FreeAct: Demonstration-Free Robot Adaptation via Action-Grounded Generated Videos

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Abstract

Adapting pretrained Vision-Language-Action (VLA) policies to new deployment environments typically requires collecting expert demonstrations in each target domain, which is costly and difficult to scale. In this paper, we present **FreeAct**, a framework for *demonstration-free robot adaptation* that converts generated videos into physically grounded supervision. A key challenge is that generated manipulation videos, while visually plausible, often contain embodiment artifacts and kinematic inconsistencies that make direct inverse-dynamics labeling unreliable. FreeAct addresses this challenge by learning a discrete latent action space from large-scale multi-lab robot videos and aligning it with camera-frame end-effector SE(3) motion and gripper-state changes. The resulting latent action tokenizer captures task-relevant motion while reducing reliance on embodiment-specific visual artifacts, enabling generated target-domain videos to be pseudo-labeled with reliable latent action tokens. These tokens are first injected into VLA pretraining and then used, together with source-domain action supervision, to adapt the policy to unseen environments. Empirically, FreeAct improves success from 2% to 57% under target-domain shift using generated videos alone, and further to 74% through self-evolution guided by a multimodal large language model (MLLM) on the policy's own rollouts, without expert demonstrations. Further analysis shows that the learned latent action space forms a kinematically structured and transferable representation, establishing generated videos as a scalable source of supervision for robot manipulation. Code and data are available at `https://freeact.pages.dev`.

1 Introduction

Building robots that can follow open-ended instructions and operate reliably across diverse, unseen environments is a long-standing goal in robot learning [Brohan et al., 2023, Zitkovich et al., 2023, Guo et al., 2026a]. VLA models have made substantial progress toward this goal: pretrained on large-scale robot datasets and tuned on target-environment demonstrations, a single policy can perform diverse manipulation tasks across objects, scenes, and embodiments [Black et al., 2025a, Gemini Robotics Team et al., 2025, NVIDIA et al., 2025b]. Yet the last step, tuning on target-environment demonstrations, remains a key bottleneck for deployment. Policies trained in one environment overfit to its distribution and degrade sharply under changes in lighting, texture, camera viewpoint, distractors, object instances, or robot appearance [Yu et al., 2023, Fei et al., 2026], while collecting demonstrations for every new environment is costly, slow, and difficult to scale [O'Neill et al., 2024]. This motivates a practically important setting we term *demonstration-free robot adaptation*: adapting a pretrained policy to a new environment without any target-environment expert demonstrations.

Recent advances in video generation [Zheng and Huang, 2026] offer a compelling path toward this goal. Trained on internet-scale corpora, foundation video generators can synthesize visually realistic

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manipulation videos in a zero-shot manner from language instructions and reference images, naturally covering the broad range of appearance variation, scene diversity, and long-tail conditions [Brooks et al., 2024, NVIDIA et al., 2025a]. In principle, such generated videos could serve as deployment-specific experience for adapting pretrained VLA policies, eliminating the need for target-environment teleoperation. The central challenge is recovering executable robot actions from these videos. A natural approach is to synthesize manipulation videos and then apply an Inverse Dynamics Model (IDM) [Du et al., 2023, Tian et al., 2025]. However, we empirically find this pipeline to be unreliable when the video generator is used without domain-specific finetuning. Generated videos look plausible, but often contain kinematic inconsistencies such as non-rigid arm deformations. These artifacts fall outside the IDM's training distribution and corrupt the inferred actions [Liu et al., 2026]. Tuning the generator on robot-specific data could suppress these artifacts, but is computationally expensive and risks eroding its broad visual coverage and physical priors [Jang et al., 2025]. We therefore ask: *can generated videos be converted into physically grounded action supervision for robot adaptation, without finetuning the generator?*

To this end, we propose **FreeAct**, a three-stage framework that learns physically grounded latent action representations and uses them to adapt pretrained VLA policies from generated videos. In the first stage, we train a latent action model (LAM) on large-scale robot videos with a VQ-VAE objective [van den Oord et al., 2017], augmented by an auxiliary Action Decoder that supervises the latent bottleneck to predict camera-frame end-effector motion. This grounding pressures the latent space to encode kinematics rather than embodiment appearance, yielding a representation that remains reliable on generated videos. In the second stage, the resulting discrete tokens serve as prediction targets for VLA pretraining, injecting a physically grounded motion abstraction into the policy backbone without requiring action labels. In the third stage, we attach a continuous action head and jointly finetune on action-labeled source data and generated target-environment videos pseudo-labeled by the stage-1 model, with a projected gradient update to reconcile the two data streams. Together, this pipeline converts generated videos into action-grounded supervision for demonstration-free policy adaptation.

The practical value of FreeAct lies in its ability to close the full adaptation loop without expert intervention. Generated target-environment videos alone lift a pretrained VLA from 2% to 57% success under substantial domain shift. The adapted policy then refines itself: a handful of its own rollouts, selected by a multimodal LLM judge, raise success to 74%. The two phases are complementary: generated videos bootstrap broad task competence, while self-refinement corrects residual errors such as depth ambiguities that generated supervision alone cannot resolve. A suite of diagnostics reveals a consistent pattern: reconstruction-only baselines yield fragmented, appearance-driven latent spaces, whereas our physically grounded model induces a continuous action manifold whose neighborhoods correspond to similar end-effector motions. This structural alignment is what enables FreeAct to turn generated videos from visually plausible trajectories into actionable supervision for robot adaptation.

Our contributions are threefold:

1. We propose FreeAct, a three-stage framework that grounds discrete latent actions in camera-frame end-effector kinematics, transfers this motion abstraction into a pretrained VLA, and adapts the policy from action-grounded generated videos to a target environment without expert demonstrations.
2. We introduce a set of diagnostics for evaluating latent action spaces and show that physical grounding produces a continuous, linearly decodable kinematic manifold, in contrast to the fragmented, appearance-driven representations learned by reconstruction-only baselines.
3. We show that FreeAct enables demonstration-free adaptation under aggressive domain shift, lifting a pretrained VLA from 2% to 57% success with generated videos alone, and to 74% through self-evolution on a handful of the policy's own rollouts.

2 Related Work

Vision-Language-Action models VLA models adapt pretrained MLLMs [Bai et al., 2025, Zhang et al., 2026] to robot control, predicting action tokens or continuous action chunks from visual observations and language instructions [Zitkovich et al., 2023, Kim et al., 2025, Black et al., 2025b,

NVIDIA et al., 2025b]. Recent generalist policies scale this paradigm with large robot datasets, cross-embodiment mixtures, expressive action decoders, and richer conditioning signals such as memory, subtask prompts, subgoal images, and embodiment-aware prompts [O'Neill et al., 2024, Ghosh et al., 2024, Zheng et al., 2026, Physical Intelligence et al., 2026]. Despite their growing generality, deploying these policies to a new environment typically still requires target-domain robot data, whether through demonstrations, post-training, or carefully curated cross-embodiment pretraining. We target the more practical regime in which no such target-domain robot data is provided.

Video generation for robot learning Video generators provide spatio-temporal priors increasingly exploited for robot learning. One line executes generated videos at inference time, recovering actions with an IDM or a goal-conditioned policy [Du et al., 2023, 2024] or by tracking a tool or object across frames [Liang et al., 2025, Patel et al., 2026]; Gen2Act [Bharadhwaj et al., 2025] instead conditions a policy on generated human videos while learning actions from robot demonstrations. Another line trains a world model, typically from a pretrained generator, and either labels or evaluates its rollouts [Jang et al., 2025, Guo et al., 2026b, Gao et al., 2026] or predicts actions jointly with future visual states [Zhu et al., 2025a, Bi et al., 2026, Kim et al., 2026, Li et al., 2026, Ye et al., 2026, Lyu et al., 2026]. We instead keep the generator off-the-shelf and convert its videos into action supervision through a physically grounded LAM.

Latent action learning Another line of work learns latent actions from action-free videos by encoding inter-frame transitions through a discrete bottleneck and using the resulting codes for control or policy pretraining [Bruce et al., 2024, Schmidt and Jiang, 2024, Cui et al., 2024, Ye et al., 2025, Bu et al., 2025, Chen et al., 2026]. Such objectives primarily constrain visual predictability, leaving the relationship between latent codes and executable robot motion only indirectly specified. Liu et al. [2025] align video-derived latent actions with environment actions through online interaction; we instead retain the action-free latent objective and ground it offline with end-effector motion from a calibrated subset of a multi-lab robot corpus.

3 Method

Problem setup We study *demonstration-free robot adaptation*: given a VLA policy pretrained on source environments, our goal is to adapt it to a target environment without any target-environment expert demonstrations. Let

$$\mathcal{D}_{\mathrm{src}} = \{(o_t,\, o_{t+\Delta},\, \ell_t,\, a_t)\}$$

denote action-labeled robot data from source environments, where o_t and $o_{t+\Delta}$ are RGB observations separated by a fixed temporal horizon Δ, ℓ_t is a language instruction, and

$$a_t = [\Delta p_t,\, \Delta r_t,\, \Delta g_t] \in \mathbb{R}^7$$

is the camera-frame end-effector action comprising 3D translation $\Delta p_t \in \mathbb{R}^3$, 3D axis-angle rotation $\Delta r_t \in \mathbb{R}^3$, and scalar gripper-state change $\Delta g_t \in \mathbb{R}$. In addition, we have access to videos synthesized by an off-the-shelf video generator for the target domain,

$$\mathcal{D}_{\mathrm{gen}} = \{(o^g_t,\, o^g_{t+\Delta},\, \ell^g_t)\},$$

which provide visual trajectories under target-domain appearance but carry no real robot actions. In the *self-evolution* extension, a small number of the adapted policy's own target-environment rollouts, selected by an automated quality signal, form $\mathcal{D}_{\mathrm{self}}$.

FreeAct addresses this setting through three stages: Stage 1 learns a *physically grounded LAM* from large-scale multi-lab robot videos, using a calibrated subset to anchor the latent space to camera-frame kinematics. Stage 2 uses the resulting discrete latent action tokens as supervision for VLA pretraining, injecting motion abstraction into the policy backbone without requiring dense action labels. Stage 3 adapts the pretrained VLA to the target environment by jointly optimizing over source action-labeled data and pseudo-labeled generated videos. At test time, the adapted policy maps a target-environment observation and language instruction directly to a continuous robot action.

3.1 Physically grounded latent action learning

Stage 1 builds on the standard latent action model [van den Oord et al., 2017, Schmidt and Jiang, 2024] to learn a discrete latent representation of motion from frame pairs and ground it in executable

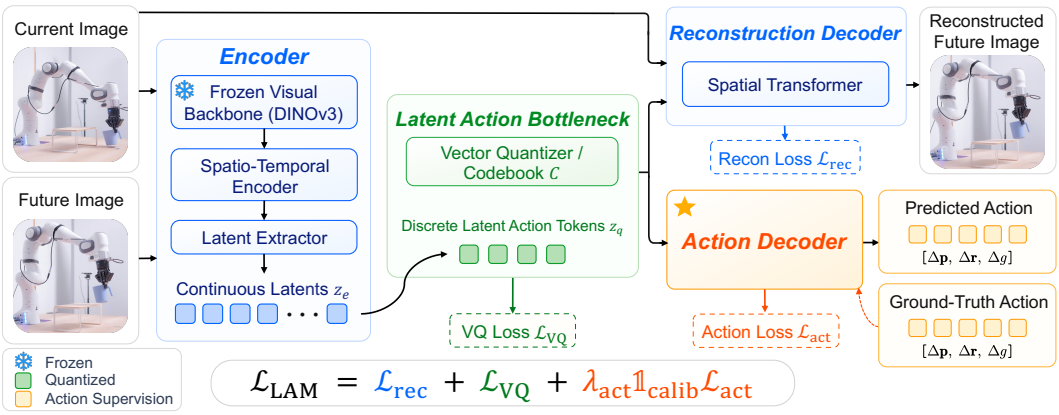


Figure 1: **Stage-1 latent action model.** A frozen DINOv3 encoder maps a frame pair to continuous latents z_e, vector-quantized into discrete tokens z_q against codebook $\mathcal{C}$. A reconstruction decoder predicts the future frame ($\mathcal{L}_{\text{rec}}$, $\mathcal{L}_{\text{VQ}}$). Our key addition ($\star$) is an Action Decoder that maps z_q to the camera-frame end-effector action and is supervised on the calibrated subset ($\mathcal{L}_{\text{act}}$), grounding the codebook in executable kinematics.

robot kinematics. A spatio-temporal encoder Q_ϕ maps a frame pair $(o_t, o_{t+\Delta})$ into a sequence of K continuous latents, which are vector-quantized against a learnable codebook $\mathcal{C}$ to yield discrete tokens

$$z_t = [z_t^{(1)}, \ldots, z_t^{(K)}], \qquad z_t^{(k)} \in \{1, \ldots, |\mathcal{C}|\},$$

and a decoder D_{rec} reconstructs the future frame from z_t and o_t. We use a frozen DINOv3 ViT [Siméoni et al., 2026] as the visual backbone and a transformer encoder–decoder [Xu et al., 2022, Bao et al., 2025] for the spatio-temporal and reconstruction modules; full architectural specifications are deferred to Appendix A. Figure 1 illustrates the resulting pipeline, including our auxiliary Action Decoder branch.

Physical grounding Trained with reconstruction alone, this template offers no pressure on *what* the latent space encodes. The bottleneck is free to organize itself around appearance, texture, or embodiment-specific cues, and prior LAMs exhibit exactly this failure: fragmented, appearance-driven codebooks whose neighborhoods carry little kinematic meaning (Sec. 4.2). We address this with an auxiliary Action Decoder

$$\hat{a}_t = D_{\text{act}}(z_t),$$

a lightweight multi-layer perceptron (MLP) that maps the quantized latents directly to a predicted camera-frame end-effector action. The branch is supervised only on the calibrated subset of $\mathcal{D}_{\text{src}}$ for which camera–robot extrinsics are available.

The design decision is to use the *camera frame* rather than a shared world frame as the supervision target. Camera extrinsics vary substantially across laboratories and episodes, so a model that shortcuts action prediction via embodiment appearance or scene layout cannot generalize across episodes. The latent space is instead pressured to encode end-effector motion relative to the camera in a manner that generalizes across viewpoints. This inductive bias remains valid on generated videos: while full-arm geometry is frequently hallucinated, end-effector motion relative to the scene tends to stay faithful to the task.

Training objective The stage-1 loss combines reconstruction, VQ commitment, and the action supervision above:

$$\mathcal{L}_{\text{LAM}} = \mathcal{L}_{\text{rec}} + \mathcal{L}_{\text{VQ}} + \lambda_{\text{act}}\, \mathbb{1}_{\text{calib}}\, \mathcal{L}_{\text{act}} \tag{1}$$

where $\mathbb{1}_{\text{calib}}$ gates the action loss to the calibrated subset. The 7D action is decomposed into translation (p), rotation (r), and gripper (g) components, balanced by homoscedastic uncertainty weighting [Kendall et al., 2018]:

$$\mathcal{L}_{\text{act}} = \sum_{m \in \{p,r,g\}} \left(e^{-s_m}\, \text{SmoothL1}\left(\hat{a}_t^{(m)},\, a_t^{(m)}\right) + s_m \right) \tag{2}$$

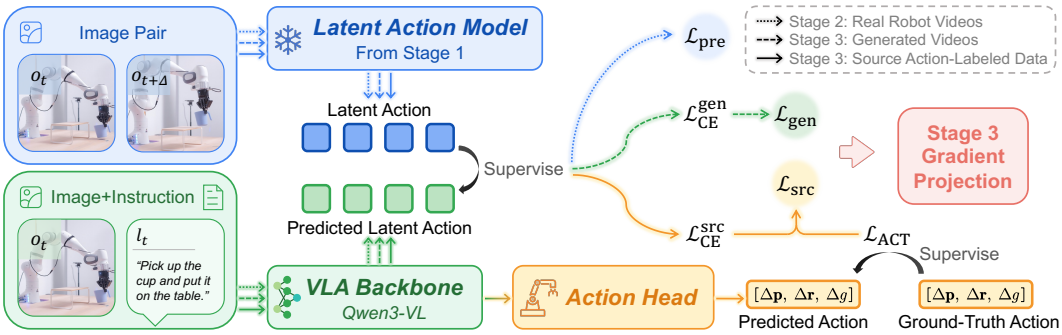


Figure 2: **Stages 2 and 3 of FreeAct.** The frozen stage-1 latent action model (top-left) tokenizes a frame pair into a discrete sequence, which the VLA backbone is trained to autoregressively predict from the current image and instruction ℓ_t. Stage 2 (*dotted*) pretrains the backbone on real robot videos with cross-entropy loss $\mathcal{L}_{\text{pre}}$. Stage 3 jointly trains two streams: source action-labeled data (*solid*), supervising both the latent tokens and a continuous action head ($\mathcal{L}_{\text{src}}$); and pseudo-labeled generated target-environment videos (*dashed*), supervising only the latent tokens ($\mathcal{L}_{\text{gen}}$). The two stage-3 streams are combined through the gradient projection update of Sec. 3.3.

with learnable log-variances $s_m = \log \sigma_m^2$ that absorb relative modality scales during training.

After stage 1, the model serves two roles: it provides a physically grounded latent action space whose neighborhoods reflect executable motion rather than visual similarity, and it acts as a fixed tokenizer that maps real and generated frame pairs to discrete action sequences for downstream stages.

3.2 Latent action-guided VLA pretraining

The second stage transfers the motion abstraction into the VLA backbone (Figure 2). We augment the backbone's text tokenizer vocabulary with $|\mathcal{C}|$ special action tokens $\{\texttt{<la}_0\texttt{>}, \ldots, \texttt{<la}_{|\mathcal{C}|-1}\texttt{>}\}$, one per codebook entry, and cast latent action prediction as next-token prediction within the backbone's chat template:

$$\begin{aligned} \texttt{User:} \quad & \texttt{<image>}\, \ell_t \\ \texttt{Assistant:} \quad & \texttt{<la}_{z_t^{(1)}}\texttt{>} \cdots \texttt{<la}_{z_t^{(K)}}\texttt{>}. \end{aligned}$$

For each training sample $(o_t, o_{t+\Delta}, \ell_t)$, the frozen stage-1 tokenizer provides the target sequence $z_t = Q_\phi(o_t, o_{t+\Delta})$. The VLA backbone is then trained to predict it autoregressively:

$$\mathcal{L}_{\text{pre}} = -\sum_{k=1}^{K} \log p_\theta\left(z_t^{(k)} \mid o_t,\, \ell_t,\, z_t^{(<k)}\right). \tag{3}$$

The visual encoder is kept frozen throughout; only the vision–language projector and language model are updated. This objective scales beyond densely annotated trajectories, since latent action tokens can be extracted from any unlabeled video. It exposes the backbone to a physically grounded motion representation before continuous control is introduced in stage 3.

3.3 Deployment adaptation via generated videos

In the final stage, we adapt the pretrained VLA to the target environment by jointly optimizing over action-labeled source data and generated target-environment videos (right side of Figure 2).

Continuous action head We attach a continuous action head H_ψ that decodes the hidden states at the latent-action token positions into a continuous robot action, $\hat{a}_t = H_\psi(h_t)$. H_ψ is built on multihead attention pooling (MAP) [Lee et al., 2019]: it pools the latent-token hidden states into a compact action embedding and projects it to the action space. The head is trained from scratch in stage 3, while the backbone inherits the representation from stage 2.

Joint finetuning For source samples $(o_t, o_{t+\Delta}, \ell_t, a_t) \in \mathcal{D}_{\text{src}}$, we supervise both the latent token sequence and the continuous action:

$$\mathcal{L}_{\text{src}} = \mathcal{L}_{\text{CE}}^{\text{src}} + \lambda_a \mathcal{L}_{\text{ACT}}, \qquad \mathcal{L}_{\text{ACT}} = \|\hat{a}_t - a_t\|_1. \tag{4}$$

For generated video samples $(o_t^g, o_{t+\Delta}^g, \ell_t^g) \in \mathcal{D}_{\text{gen}}$, no real actions are available; we pseudo-label each sample with the frozen stage-1 tokenizer, $\tilde{z}_t^g = Q_\phi(o_t^g, o_{t+\Delta}^g)$, and supervise only the latent token prediction:

$$\mathcal{L}_{\text{gen}} = \lambda_v \mathcal{L}_{\text{CE}}^{\text{gen}}. \tag{5}$$

The two streams thus play asymmetric roles: source data anchors continuous control fidelity, while generated videos expose the backbone to how motion manifests under target-domain appearance, viewpoint, and object variation.

Gradient conflict mitigation This asymmetry makes naive joint optimization unstable: the two streams carry different supervision signals, one continuous and one token-level, and their gradients frequently conflict. When this happens, the generated gradient erodes the precise control signal carried by action labels. To mitigate this, we adopt a gradient projection update tailored to our two-stream setting [Yu et al., 2020]. Let g_{src} and g_{gen} denote the per-parameter gradients from each stream. Whenever the gradients conflict, $g_{\text{src}}^\top g_{\text{gen}} < 0$, we project away the conflicting component

$$\tilde{g}_{\text{gen}} \leftarrow g_{\text{gen}} - \frac{g_{\text{src}}^\top g_{\text{gen}}}{\|g_{\text{src}}\|^2} g_{\text{src}} \tag{6}$$

and update with $g_{\text{src}} + \tilde{g}_{\text{gen}}$. This preserves the continuous control signal from source data while keeping the target-domain visual gradient alive on parameters where the two streams agree.

4 Experiments

We evaluate FreeAct along the full pipeline from latent action learning to deployment adaptation. Our experiments are organized around three research questions:

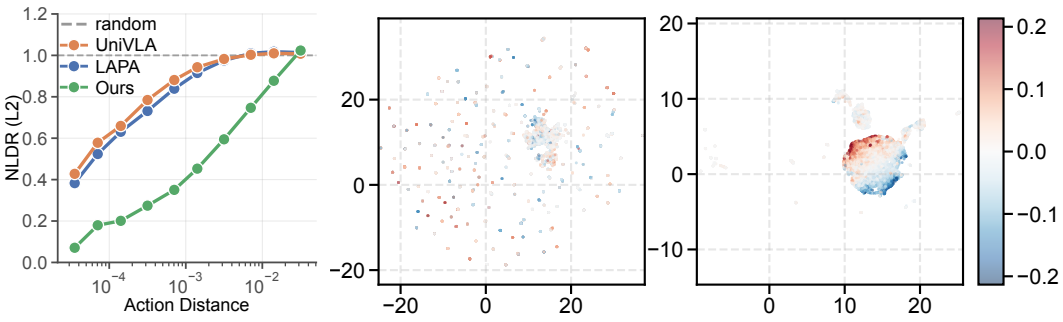
- **RQ1** Does physically grounded supervision yield a kinematically structured latent action space, relative to purely reconstruction-based baselines? (Sec. 4.2)
- **RQ2** Can generated videos alone adapt a pretrained VLA policy to unseen target environments without any real demonstrations, and does our grounded LAM provide more reliable pseudo-supervision than IDM-based and reconstruction-only alternatives? (Sec. 4.3)
- **RQ3** Can the adapted policy further improve through self-evolution on its own rollouts, without expert intervention? (Sec. 4.4)

4.1 Experimental setup

Datasets Stages 1 and 2 use DROID [Khazatsky et al., 2024] for latent action learning and VLA pretraining; the calibrated subset with camera extrinsics provides $\mathcal{L}_{\text{act}}$ supervision. Stage 3 draws source data from Liu et al. [2023] and evaluates on a custom robosuite [Zhu et al., 2025b] target environment with substantial visual and task shift. Target-domain videos are synthesized with Wan 2.6 [Wan et al., 2025] (20 rollouts per task). Full setup details are in Appendix B.

Baselines For the latent space evaluation (RQ1), we compare against LAPA [Ye et al., 2025] and UniVLA [Bu et al., 2025], two LAMs trained with reconstruction objectives alone. For end-to-end adaptation (RQ2), we compare against UniPi [Du et al., 2023], which recovers continuous actions from generated videos via an IDM, DreamGen [Jang et al., 2025], which finetunes the generator before IDM labeling, and the LAPA and UniVLA tokenizers swapped into our stage-2/3 pipeline.

Implementation details Stage 1 uses a frozen DINOv3 ViT-B/16 [Siméoni et al., 2026] as the visual backbone with a transformer encoder–decoder for the VQ-VAE. Stage 2 initializes from Qwen3-VL-4B [Bai et al., 2025], keeping the visual encoder frozen and finetuning the projector and language model. Stage 3 inherits the stage-2 checkpoint and jointly trains the continuous action head and backbone on source and generated data. Full hyperparameters and training schedules are in Appendix A.



(a) NLDR. (b) UMAP projection of test-set latents.

Figure 3: **Latent action space structure on the DROID held-out test split.** (a) NLDR vs. action-distance threshold τ; lower values indicate that physically similar actions are colocated in the latent space. (b) UMAP projection of test-set latents, colored by end-effector x-displacement in meters (left: UniVLA; right: ours). LAPA and additional axes are deferred to Appendix D.

4.2 RQ1: Physically grounded latent action space

We first evaluate the intrinsic quality of the latent action space learned in stage 1, asking whether physical action supervision produces a representation whose geometry reflects executable kinematics rather than visual texture. All metrics below are computed on a held-out DROID test split disjoint from our training trajectories. Baselines are LAPA [Ye et al., 2025] and UniVLA [Bu et al., 2025], using their official checkpoints; both were trained on broader datasets that include our test trajectories.

Topology preservation A well-structured latent space should bring physically similar actions closer than dissimilar ones. We quantify this with a *normalized latent-distance ratio* (NLDR): for an action-distance threshold τ, we compare the mean latent distance among sample pairs whose ground-truth actions are within τ to the mean distance over random pairs,

$$\mathrm{NLDR}(\tau) = \frac{\mathbb{E}_{(i,j)\in\mathcal{S}_\tau}\|z_i - z_j\|_2}{\mathbb{E}_{\text{random}}\|z_u - z_v\|_2}, \qquad \mathcal{S}_\tau = \{(i,j) : d_a(a_i, a_j) < \tau\}. \tag{7}$$

The action distance d_a sums the mean SmoothL1 distance over the three semantic components of the 7D action: translation (p), rotation (r), and gripper (g), giving each component equal weight regardless of its dimensionality. A value near 1 indicates no correlation between latent and physical distance; values near 0 indicate that physically similar actions form tight latent clusters. As shown in Figure 3a, our model reaches NLDR below 0.1 at the smallest τ and stays well below the baselines across the full range; LAPA and UniVLA improve only marginally over random as τ shrinks, with NLDR remaining around 0.4 even at the tightest threshold.

Manifold structure Figure 3b projects test-set latents into 2D [Yuan et al., 2021] via UMAP [McInnes et al., 2020], colored by ground-truth end-effector x-displacement. The UniVLA latent space disperses into a noisy central cluster in which colors are intermixed with no discernible gradient: the continuous action space is fractured into unrelated fragments, leaving no geometric reference along which a downstream policy can interpolate. Our model instead forms a dense manifold whose color varies smoothly from one side to the other, mapping the topology of physical motion onto the latent space. Adjacent latent vectors thus correspond to neighboring physical actions, the prerequisite for fine-grained control and smooth skill generalization in downstream stages.

Linear decodability A continuous manifold structure is only useful if downstream modules can read off action information from it. We probe this with ridge regression from frozen latents

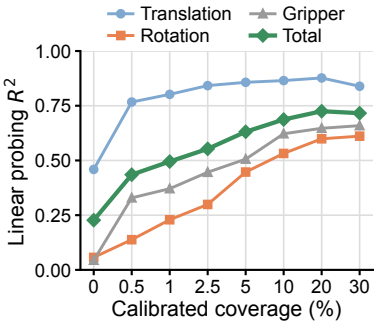
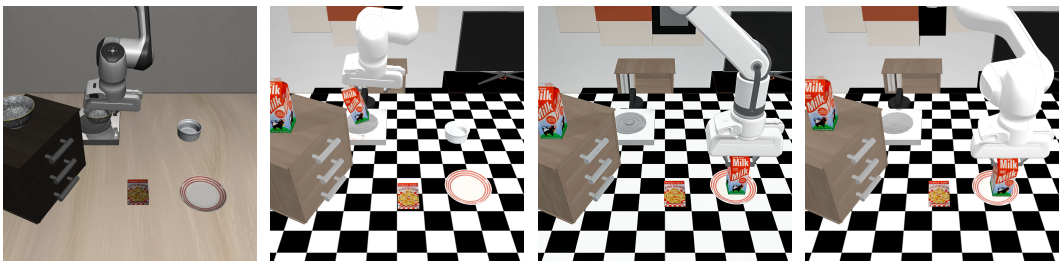


Figure 4: **Linear probing R^2 vs. action-supervision coverage.** Stage 1 is retrained with $\mathcal{L}_{\text{act}}$ restricted to nested subsets of calibrated trajectories.

Table 1: **Linear probing R^2 on the DROID held-out test set.** Reconstruction-only baselines fail on rotation and gripper dimensions; our model achieves high decodability across all components.

Method	LAPA		UniVLA		Ours	
	Train	Test	Train	Test	Train	Test
Total R^2	0.104	0.107	0.096	0.090	0.794	**0.761**
Translation R^2	0.223	0.226	0.201	0.189	0.899	**0.878**
Rotation R^2	0.013	0.014	0.016	0.013	0.711	**0.660**
Gripper R^2	0.022	0.029	0.019	0.021	0.727	**0.712**
Norm. MSE	0.896	0.990	0.904	1.008	0.206	**0.264**



(a) Source Env (b) Target Env (c) Generated Video (d) Rollout

Figure 5: **An example of the source–target shift, generated supervision, and resulting rollout (Task E).** (a) Source environment. (b) Target environment, exemplifying the visual and task changes considered in this paper; without adaptation, the source policy topples the milk carton with its pinch trajectory. (c) Frame from a Wan 2.6 generated rollout: the arm shows kinematic hallucinations, yet the gripper and end-effector remain faithful. (d) Successful FreeAct rollout after adaptation.

to the 7D ground-truth action, reporting the coefficient of determination R^2 (higher is better) on train and test splits. Table 1 shows that LAPA and UniVLA achieve $R^2 \approx 0.1$ overall, with rotation and gripper components effectively undecodable ($R^2 < 0.03$). Our model reaches $R^2 = 0.76$ overall, with translation, rotation, and gripper all linearly decodable in their own right. The latent space not only clusters by kinematics, it explicitly encodes them.

Supervision coverage Camera extrinsics are available for only $\sim$40% of DROID, so we vary action-supervision coverage to assess how much calibrated data grounding requires. We retrain stage 1 with the action loss restricted to nested subsets of calibrated trajectories, keeping all other data and settings fixed (Figure 4). Within this sweep, reducing coverage from 30% to 0% ($\lambda_{\text{act}} = 0$) lowers R^2 from 0.72 to 0.23, with rotation and gripper falling from 0.61/0.66 to 0.06/0.04. Performance levels off around 20% coverage; 1% already attains 69% of the plateau value, indicating that limited calibration can substantially improve action decodability.

Across these diagnostics, the picture is consistent: physically grounded supervision through the auxiliary Action Decoder is sufficient to convert a reconstruction-only codebook into a continuous, linearly decodable kinematic manifold. This structural property is what allows downstream stages to convert generated videos into reliable adaptation supervision (Sec. 4.3).

4.3 RQ2: Demonstration-free adaptation from generated videos

We now turn to the central question of this paper: can a pretrained VLA policy be adapted to a new environment using only generated videos, with zero expert demonstrations? We construct a target environment with changes in lighting, desk textures, robot link colors, initial joint configurations, task instructions, and most importantly the target manipulation skill itself (Figure 5a, b). Source tasks reduce to a *precision pinch* on a thin protrusion, exemplified by the rim of a bowl, where the policy only needs to align one finger with a narrow edge before closing. Target tasks instead require an *enclosing grasp* on a milk carton, an object never seen in the source distribution: the gripper must approach with both fingers straddling the full width of the body, at a different height, direction, and

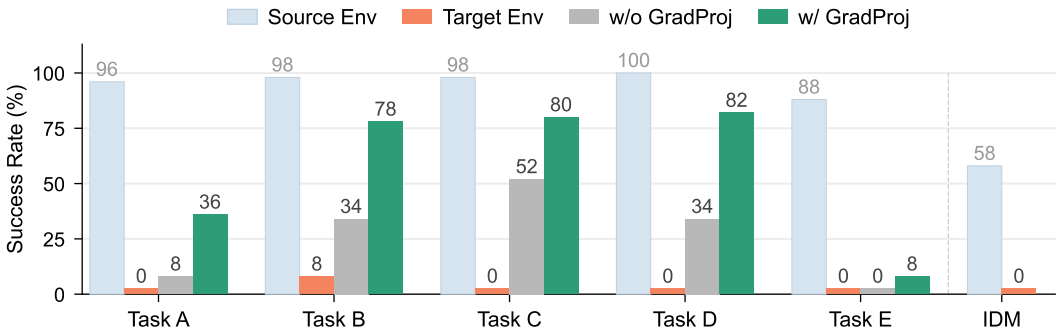


Figure 6: **Demonstration-free adaptation results on five target tasks.** *Source Env*: pretrained VLA on the source environment (sanity check). *Target Env*: same policy deployed on the target environment without adaptation. *w/ GradProj* (FreeAct): adaptation using only Wan 2.6 generated videos pseudo-labeled by our latent action model, with the gradient projection update of Sec. 3.3. *w/o GradProj*: the same setup with the projection removed. *IDM*: UniPi-style baseline, evaluated on real source videos (left, 58%) and on generated target videos (right, 0%). Each bar averages 50 closed-loop rollouts.

closing pattern. The two regimes thus exercise different aspects of low-level control, not merely different appearances.

Figure 6 reports closed-loop success across five target tasks, averaged over 50 trials each. The pretrained VLA, despite near-saturated source performance (96% on average), collapses to 1.6% when deployed directly on the target environment. Lacking any prior exposure to carton-shaped objects, the policy keeps executing its source-domain pinch trajectory, swinging one finger of the parallel gripper into the carton and toppling it (Figure 5b). FreeAct, supervised only by Wan 2.6 generated videos (Figure 5c), recovers an average success rate of 57% (Figure 5d), with four of five tasks exceeding 35% and three exceeding 75%.

A natural alternative is to recover actions directly from generated videos via IDM, as in UniPi. We evaluate it on two inputs separately. On real teleoperated source-environment videos the IDM is faithful, replaying its predictions with 58% success and confirming our reimplementation is sound. On Wan 2.6 generated videos the same IDM collapses to 0%: kinematic inconsistencies push the inputs outside its training distribution, and the recovered action sequences become physically incoherent. DreamGen's official pipeline, which uses a robot-finetuned video generator followed by IDM labeling, also yields 0% success. While the generated arm is hallucinated, the gripper and end-effector motion remain faithful to the task; our latent action model is designed to extract exactly this signal (Sec. 3.1). For comparison, we use the official reconstruction-only LAPA or UniVLA tokenizer in the same stage-2/3 pipeline. Source success remains high (87% and 89%), but target success reaches only 12% and 4% (Table 6), consistent with their lower action decodability in RQ1.

Removing the gradient projection step (w/o GradProj in Figure 6) drops the average success rate from 57% to 26%, with three of five tasks losing more than half of their success and Task E collapsing to 0%. This confirms the prediction of Sec. 3.3: a naive sum of the two losses lets the generated-video gradient cancel parts of the source-stream update, eroding the precise control signal carried by action labels. The projected update strips the conflicting component from the generated gradient, so source data continues to deliver clean control supervision while the generated stream still propagates target-domain visual information through the parameters where the two streams agree.

Task E remains the hardest case across all settings, including for FreeAct (8%). The cause traces to the target scene geometry: the milk carton sits almost directly beneath the gripper and slightly farther from the camera, weakening the perspective cues that disambiguate depth. Wan 2.6 interprets this as a vertical descent and generates videos in which the gripper drops straight down, ignoring the small forward displacement required for accurate grasping. The downstream policy is therefore upper-bounded by the fidelity of the generated supervision: when the generator misreads the scene geometry, no amount of action grounding can recover the missing kinematic content. This points toward generation-side improvements such as multi-view conditioning or depth priors [Xu et al., 2026] as a complementary axis to action grounding.

4.4 RQ3: Self-evolution from policy rollouts

The adapted policy from RQ2 recovers basic task competence from generated videos alone. We now ask whether it can further improve through its own experience. We deploy the stage-3 policy in the target environment, score each rollout with GPT-5.5 [OpenAI, 2026] on task completion and execution quality (prompt in Appendix C), and finetune on up to five of the highest-scoring rollouts per task, drawn from the 50 evaluation rollouts per task in Figure 6. Ground-truth success labels are not used for selection; a post hoc check confirms that all selected rollouts are successful.

Figure 7 reports success rates after one round of self-evolution. The average rises from 57% to 74%. Task E, previously capped at 8% due to depth ambiguity in the generated videos, jumps to 52%, confirming that even minimal real interaction can correct biases that generated supervision alone cannot resolve. Task D falls from 82% to 56% despite successful selected rollouts. Pooling data across tasks may introduce interference during finetuning, a possible explanation for this decline.

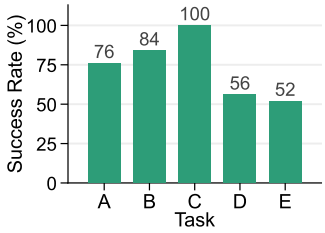


Figure 7: **Self-evolution from rollouts.** Success rates after one round of self-evolution. Each bar averages 50 closed-loop rollouts.

No target-domain expert demonstration is introduced at any point: stage 3 adapts from generated videos, and self-evolution draws on the policy's own rollouts as judged by an MLLM. This establishes a complete adaptation loop for deployment to novel environments, in which generated videos bootstrap competence and autonomous refinement lifts performance to practical levels.

5 Conclusion

We presented FreeAct, a demonstration-free adaptation framework that anchors a discrete latent action space to camera-frame end-effector kinematics, enabling reliable pseudo-labeling of generated videos despite their kinematic artifacts. Generated videos alone lift a pretrained VLA from 2% to 57% under aggressive domain shift; the adapted policy then self-evolves on its own rollouts to 74%. These results establish a complete adaptation loop that requires no target-domain expert demonstrations.

Limitations and future work Our evaluation is confined to simulation, a single embodiment, and single-arm tabletop manipulation; real robots, cross-embodiment transfer, and bimanual or dexterous settings with richer contact dynamics are natural next steps. Adaptation is bounded by generator fidelity (Task E), which multi-view conditioning or depth priors could improve. Pooled self-evolution can also reduce performance on individual tasks (Task D); per-task balancing is a possible remedy.

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A Hyperparameters and Training Details

Table 2, Table 3, and Table 4 list the full hyperparameter configurations for the three training stages. All experiments are run on a single node with 8 NVIDIA RTX 4090 GPUs (24 GB each). End-to-end wall-clock training time is approximately 19 hours for stage 1, 120 hours for stage 2, and 7 hours for stage 3.

Table 2: Stage 1 (LAM Training) hyperparameters.

Component	**Setting**
Visual backbone	DINOv3 ViT-B/16 (frozen)
Encoder / decoder	12 layers, dim 768, 12 heads
VQ codebook size C	64
Latent dimension	128
Tokens per frame pair K	4
Action Decoder	3-layer MLP, hidden $[256, 128]$, GELU
Training data	DROID
Global batch size	512 (64 per GPU)
Optimizer	AdamW (lr 10^{-4}, wd 10^{-2})
Gradient clipping	0.1
Epochs	1
Action loss weight λ_{act}	0.01

Table 3: Stage 2 (VLA Pretraining) hyperparameters.

Component	**Setting**
Backbone	Qwen3-VL 4B-Instruct
Visual encoder	frozen
Projector	full precision, fully trained
Language model	LoRA (rank 64, $\alpha = 128$)
Global batch size	256
Optimizer	AdamW (lr 5×10^{-5}, wd 10^{-2})
Schedule	constant with 3000-step warmup
Parallelism	DeepSpeed ZeRO-2
Epochs	2
Latent tokenization	on-the-fly (lazy encoding)

Table 4: Stage 3 (Deployment Adaptation) hyperparameters.

Component	Setting
Initialization	Stage 2 checkpoint
Action head hidden dim	512
Backbone learning rate	10^{-4} (cosine decay to 10% of peak)
Action head learning rate	3.5×10^{-4} (wd 10^{-3})
Global batch size	256
Epochs	75
Warmup steps	200
Generated data weight λ_v	0.1
Action window W	16
Gradient projection	enabled at every step

B Data and Task Details

DROID (Stages 1 and 2) The DROID dataset provides approximately 362 hours of teleoperated manipulation across 564 scenes. The $\sim$40% of trajectories with precise camera extrinsics form the calibrated subset on which the action loss $\mathcal{L}_{\text{act}}$ is applied; the remaining trajectories contribute only to the reconstruction and VQ objectives.

LIBERO (Stage 3 source) Source data $\mathcal{D}_{\text{src}}$ is drawn from LIBERO [Liu et al., 2023]. We use its standard task suite as the source-domain action-labeled data for joint finetuning.

Target environment (Stage 3) The target environment is a custom robosuite [Zhu et al., 2025b] scene that differs from the source in lighting, desk textures, object identities and layout, and task instruction. Target-domain videos $\mathcal{D}_{\text{gen}}$ are synthesized with Wan 2.6 [Wan et al., 2025], conditioned on the initial frame and the language instruction, yielding 20 rollouts per task.

Target task suite The five target tasks instantiate a single unseen manipulation skill (enclosing power grasp followed by short-range relocation) under systematically varied spatial contexts. This controlled design is deliberate: by fixing the grasp type and success criterion, we isolate how well generated-video supervision generalizes across different approach geometries without confounding from semantic task variation. The five variants differ in support surface, surrounding distractors, and spatial relation between the target object and nearby landmarks, producing meaningfully different trajectory requirements (collision avoidance, depth estimation, pre-grasp alignment). Table 5 lists the instruction templates.

Table 5: Target task suite. Each task instantiates the same unseen-object relocation skill under a different spatial configuration, varying the approach geometry, support relation, and surrounding distractors while keeping the target object and success criterion controlled. `[obj]`, `[ref]`, and `[goal]` denote the target object, reference landmark(s), and goal location, respectively.

Task	Spatial context	Instruction template
A	Between distractors	Pick up `[obj]` between $\texttt{[ref}_1\texttt{]}$ and $\texttt{[ref}_2\texttt{]}$ and place it on `[goal]`.
B	Open table surface	Pick up `[obj]` from `[ref]` and place it on `[goal]`.
C	On supporting object	Pick up `[obj]` on `[ref]` and place it on `[goal]`.
D	Adjacent to distractor	Pick up `[obj]` next to `[ref]` and place it on `[goal]`.
E	Depth-ambiguous region	Pick up `[obj]` on `[ref]` and place it on `[goal]`.

C MLLM Evaluation Prompt

In RQ3 (Sec. 4.4), we use GPT-5.5 as a rollout evaluator. The model receives the full rollout video along with the task instruction and returns a composite score (five dimensions, each 0–4, totaling 20 points) assessing task completion and execution quality. The prompt template is shown below.

```
You will watch a rollout video of a robot completing the <task objective> and
    score it based on the quality of the task execution process.
Please inspect the video frame by frame. Do not score based only on key frames,
    sampled frames, or an overall impression. Before scoring, you must clearly
    observe the continuous process from the robot approaching the target object,
    making contact, performing the operation, and reaching the end of the task.
    Pay close attention to the approach path, pauses, jitter, incorrect contact,
    corrective actions, environmental collisions, operation effect, and final
    state.
Please score the performance across the following five dimensions. Each dimension
    is scored from 0 to 4, for a total of 20 points. Each score must be an
    integer and include a brief reason.

(1) Approach and Initial Operation Smoothness
Evaluate whether the robot's process from approaching the target object to
    forming effective contact is natural, continuous, and accurate.
4 points: The robot approaches accurately in one attempt and forms effective
    contact. The path is natural and continuous, with no obvious jitter, pauses,
    probing, incorrect contact, or secondary adjustment.
3 points: Overall fairly smooth, with only slight deceleration, small pose
    correction, or very brief alignment. No obvious pause, hesitation, jitter,
    poking, pushing, retreating, or post-contact readjustment.
2 points: Average process, with visible pauses, hesitation, jitter, path
    deviation, obvious pose correction, brief incorrect stopping, slight poking,
    pushing, or post-contact adjustment. Effective contact is eventually formed.
1 point: Effective contact is formed only after multiple pokes, pushes, probing
    actions, retreats, or repeated adjustments.
0 points: The robot is unable to form effective contact for a long time,
    repeatedly collides with or pushes away the target object, or makes
    incorrect contact; the initial stage is chaotic.

(2) Contact Position Accuracy and Operation Quality
Evaluate whether the robot's contact position, pose, contact method, force
    direction, and stability are reasonable.
4 points: The contact position is ideal, the pose and force application are
    reasonable, contact is stable and sufficient, and the target object shows no
    obvious sliding, rotation, tilting, or instability.
3 points: The contact position is generally accurate, with only slight offset or
    slightly insufficient contact. The target object remains basically stable,
    with no obvious sliding, rotation, tilting, slipping, or instability risk.
2 points: The contact position is not ideal, with obvious offset, insufficient
    contact area, poor force direction, or uneven force, causing visible
    tilting, sliding, rotation, slight slipping, or instability of the target
    object. The task can still continue.
1 point: The contact position is poor, contacting only an edge, a small area, or
    the wrong area. The target object is clearly unstable, nearly drops, gets
    stuck, or fails.
0 points: The contact position is extremely poor, causing clear operation
    failure, severe instability, or requiring recovery from a failed state.

(3) Execution Stability and Trajectory Smoothness
Evaluate whether the main execution phase is stable, smooth, and continuous. Do
    not separately evaluate environmental collisions here.
4 points: The execution process is continuous and natural, with steady speed and
    no obvious jitter, sudden stops, retreats, detours, or unnecessary
    adjustments. The target object and end effector remain stable.
3 points: Overall stable, with only slight speed changes, small trajectory
    adjustments, very brief pauses, or slight shaking. No obvious pose changes,
    instability, or unnecessary corrections.
2 points: The process is not very smooth, with obvious pauses, jitter, uneven
    speed, path corrections, pose adjustments, repeated micro-adjustments, brief
    retreats, or unnecessary detours. The target object or end effector visibly
    shakes, tilts, or becomes unstable, but the task can still continue.
```

```
1 point: Multiple jitters, sudden stops, retreats, or repeated adjustments occur.
    The trajectory is clearly unnatural, and the target object or end effector
    is obviously unstable.
0 points: The execution process is chaotic, with long stagnation, severe jitter,
    or multiple ineffective movements. The task state is severely unstable or
    close to losing control.

(4) Environmental Interaction and Collision Control
Evaluate whether the robot, end effector, or target object makes unnecessary
    contact with the environment and causes disturbances.
4 points: No obvious collision or unnecessary contact throughout the process; no
    non-target objects or environmental structures are disturbed.
3 points: Only slight, brief scraping or near-contact occurs, without visible
    movement, shaking, squeezing, dragging, mistaken contact, or task
    interference.
2 points: Obvious but not severe collision, scraping, pressing, dragging, or
    mistaken contact occurs, causing small movement, shaking, pose change, brief
    obstruction, or slight interference, but does not lead to failure.
1 point: The robot collides with environmental objects multiple times, or clearly
    pushes, squeezes, drags, or mistakenly contacts objects, causing noticeable
    disturbance or affecting the task.
0 points: Severe collision or major environmental disturbance occurs, causing
    objects to be knocked away, dragged, toppled, mistakenly triggered, or
    seriously interfering with the task.

(5) Task Success and Final State Accuracy
Evaluate whether the task is completed and whether the final result reaches the
    target position or target state.
4 points: The task succeeds. The final result is accurately in place and stable,
    with no obvious deviation, over-operation, or risk of failure.
3 points: The task succeeds. The final result is basically in place, with only
    slight position or pose deviation. The target object is stable, with no
    obvious edge offset, tilting, slipping, or subsequent instability risk.
2 points: The task is basically successful, but the final position, pose, or
    state is clearly not ideal, such as obvious deviation from the target
    center, edge offset, tilting, incomplete placement, or risk of slipping,
    toppling, deviation, rebound, or later instability.
1 point: The task barely succeeds or is close to succeeding. The final state is
    unstable, clearly deviates from the target, or only part of the objective is
    completed.
0 points: The task fails. The target position or state is not reached, or
    dropping, non-triggering, severe deviation, jamming, instability, or another
    issue prevents task completion.

Please output in the following format:
(1) Approach and Initial Operation Smoothness: X/4
Reason: ...
(2) Contact Position Accuracy and Operation Quality: X/4
Reason: ...
(3) Execution Stability and Trajectory Smoothness: X/4
Reason: ...
(4) Environmental Interaction and Collision Control: X/4
Reason: ...
(5) Task Success and Final State Accuracy: X/4
Reason: ...
Total Score: X/20
```

D Additional Results

Table 6 gives the per-task results of the tokenizer-swap experiment of Sec. 4.3.

Table 6: **Tokenizer swap.** Success rate (%) when the official LAPA and UniVLA latent action models replace ours in an otherwise identical stage-2/3 pipeline on the same training data. Each entry averages 50 closed-loop rollouts.

	Tokenizer	A	B	C	D	E	Avg
Source Env	UniVLA	74	96	100	94	80	88.8
	LAPA	78	84	92	92	90	87.2
	Ours	96	98	98	100	88	**96.0**
Target Env (adapted)	UniVLA	14	4	0	0	2	4.0
	LAPA	10	32	18	0	0	12.0
	Ours	36	78	80	82	8	**56.8**

Figures 8–11 provide per-axis and magnitude UMAP visualizations supplementing the codebook analysis in Sec. 4.2. Our codebook exhibits smooth, axis-aligned gradients across all translational dimensions, whereas LAPA and UniVLA show fragmented clusters with no consistent directional structure.

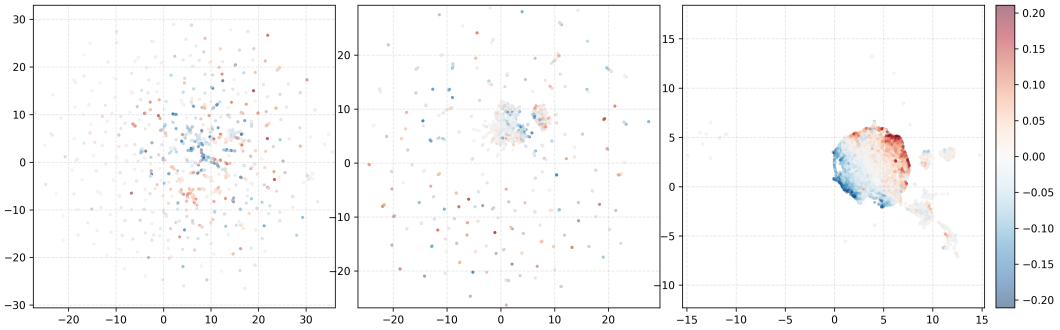

Figure 8: UMAP visualization colored by X-axis displacement. **Left**: LAPA; **Middle**: UniVLA; **Right**: Ours.

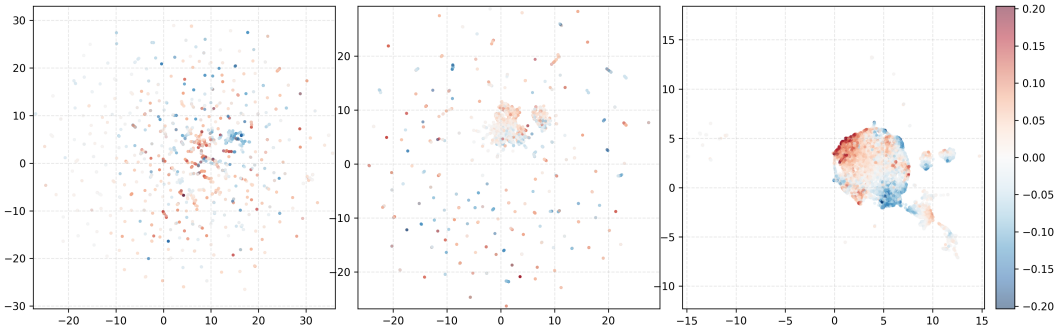

Figure 9: UMAP visualization colored by Y-axis displacement. **Left**: LAPA; **Middle**: UniVLA; **Right**: Ours.

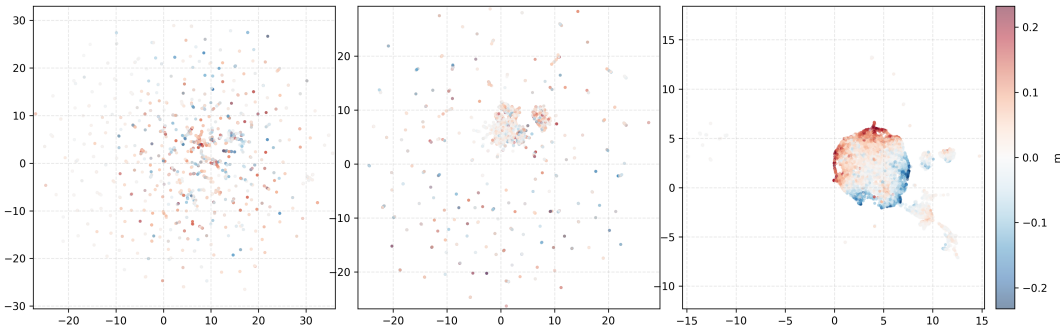

Figure 10: UMAP visualization colored by Z-axis displacement. **Left**: LAPA; **Middle**: UniVLA; **Right**: Ours.

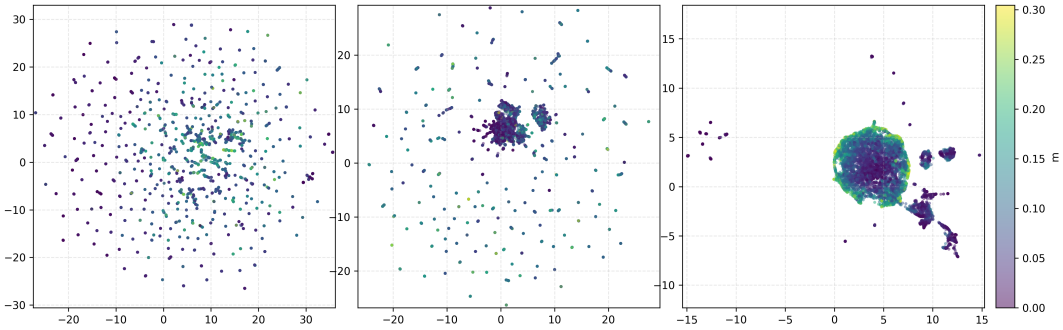

Figure 11: UMAP visualization colored by displacement magnitude. **Left**: LAPA; **Middle**: UniVLA; **Right**: Ours.

Additional target environments To assess adaptation beyond the five-task suite, we evaluate two additional simulated target environments: one replaces the milk carton with a round, slender ketchup bottle and updates the instruction; the other shifts the camera azimuth by 5°. Evaluated on 50 fixed initial states per environment, adaptation from generated videos achieves 60% and 74% success, respectively, rising to 94% and 92% after one round of self-evolution. Here, self-evolution is performed separately per task, without cross-task pooling. These results are also available in our code repository.

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