50 0.50 0.40
3	0.50 0.70 0.75	0.55 0.60 0.75	0.80 0.70 0.95	0.15 0.40 0.30	0.85 0.90 0.85	0.35 0.50 0.40	0.40 0.30 0.15	0.95 0.55 0.60	0.50 0.70 0.65	0.55 0.85 0.60
4	0.15 0.15 0.20	0.55 0.70 0.80	0.50 0.05 0.45	0.35 0.30 0.20	0.45 0.55 0.40	0.35 0.25 0.40	0.25 0.15 0.15	0.60 0.50 0.70	0.60 0.60 0.80	0.70 0.70 0.50
5	0.45 0.10 0.10	0.65 0.40 0.30	0.30 0.20 0.35	0.55 0.45 0.45	0.65 0.50 0.45	0.40 0.30 0.70	0.55 0.60 0.60	0.55 0.30 0.25	0.05 0.05 0.15	0.35 0.35 0.30
6	0.30 0.35 0.45	0.55 0.25 0.95	0.40 0.30 0.40	0.20 0.25 0.10	0.75 0.70 0.85	0.45 0.55 0.55	0.40 0.35 0.05	0.45 0.75 0.65	0.60 0.70 0.35	0.35 0.45 0.30
7	0.10 0.20 0.25	0.50 0.35 0.45	0.05 0.00 0.10	0.30 0.15 0.25	0.30 0.30 0.20	0.30 0.60 0.65	0.15 0.05 0.05	0.60 0.65 0.60	0.10 0.20 0.40	0.40 0.15 0.45
8	0.55 0.70 0.50	0.35 0.65 0.70	0.40 0.15 0.55	0.30 0.55 0.30	0.85 0.70 0.60	0.30 0.55 0.60	0.65 0.40 0.35	0.70 0.40 0.55	0.70 0.60 0.70	0.75 0.70 0.40
9	0.55 0.05 0.10	0.85 0.75 0.50	0.20 0.05 0.25	0.20 0.20 0.20	0.55 0.50 0.30	0.35 0.50 0.30	0.45 0.40 0.35	0.45 0.45 0.30	0.50 0.55 0.65	0.35 0.50 0.45
<i>LIBERO-GOAL</i>										
0	0.45 0.70 0.75	0.70 0.85 0.80	0.15 0.10 0.30	0.25 0.40 0.35	0.70 0.60 0.60	0.75 0.65 0.75	0.25 0.35 0.35	0.75 0.60 0.95	0.45 0.85 1.00	0.85 1.00 0.85
1	0.70 0.60 0.80	0.65 0.50 0.90	0.25 0.55 0.25	0.20 0.15 0.25	0.70 0.80 0.80	0.90 0.90 1.00	0.40 0.15 0.15	0.90 0.80 0.95	0.65 0.65 0.65	1.00 0.85 0.90
2	0.50 0.20 0.15	0.10 0.40 0.35	0.10 0.05 0.15	0.30 0.25 0.30	0.65 0.75 0.75	0.40 0.75 0.45	0.50 0.35 0.35	0.45 0.25 0.65	0.40 0.60 0.35	0.50 0.55 0.35
3	0.75 0.45 0.60	0.40 0.75 0.55	0.20 0.10 0.10	0.05 0.20 0.55	0.30 0.15 0.15	0.30 0.50 0.65	0.20 0.25 0.25	0.70 0.70 0.15	0.75 0.55 0.50	0.65 0.35 0.80
4	0.20 0.25 0.05	0.35 0.40 0.25	0.10 0.00 0.05	0.40 0.30 0.15	0.15 0.10 0.10	0.20 0.15 0.10	0.15 0.20 0.20	0.55 0.60 0.25	0.15 0.30 0.30	0.30 0.35 0.35
5	0.10 0.75 0.80	0.60 0.85 0.80	0.65 0.50 0.50	0.35 0.45 0.50	0.80 0.75 0.75	0.70 0.55 0.45	0.55 0.45 0.45	0.80 0.75 0.85	0.65 0.75 0.80	0.80 0.65 0.65
6	0.45 0.05 0.15	0.00 0.10 0.05	0.00 0.05 0.00	0.10 0.10 0.00	0.00 0.65 0.65	0.50 0.40 0.30	0.00 0.00 0.00	0.15 0.35 0.70	0.25 0.50 0.45	0.40 0.30 0.35
7	0.25 0.75 0.90	0.80 0.65 1.00	0.45 0.45 0.35	0.50 0.65 0.80	1.00 1.00 1.00	1.00 1.00 0.95	0.70 0.85 0.85	0.95 1.00 0.95	1.00 0.95 0.70	0.95 1.00 1.00
8	0.50 0.80 0.75	0.85 0.55 0.90	0.45 0.40 0.20	0.60 0.25 0.50	0.90 0.35 0.35	0.95 0.65 0.55	0.65 0.25 0.25	0.70 0.65 0.70	0.50 0.75 0.55	0.80 0.65 0.80
9	0.10 0.65 0.60	0.50 0.20 0.50	0.10 0.00 0.10	0.10 0.10 0.00	0.15 0.70 0.70	0.60 0.40 0.20	0.15 0.35 0.35	0.30 0.50 0.55	0.20 0.35 0.70	0.55 0.60 0.45
<i>LIBERO-10</i>										
0	0.15 0.20 0.10	0.15 0.25 0.10	0.00 0.05 0.10	0.00 0.05 0.05	0.25 0.35 0.10	0.35 0.10 0.25	0.15 0.15 0.00	0.05 0.15 0.20	0.10 0.45 0.25	0.05 0.10 0.05
1	0.25 0.20 0.20	0.30 0.15 0.25	0.15 0.15 0.15	0.40 0.30 0.15	0.65 0.10 0.60	0.15 0.50 0.45	0.00 0.25 0.35	0.15 0.10 0.15	0.20 0.40 0.15	0.25 0.05 0.45
2	0.70 0.60 0.75	0.30 0.60 0.75	0.55 0.45 0.50	0.25 0.45 0.40	0.75 0.55 0.65	0.45 0.80 0.55	0.70 0.80 0.75	0.75 0.65 0.55	0.85 1.00 0.90	0.70 0.80 0.50
3	0.50 0.80 0.55	0.55 0.60 0.80	0.40 0.45 0.45	0.60 0.65 0.60	0.80 0.90 0.75	0.75 0.65 0.50	0.75 0.60 0.60	0.75 0.70 0.65	0.80 0.70 0.70	0.70 0.90 0.70
4	0.25 0.20 0.05	0.35 0.25 0.30	0.10 0.10 0.05	0.20 0.05 0.05	0.15 0.10 0.15	0.15 0.15 0.05	0.15 0.20 0.15	0.25 0.20 0.35	0.30 0.25 0.30	0.40 0.30 0.25
5	0.40 0.60 0.75	0.55 0.70 0.80	0.50 0.65 0.75	0.40 0.40 0.30	0.85 0.65 0.75	0.75 0.55 0.75	0.45 0.55 0.45	0.60 0.70 0.75	0.80 0.90 0.60	0.70 0.70 0.45
6	0.20 0.25 0.10	0.40 0.35 0.40	0.05 0.20 0.05	0.25 0.15 0.15	0.20 0.30 0.35	0.10 0.15 0.20	0.20 0.25 0.05	0.40 0.30 0.35	0.30 0.10 0.20	0.20 0.20 0.15
7	0.40 0.30 0.25	0.50 0.50 0.50	0.10 0.30 0.60	0.30 0.40 0.20	0.45 0.30 0.25	0.40 0.35 0.35	0.35 0.70 0.25	0.35 0.30 0.25	0.30 0.25 0.30	0.50 0.45 0.40
8	0.10 0.10 0.15	0.10 0.30 0.20	0.35 0.20 0.05	0.10 0.10 0.10	0.15 0.20 0.10	0.20 0.00 0.25	0.05 0.20 0.05	0.10 0.30 0.20	0.25 0.30 0.25	0.25 0.05 0.15
9	0.20 0.60 0.35	0.40 0.65 0.30	0.35 0.25 0.45	0.45 0.45 0.30	0.40 0.70 0.50	0.50 0.45 0.60	0.50 0.25 0.40	0.40 0.55 0.50	0.00 0.00 0.00	0.50 0.65 0.50

Table 14: All results on LIBERO-90.

	MoCoV3			MAE			DINOv2			CLIP			EVA			InternViT-300M			InternViT-6B			MVP			VC-1			SPA			
Seed	100	200	300	100	200	300	100	200	300	100	200	300	100	200	300	100	200	300	100	200	300	100	200	300	100	200	300	100	200	300	
LIBERO-90																															
0	0.95	0.85	0.90	1.00	0.90	0.80	0.80	1.00	0.60	0.90	0.80	0.80	1.00	1.00	1.00	0.90	0.80	0.85	0.75	0.80	0.95	0.95	0.95	1.00	0.95	1.00	0.95	1.00	1.00	0.95	
1	0.60	0.35	0.60	0.35	0.50	0.15	0.50	0.55	0.30	0.40	0.65	0.35	0.70	0.50	0.25	0.30	0.45	0.40	0.25	0.35	0.55	0.80	0.55	0.30	0.40	0.50	0.05	0.65	0.40	0.50	
2	0.85	0.50	0.80	0.55	0.55	0.20	0.65	0.60	0.30	0.45	0.30	0.50	0.35	0.50	0.70	0.85	0.65	0.80	0.25	0.35	0.30	0.45	0.70	0.70	0.75	0.55	0.35	0.70	0.85	0.60	
3	0.10	0.10	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.15	0.00	0.00	0.00	0.10	0.15	0.00	0.05	0.05	0.00	0.00	0.05	0.10	0.00	0.05	0.05	0.10	0.00	0.10	0.10	0.00	
4	0.40	0.05	0.20	0.30	0.25	0.30	0.15	0.40	0.55	0.40	0.40	0.35	0.10	0.25	0.15	0.40	0.05	0.25	0.20	0.45	0.40	0.30	0.40	0.15	0.25	0.05	0.15	0.15	0.15	0.35	
5	0.05	0.05	0.05	0.10	0.05	0.20	0.00	0.20	0.00	0.05	0.05	0.20	0.25	0.25	0.10	0.10	0.05	0.30	0.20	0.10	0.25	0.05	0.15	0.10	0.10	0.05	0.05	0.35	0.00	0.15	
6	0.10	0.00	0.00	0.00	0.00	0.05	0.05	0.05	0.10	0.05	0.10	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.05	0.10	0.10	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.05	0.05	
7	0.35	0.30	0.65	0.20	0.60	0.30	0.35	0.25	0.40	0.50	0.60	0.35	0.60	0.10	0.20	0.15	0.25	0.10	0.40	0.25	0.45	0.50	0.20	0.40	0.20	0.30	0.25	0.30	0.30	0.65	
8	0.10	0.15	0.00	0.05	0.20	0.10	0.15	0.25	0.10	0.20	0.10	0.10	0.10	0.05	0.00	0.05	0.00	0.10	0.20	0.15	0.20	0.10	0.00	0.20	0.05	0.15	0.20	0.05	0.05	0.15	
9	0.30	0.25	0.35	0.50	0.25	0.30	0.35	0.60	0.70	0.25	0.20	0.50	0.25	0.10	0.50	0.10	0.10	0.25	0.60	0.25	0.30	0.20	0.25	0.15	0.45	0.25	0.05	0.35	0.25	0.20	0.25
10	0.50	0.75	0.50	0.50	0.60	0.55	0.65	0.60	0.60	0.90	0.45	0.55	0.40	0.85	0.35	0.35	0.05	0.25	0.45	0.45	0.65	0.40	0.50	0.55	0.45	0.75	0.40	0.40	0.35	0.35	
11	0.45	0.35	0.75	0.45	0.70	0.65	0.35	0.20	0.15	0.40	0.70	0.55	0.80	0.25	0.70	0.50	0.50	0.10	0.35	0.25	0.40	0.80	0.60	0.95	0.70	0.75	0.60	0.60	0.60	0.65	
12	0.15	0.15	0.10	0.15	0.15	0.05	0.20	0.20	0.15	0.10	0.05	0.05	0.10	0.25	0.05	0.05	0.00	0.00	0.25	0.30	0.10	0.15	0.10	0.10	0.20	0.25	0.10	0.05	0.10	0.15	
13	0.20	0.35	0.30	0.15	0.30	0.20	0.30	0.35	0.10	0.30	0.40	0.35	0.30	0.10	0.45	0.20	0.35	0.40	0.25	0.15	0.55	0.30	0.30	0.15	0.45	0.10	0.10	0.10	0.20	0.10	
14	0.05	0.10	0.00	0.30	0.30	0.20	0.10	0.10	0.15	0.15	0.40	0.20	0.25	0.35	0.10	0.15	0.15	0.05	0.20	0.15	0.10	0.20	0.35	0.10	0.20	0.10	0.15	0.15	0.15	0.10	
15	0.60	0.75	0.45	0.70	0.50	0.65	0.35	0.50	0.55	0.45	0.65	0.40	0.70	0.75	0.40	0.40	0.65	0.50	0.35	0.55	0.45	0.70	0.60	0.55	0.80	0.80	0.70	0.65	0.80	0.55	
16	0.05	0.20	0.00	0.30	0.15	0.05	0.10	0.10	0.05	0.10	0.00	0.10	0.20	0.20	0.15	0.15	0.15	0.20	0.05	0.00	0.10	0.15	0.05	0.10	0.00	0.15	0.15	0.05	0.10	0.15	
17	0.05	0.15	0.15	0.10	0.25	0.05	0.05	0.10	0.05	0.05	0.00	0.05	0.05	0.20	0.15	0.10	0.10	0.15	0.00	0.10	0.10	0.00	0.20	0.10	0.20	0.15	0.10	0.00	0.25	0.10	0.10
18	0.45	0.40	0.60	0.40	0.75	0.65	0.30	0.35	0.40	0.45	0.25	0.35	0.25	0.35	0.60	0.40	0.05	0.70	0.60	0.50	0.35	0.35	0.25	0.45	0.30	0.60	0.35	0.60	0.35	0.55	
19	0.30	0.30	0.25	0.35	0.40	0.20	0.20	0.05	0.35	0.45	0.45	0.30	0.30	0.35	0.25	0.15	0.25	0.20	0.35	0.30	0.15	0.55	0.30	0.40	0.40	0.45	0.35	0.45	0.20	0.35	
20	0.85	0.75	0.80	1.00	1.00	0.95	0.95	1.00	1.00	0.75	0.85	0.30	1.00	1.00	1.00	0.95	0.95	0.90	1.00	0.50	0.80	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
21	0.40	0.20	0.40	0.35	0.25	0.30	0.25	0.40	0.20	0.25	0.10	0.45	0.30	0.70	0.05	0.00	0.05	0.10	0.35	0.10	0.30	0.40	0.15	0.30	0.30	0.70	0.60	0.65	0.40	0.60	
22	0.90	0.95	0.95	1.00	0.85	0.95	0.25	0.60	0.40	0.75	0.75	0.75	0.95	1.00	0.95	0.85	0.95	0.60	0.45	0.25	0.25	0.90	1.00	1.00	0.90	0.90	0.95	1.00	0.95	1.00	
23	0.15	0.05	0.15	0.05	0.10	0.00	0.05	0.10	0.05	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.25	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
24	0.80	0.30	0.85	0.85	0.50	0.80	0.60	0.50	0.65	0.70	0.45	0.60	0.70	0.70	0.80	0.40	0.65	0.60	0.55	0.80	0.45	0.65	0.60	0.90	0.90	0.80	0.80	0.90	0.80	0.75	
25	1.00	0.80	0.85	1.00	1.00	0.90	0.75	0.90	0.90	0.80	0.95	0.90	0.90	1.00	0.95	0.70	0.70	0.85	0.95	0.60	0.65	1.00	0.85	1.00	1.00	1.00	0.90	1.00	1.00	1.00	
26	0.15	0.20	0.25	0.25	0.40	0.40	0.05	0.30	0.40	0.45	0.05	0.15	0.05	0.30	0.15	0.25	0.40	0.20	0.25	0.15	0.20	0.20	0.30	0.60	0.25	0.45	0.25	0.25	0.20	0.20	
27	0.30	0.15	0.20	0.35	0.35	0.10	0.05	0.10	0.00	0.35	0.05	0.10	0.05	0.20	0.05	0.05	0.15	0.00	0.10	0.10	0.05	0.35	0.20	0.30	0.10	0.45	0.40	0.10	0.40	0.20	
28	0.90	0.90	1.00	0.95	0.70	0.70	0.80	0.50	0.80	0.90	0.75	0.90	0.95	1.00	0.85	0.90	0.85	1.00	0.50	0.60	0.45	0.85	0.75	0.90	0.75	0.95	0.60	0.90	0.65	0.90	
29	0.15	0.50	0.35	0.60	0.55	0.20	0.50	0.50	0.40	0.50	0.50	0.30	0.65	0.30	0.30	0.15	0.30	0.40	0.25	0.35	0.25	0.35	0.50	0.25	0.60	0.60	0.10	0.30	0.35	0.70	
30	0.15	0.25	0.15	0.60	0.35	0.35	0.35	0.10	0.50	0.25	0.20	0.45	0.30	0.70	0.20	0.10	0.15	0.20	0.50	0.20	0.25	0.00	0.05	0.20	0.10	0.25	0.10	0.40	0.25	0.40	
31	0.70	0.60	0.80	0.70	0.75	0.60	0.45	0.70	0.75	0.95	0.65	0.95	0.80	0.75	0.45	0.50	0.55	0.35	0.95	0.80	0.85	0.80	0.70	0.75	0.75	0.75	0.45	0.70	0.90	0.80	
32	0.30	0.05	0.20	0.05	0.10	0.05	0.00	0.00	0.05	0.35	0.10	0.10	0.20	0.10	0.15	0.10	0.15	0.10	0.05	0.15	0.05	0.20	0.25	0.10	0.75	0.10	0.05	0.20	0.10	0.05	
33	0.50	0.55	0.40	0.15	0.30	0.30	0.10	0.20	0.35	0.30	0.25	0.30	0.00	0.50	0.40	0.35	0.20	0.25	0.25	0.25	0.30	0.20	0.35	0.40	0.35	0.45	0.65	0.15	0.15	0.15	
34	0.30	0.35	0.30	0.40	0.40	0.25	0.35	0.40	0.15	0.40	0.40	0.50	0.10	0.40	0.10	0.15	0.05	0.25	0.35	0.30	0.50	0.25	0.30	0.30	0.55	0.25	0.05	0.05	0.30	0.10	
35	0.65	0.40	0.60	0.85	0.95	0.75	0.80	0.80	0.60	0.65	0.55	0.90	0.90	1.00	0.80	0.10	0.20	0.55	0.85	0.75	0.70	0.85	0.80	0.85	0.25	0.80	0.55	1.00	0.70	1.00	
36	0.05	0.10	0.15	0.05	0.00	0.00	0.00	0.25	0.05	0.05	0.05	0.00	0.15	0.20	0.10	0.15	0.10	0.25	0.00	0.00	0.10	0.20	0.00	0.15	0.30	0.80	0.20	0.05	0.20	0.10	
37	0.35	0.30	0.40	0.55	0.20	0.25	0.65	0.50	0.35	0.30	0.60	0.60	0.70	0.80	0.60	0.45	0.55	0.45	0.50	0.55	0.55	0.45									