

MAPS: Preserving Vision-Language Representations via Module-Wise Proximity Scheduling for Better Vision-Language-Action Generalization

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[mapsvla.github.io](https://github.com/mapsvla)

Abstract

*Vision-Language-Action (VLA) models inherit strong priors from pretrained Vision-Language Models (VLMs), but naïve fine-tuning often disrupts these representations and harms generalization. Existing fixes – freezing modules or applying uniform regularization – either overconstrain adaptation or ignore the differing roles of VLA components. We present **MAPS (Module-Wise Proximity Scheduling)**, the first robust fine-tuning framework for VLAs. Through systematic analysis, we uncover an empirical order in which proximity constraints should be relaxed to balance stability and flexibility. MAPS linearly schedules this relaxation, enabling visual encoders to stay close to their pretrained priors while action-oriented language layers adapt more freely. MAPS introduces no additional parameters or data, and can be seamlessly integrated into existing VLAs. Across MiniVLA-VQ, MiniVLA-OFT, OpenVLA-OFT, and challenging benchmarks such as SimplerEnv, CALVIN, LIBERO, as well as real-world evaluations on the Franka Emika Panda platform, MAPS consistently boosts both in-distribution and out-of-distribution performance (up to +30%). Our findings highlight empirically guided proximity to pretrained VLMs as a simple yet powerful principle for preserving generalization in VLM-to-VLA transfer.*

1. Introduction

Vision-Language-Action (VLA) models have recently emerged as a unifying framework for robotic learning, enabling agents to perceive their environment, understand natural language instructions, and execute actions in an end-to-end manner [1–4]. However, the scarcity of large-scale robotics data makes it infeasible to train these models from scratch. As a result, most VLA systems initialize from powerful vision-language models (VLMs) [5–7] pretrained on

web-scale data, leveraging their rich visual and semantic priors before finetuning on robotics datasets to learn action policies. However, while this strategy has led to impressive task performance, it often comes at the cost of generalization – models degrade in performance when faced with novel tasks, objects, or environments [8, 9].

This loss of generalization arises from a fundamental mismatch between large-scale pretraining and the limited scope of robot-specific finetuning [1]. Robotics datasets are typically sparse and task-specific, and finetuning extensively on them induces spurious correlations and overfitting, which in turn causes catastrophic forgetting of spatial reasoning, world knowledge, and linguistic grounding. The core challenge in VLA training therefore lies in balancing the tradeoff between action adaptation and preservation of pretrained generalization. Excessive finetuning causes the model to drift too far from its pretrained initialization, diminishing robustness to distribution shifts [10]. Conversely, insufficient finetuning limits the model’s ability to align with the action space.

Several approaches attempt to balance adaptation and generalization. Freezing visual encoders preserves pretrained perception but limits adaptation to robotics-specific cues. Dual-encoder designs [9] maintain both frozen and trainable visual pathways, improving flexibility at the cost of doubled memory and compute. Weight interpolation techniques [8] gradually revert visual weights to their pretrained state while adapting the language backbone, but require multiple training stages. In these efforts, generalization often comes at the expense of higher computational and architectural complexity, with most methods emphasizing visual preservation while overlooking the role of semantic priors in language components.

Seeking a lightweight alternative to preserving pretrained knowledge, we begin by revisiting the common practice of model freezing. Through a systematic analysis of freezing different VLM components during action fine-

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tuning, we confirm a widely held but rarely quantified intuition: visual modules should remain strongly constrained. Early visual backbones such as DINOv2 [11] capture essential geometric and spatial priors for manipulation, whereas language-aligned modules like SigLIP [12] and deeper language layers benefit from greater flexibility to adapt task-specific semantics and action grounding. However, we also find that freezing itself introduces task-specific inductive biases, and certain freeze configurations fail to generalize across new domains and environments.

Instead of hard constraints from model freezing, soft regularization offers a more flexible and robust alternative with comparable efficiency [10, 13–16]. Projection-based selective tuning methods, such as selective projection decay [13], replace conventional weight decay with a projection operator that limits how far parameters drift from their pretrained values – enabling adaptive regularization across layers without added complexity. However, existing approaches typically use a single hyperparameter to enforce a uniform regularization strength, implicitly assuming all layers should deviate equally. We find this assumption ill-suited for VLA models, where different components encode distinct priors and vary in their sensitivity to fine-tuning. Some modules must stay near their pretrained state to preserve structural knowledge, while others require greater flexibility to adapt task-specific grounding.

This introduces a new tradeoff: naive freezing provides modularity but is brittle due to strong inductive bias, whereas robust finetuning relaxes this bias but sacrifices modularity. To bridge this tradeoff and successfully adapt the robust finetuning paradigm to the action domain, we propose **MAPS (Module-Wise Proximity Scheduling)**, a robust finetuning framework designed specifically for VLA models. MAPS extends traditional projection-based selective tuning [13] by modulating the *projection strength rate of change* hyperparameter across model components and training steps via a linear scheduler. This encourages more careful updates of the visual components to preserve pretrained geometric priors while allowing more explorative updates of the language components to quickly adapt to the action space. Importantly, this scheduling is implemented with no additional models, data, or parameters and integrates seamlessly with existing VLA architectures.

We validate MAPS across a wide range of VLA backbones, including MiniVLA-VQ [17, 18], MiniVLA-OFT, OpenVLA-OFT [19], etc. Experiments on a diverse set of evaluation benchmarks - SimplerEnv Bridge Data [20], CALVIN [21] (ABC→D), LIBERO [22] (train on LIBERO-90, test on Goal/Spatial/Object/Long), and real-world evaluations on a Franka Emika Panda robot consistently show that MAPS improves out-of-distribution (OOD) generalization while preserving pretrained structure and in-distribution (ID) performance. These findings suggest that

maintaining proximity to pretrained VLMs in a selective manner is a simple yet powerful principle that could guide future scaling and pre-training of VLA systems.

2. Related Works

Vision-Language-Action Models. Vision-Language-Action (VLA) models advance unified embodied intelligence by leveraging large pretrained foundation models [5–7] and their components [11, 12, 23]. Systems like RT-1, PaLM-E, and RT-2 [2, 3, 24] showed that grounding vision-language pretraining in experience enables cross-task transfer. Large frameworks such as Open-X Embodiment, OpenVLA, and π_0 [1, 4, 19, 25–27] scale data and architectures for generalization. Recent work improves action tokenization [18, 28–32], efficiency [17, 33, 34], and grounding/reasoning [35–41], while emerging work explores chain-of-thought reasoning for interpretable control [42–44]. Despite progress, most VLAs rely on fine-tuning that disrupts pretrained priors; MAPS instead preserves them via module-wise proximity scheduling for selective adaptation.

VLA Generalization. Improving generalization in VLA models focuses on preserving pretrained representations while adapting to new tasks. Data-oriented approaches reformulate robotic data for better VLM alignment (directional prediction [45] or textual trajectory conversion [46]) and co-train with action objectives [9, 28]. Training-oriented methods retain learned priors via weight interpolation [8], dual encoders [9], frozen cross-attention [47], embedding regularization [48], or action perturbation [49]. These add computational overhead, whereas MAPS constrains updates by module importance and proximity to pretrained weights, preserving priors and improving OOD generalization without extra data or parameters.

3. Background

3.1. Vision-Language-Action Models

A Vision-Language-Action (VLA) model [1, 3, 4, 15] seeks to learn a policy $\pi_\theta(a_t \mid o_t, x)$ that maps a multimodal observation o_t and a language instruction x to an action a_t in an embodied environment. Typically, the visual and language inputs are encoded by f_v and f_l separately, and fused by a multimodal transformer f_m to produce a policy embedding $z_t = f_m([f_v(o_t), f_l(x)])$. Action parameterization varies across families of VLAs: **continuous-action models** predict low-level control vectors directly and are trained to make their outputs closely match the expert’s actions, using objectives such as ℓ_1 regression [19], diffusion-based denoising [44], or flow matching [4]. In contrast, **discrete-action models** convert actions or short action segments into a finite set of tokens [1]. Modern VLAs build upon pretrained vision-language backbones such as DINOv2 [11],

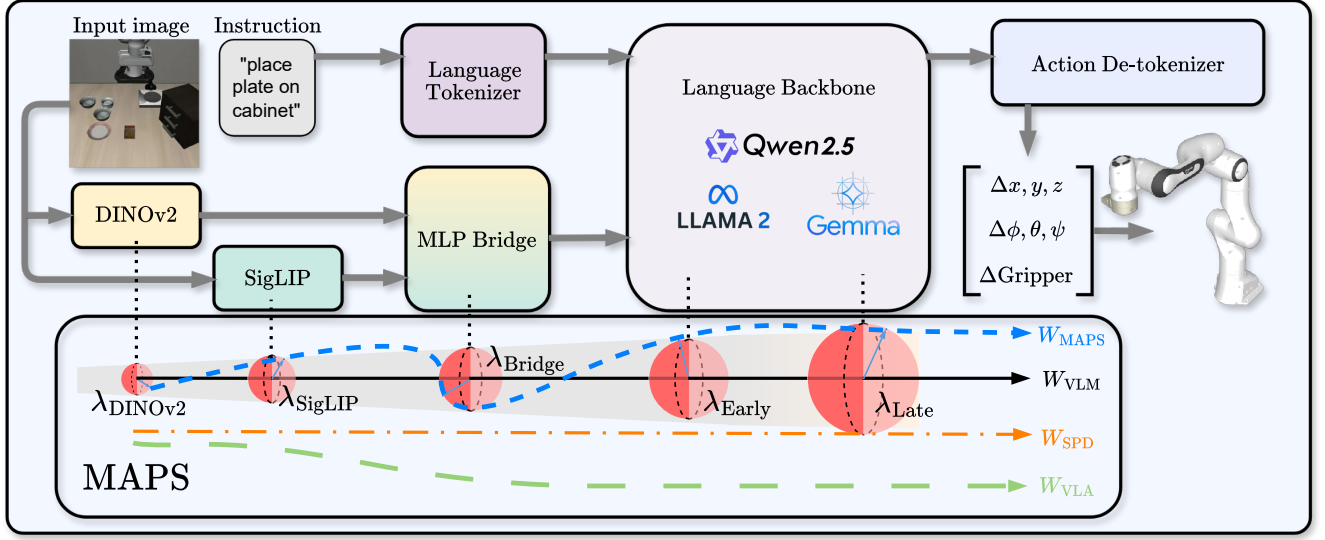


Figure 1. **Module-Wise Proximity Scheduling (MAPS)**. MAPS is applied on pretrained VLM components during the action finetuning stage. MAPS (blue dash line) enforces strong preservation on early vision layers while progressively relaxing constraints toward higher-level language layers. In contrast, vanilla finetuning (green dash line) distorts the VLM representation completely away from its pretrained weights (black solid line), and uniform SPD (orange dash/dot line) applies the same constraint everywhere.

SIGLIP [12], and LLAMA [7], using either a multi-modal transformer or a lightweight cross-attention “bridge” to fuse representations before an action head maps z_t into either continuous controls or discrete tokens. Models such as π_0 -Fast [29], and OpenVLA-OFT [19] follow this template but introduce small projection heads or adapters for rapid finetuning and deploying. During training on robot demonstrations, the model grounds linguistic semantics in action-conditioned representations that transfer across tasks, objects, and embodiments.

3.2. Robust Fine-Tuning

We revisit projection-based robust fine-tuning (RFT) methods [10, 13, 15, 50, 51] that constrain fine-tuning to remain close to the pretrained weights, enabling models to adapt to downstream tasks while preserving pretrain generalization.

From L2 regularization to projection. Vanilla fine-tuning updates model parameters to minimize the task loss $\mathcal{L}$ without constraining deviation from the pretrained model. This often leads to feature drift and catastrophic forgetting [10, 14, 15]. L2-SP [14] addresses this issue by penalizing the distance between the fine-tuned parameters θ_t and the pretrained initialization θ_0 with regularization strength λ_{reg} at each gradient iteration step t :

$$\mathcal{L}_{\text{L2-SP}} = \mathcal{L}(\theta_t) + \frac{\lambda_{\text{reg}}}{2} \|\theta_t - \theta_0\|_2^2. \quad (1)$$

Instead of regularizing $\|\theta_t\|_2$, L2-SP explicitly preserves proximity to the pretrained model. Building on this idea, TPGM [10] reformulates L2-SP by enforcing the model to

stay within a distance of γ from the pre-trained model:

$$\min \mathcal{L}(x, y; \theta_t), \quad \text{s.t.} \quad \|\theta_t - \theta_0\|_2 \leq \gamma. \quad (2)$$

To enforce this constraint during training, TPGM applies the *Projected Gradient Method* (PGM), projecting the updated weights back into an ℓ_2 ball with radius γ around θ_0 , where $\tilde{\theta}_t$ is the unconstrained updated weight:

$$\theta_t = \theta_0 + \frac{1}{\max\left(1, \frac{\|\tilde{\theta}_t - \theta_0\|_2}{\gamma}\right)} (\tilde{\theta}_t - \theta_0). \quad (3)$$

Selective Projection Decay (SPD). SPD [13] builds on the projection view of L2-SP and TPGM by determining whether and how much the unconstrained update $\tilde{\theta}_t$ should be projected back toward the pretrained weights θ_0 .

Step 1: When to project. Motivated by the derivative of $\mathcal{L}$ w.r.t. λ_{reg} , i.e. $\frac{\partial \mathcal{L}(\theta_t)}{\partial \lambda_{\text{reg}}} = \frac{\partial \mathcal{L}(\theta_t)}{\partial \theta_t}^\top \frac{\partial \theta_t}{\partial \lambda_{\text{reg}}} = \alpha * -g_{t+1}^\top (\tilde{\theta}_t - \theta_0)$ where α is the learning rate and g is the gradient, SPD uses the sign of $c_t := -g_{t+1}^\top (\tilde{\theta}_t - \theta_0)$ as the selection condition, since it determines the direction of the hyper-update: if $c_t < 0$, gradient descent increases λ_{reg} and strengthens L2-SP regularization, whereas if $c_t > 0$, it decreases λ_{reg} and weakens the regularization. Thus, SPD triggers a projection step if $c_t < 0$; otherwise the update is left unchanged.

Step 2: How much to project. L2-SP’s optimization step after unconstrained update can be written as $\theta_t = \tilde{\theta}_t - \lambda_{\text{reg}} \alpha (\tilde{\theta}_t - \theta_0)$. Reformulating Eq. (3) as $\theta_t = \tilde{\theta}_t - \left(1 - \frac{\gamma}{\max\{\gamma, \|\tilde{\theta}_t - \theta_0\|_2\}}\right) * (\tilde{\theta}_t - \theta_0)$, L2-SP (regularization) and projection are equivalent if $\lambda_{\text{reg}} \alpha = \left(1 - \frac{\gamma}{\max\{\gamma, \|\tilde{\theta}_t - \theta_0\|_2\}}\right)$. SPD then defines a deviation ratio $r_t =$

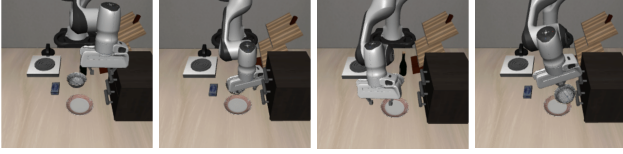


Figure 2. Qualitative comparison of freezing configurations for LIBERO-90 task "put the bowl on the plate" (left to right: full fine-tuning (FFT), freeze VLM, freeze language, freeze vision). FFT fails most, targeting the cabinet instead of the bowl. Freezing VLM/language/vision preserves 2D localization of the bowl but impairs depth reasoning. When vision is frozen, the policy can grasp the bowl but fails to accurately place it on the plate.

$\frac{\max\{\gamma_t - \gamma_{t-1}\}}{\gamma_t}$ based on the current deviation radius (before regularization) $\gamma_t = \|\tilde{\theta}_t - \theta_0\|_2$ and the previous radius $\gamma_{t-1} = \|\tilde{\theta}_{t-1} - \theta_0\|_2$, and replace the learning rate α in L2-SP with the deviation ratio r_t . This makes the *new hyperparameter* λ tuning more intuitive, where $\lambda_{\text{reg}}\alpha = \lambda r_t$. Intuitively, with $\lambda = 1$, $\theta_t = \tilde{\theta}_t - \frac{\max\{0, \gamma_t - \gamma_{t-1}\}}{\gamma_t}(\tilde{\theta}_t - \theta_0) = \theta_0 + \frac{\gamma_{t-1}}{\max\{\gamma_{t-1}, \gamma_t\}} * (\tilde{\theta}_t - \theta_0)$, the regularization is equivalent to projecting the updated parameters onto a ball with radius equal to the previous deviation whenever the current deviation exceeds that value. Now, a single hyperparameter λ replaces the conventional weight decay and controls how aggressively the constraint radius expands or contracts during training. When $\lambda = 0$, SPD reduces to full fine-tuning with no projection; $0 < \lambda < 1$ allows the radius to expand, enabling flexible adaptation; $\lambda = 1$ keeps the deviation from the pretrained model fixed; and $\lambda > 1$ contracts the radius, pulling parameters back toward θ_0 . Despite being a single scalar, λ enables dynamic and layer-specific projection across optimization steps.

4. Method

4.1. Catastrophic Forgetting in VLAs

VLA models are well known to struggle with zero-shot generalization across new tasks, environments, and instructions. Prior work traces this largely to catastrophic forgetting during action finetuning. ReVLA [8] attributes the issue to collapse in the DINOv2 [11] encoder, where depth estimation degrades into low-detail, spatially uniform maps – losing the rich geometry preserved in the pretrained DINOv2 features of PrismaticVLM [52]. [48] similarly find that fine-tuned VLAs attend to irrelevant regions under OOD conditions, with t-SNE analyses revealing compressed, degenerate feature spaces. [9] further observe over-sensitivity to background variation and instruction phrasing, suggesting overfitting to language form rather than meaning. Collectively, these studies identify action finetuning as the primary source of generalization failure, motivating efforts to preserve VLM representations during adaptation.

Freezing parts of a pretrained VLM is a simple yet ef-

fective way to preserve learned representations, preventing weights from drifting in suboptimal directions during fine-tuning. Recent works have refined this idea in various ways: [9] freeze the vision encoder and train a separate copy, [48] regularize against a frozen teacher, and ReVLA [8] interpolates vision-encoder weights between pretrained and adapted models while tuning the language backbone. While these strategies improve generalization, they often incur extra computation and supervision. Motivated by this line of work, we investigate how far simple freezing alone can bridge the generalization gap between VLAs and VLAs.

4.2. How good is model freezing?

To study the impact of model freezing, we decompose the VLA architecture into four components – DINOv2, SigLIP, early language layers, and late language layers – and systematically evaluate different freezing configurations on both ID and OOD settings. We focus on the OpenVLA [1] family, which integrates a joint DINOv2–SigLIP visual encoder. This modular design allows precise control over which capabilities are retained during adaptation: DINOv2 contributes depth perception and geometric priors, while SigLIP provides strong vision–language alignment. To ensure coverage across model scales and benchmarks, we conduct experiments with VLA-Adapter [53] on LIBERO and MiniVLA-OFT [17] on SimplerEnv BridgeV2 (see Sec. 5 and Appendix Sec. 7 for experimental details).

Our results (Tables 1 and 2) reveal several key insights into the efficacy of freezing:

1. **Language adaptation is essential.** Freezing the language backbone severely limits adaptation to the action space, yielding near-zero performance on SimplerEnv and up to a 60% drop on LIBERO.
2. **Freezing the vision encoder generally improves performance.** On SimplerEnv, ID accuracy increases by 7–17% and OOD by 7–25%; on LIBERO, gains are smaller but consistent (around 5% ID). In Fig. 2, freezing vision components allows the robot arm to grasp the bowl, whereas all other configurations struggle.
3. **Late language layers drive task performance.** Fine-tuning late language layers while freezing early ones boosts OOD generalization by 1–3%, aligning with their direct role in producing action outputs.
4. **Preserving DINOv2 matters more than SigLIP.** Freezing DINOv2 yields roughly 5% higher OOD performance than freezing SigLIP, underscoring the importance of maintaining strong geometric priors.
5. **Freezing effects are not universally consistent.** Freezing demonstrates improvements over full fine-tuning. Yet, some configurations (ex. freeze early language) improve one benchmark but harm another, indicating that freezing introduces task-dependent inductive biases.

Overall, our findings suggest a hierarchy of importance

Table 1. Comparison of freezing or robust fine-tuning (RFT) different parts of VLA on SimplerEnv’s ID and OOD tasks (details in Sec. 5.2). Early L and Last L denote early and the last language layers. ❄️ and 🔥 represent freeze and full fine-tune.

Modules				ID					OOD			
DINOv2	SigLIP	Early L	Last L	T1: Spoon	T2: Carrot	T3: Stack	T4: Eggplant	Avg. ID	Visual	Novel Object	Novel Category	Avg. OOD
MiniVLA-OFT [†]				22.0	30.0	0.0	2.0	13.5	12.7	2.0	12.0	8.9
❄️	❄️	❄️	❄️	22.0	24.0	0.0	34.0	20.0	20.0	13.3	10.7	15.0
❄️	❄️	❄️	❄️	0.0	0.0	0.0	0.0	0.0	1.3	0.0	2.7	1.2
❄️	❄️	❄️	❄️	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
❄️	❄️	❄️	❄️	42.0	32.0	6.0	42.0	30.5	32.7	51.3	11.3	33.6
❄️	❄️	❄️	❄️	12.0	10.0	12.0	90.0	31.0	29.3	35.3	22.7	29.7
❄️	❄️	❄️	❄️	0.0	0.0	0.0	0.0	0.0	4.0	0.7	2.0	2.2
RFT				4.0	8.0	0.0	94.0	26.5	6.7	20.0	14.0	13.6

Table 2. Comparison of freezing different parts of VLA on LIBERO. Early L and Last L denote early and the last language layers. ❄️ and 🔥 represent freeze and full fine-tune.

Modules				ID	OOD				
DINOv2	SigLIP	Early L	Last L	LIBERO-90	-Spatial	-Object	-Goal	-Long	Avg. OOD
VLA-Adapter [†]				83.0	2.0	5.0	1.0	2.0	2.5
❄️	❄️	❄️	❄️	92.0	0.0	3.0	0.0	6.0	2.3
❄️	❄️	❄️	❄️	29.0	1.0	4.0	1.0	0.0	1.5
❄️	❄️	❄️	❄️	19.0	0.0	0.0	1.0	0.0	0.3
❄️	❄️	❄️	❄️	89.0	0.0	6.0	0.0	6.0	3.0
❄️	❄️	❄️	❄️	73.0	1.0	0.0	0.0	3.0	1.0
❄️	❄️	❄️	❄️	91.0	0.0	4.0	6.0	8.0	4.5
❄️	❄️	❄️	❄️	59.0	0.0	0.0	0.0	0.0	0.0
RFT				88.0	1.0	2.0	0.0	6.0	2.3

among modules:

DINOv2 > SigLIP > Early language > Late language

Yet, **freezing alone is not a reliable path to generalization**. While it allows selective preservation of pretrained knowledge, it also imposes strong biases that can degrade performance in unseen settings. A more robust alternative lies in soft regularization, where finetuning is guided rather than restricted.

4.3. From hard constraints to soft constraints

The robust finetuning (RFT) literature (see Sec. 3.2) offers a natural foundation for our goal of constraining weight updates while preserving pretrained representations. In principle, RFT lowers task loss while keeping parameter drift minimal. While the intuition fits seamlessly with our goals, we find that naively applying RFT directly on the action finetuning offers only modest improvements over the baseline in both SimplerEnv (Tab. 1) and LIBERO (Tab. 2). This is because RFT techniques impose a single hyperparameter constraint across the entire model, meaning that layers either constrict closer towards or expand away from the pretrained weights at a uniform rate. As shown at the bottom of Fig. 3, this results in all components of the VLM diverging equal amounts from their pretrained representations. As we observed from Sec. 4.2, however, different components should evolve at different rates – some should be allowed more flexibility to adapt to the action space, whereas others should be constrained to preserve their pretrained priors.

4.4. Module-Wise Proximity Scheduling

Our preliminary studies highlights a key tradeoff: model freezing offers high modularity at the cost of heavy inductive bias, RFT offers lighter inductive bias but has no modularity. To bridge the two paradigms and successfully adapt robust finetuning for the action domain, we introduce a new framework of RFT methods specifically tailored for VLA models, known as **Module-Wise Proximity Scheduling (MAPS)**.

MAPS assigns distinct proximity schedules to different components of the base VLM, enabling strong preservation where pretrained structure is crucial (e.g., early vision and early language layers) while allowing more aggressive adaptation where grounding to actions is most beneficial (e.g., higher-level language layers and the action head). In other words, MAPS is designed to *learn when to preserve and when to adapt*, avoiding the rigidity of full freezing and the instability of uniform finetuning.

Concretely, MAPS modifies SPD by replacing its *global* proximity hyperparameter λ with a *layer-wise*, architecture-aware schedule. Let $\mathcal{L} = (\ell_1, \dots, \ell_{|\mathcal{L}|})$ denote the ordered stack of model submodules (DINOv2 $\rightarrow$ SigLIP $\rightarrow$ BRIDGE $\rightarrow$ LANGUAGE). For each layer index k , MAPS assigns a proximity weight

$$\lambda_k = \lambda_{\max} \left(1 - \frac{k-1}{|\mathcal{L}|-1} \right),$$

yielding a linear decay from $\lambda_1 = \lambda_{\max}$ for early visual layers to $\lambda_{|\mathcal{L}|} = 0$ for language layers. In addition, MAPS assigns $\lambda_k = 0$ for all modules that are initialized from scratch, such as the action head, proprioceptive-state projector, and other non-pretrained components. Since these modules have no pretrained parameters θ_0 to preserve, MAPS simply performs full fine-tuning on them.

During optimization, let θ denote the parameters of the current layer, θ_0 their pretrained initialization, and g_t the gradient at iteration t . MAPS first computes an unconstrained step $\tilde{\theta}_t$, after which it evaluates the gradient-displacement correlation

$$c_t := -g_t^\top (\theta_{t-1} - \theta_0).$$

Whenever $c_t < 0$, indicating that the update direction is inconsistent with preserving pretrained structure, MAPS applies a projection toward θ_0 with *layer-specific* strength:

$$\theta_t \leftarrow \tilde{\theta}_t - \lambda_k r_t (\tilde{\theta}_t - \theta_0),$$

where r_t is the SPD deviation ratio (see Sec. 3.2).

Unlike SPD, which uses a single global constraint and therefore cannot differentiate between layers with distinct gradient scales or semantic roles, MAPS explicitly encodes architectural structure: visual layers remain strongly anchored to pretrained perceptual representations, while deeper language layers are allowed to adapt more flexibly to task-level semantics. This is highlighted in Fig. 3, where DINOv2 weights diverge least, followed by SigLIP weights, and finally language weights adapt most. As shown in Appendix Sec. 9, the linear schedule outperforms constant and cosine alternatives, underscoring the importance of structured, layer-wise proximity control. Additional intuition on MAPS is also included in Appendix Sec. 11.

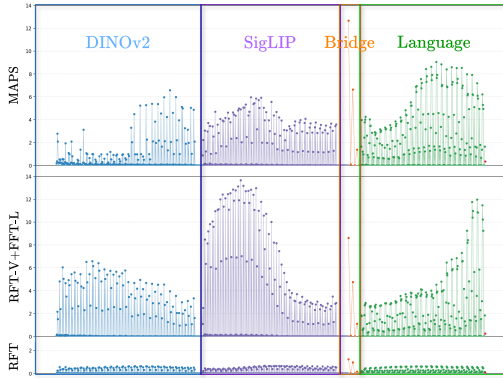


Figure 3. We calculate the ℓ_2 distance between fine-tuned and pre-trained weights. MAPS produces a smooth, module-aware decay in deviation from pretrained initialization (top). Applying robust finetuning only to the vision stack and full finetuning on language (RFT-V+FFT-L) constrains DINOv2 heavily but leaves SigLIP and language relatively unconstrained (middle). Uniform λ (RFT) constrains all layers equally (bottom).

Crucially, MAPS is lightweight and plug-and-play: it introduces no additional parameters, requires no auxiliary networks or extra data, and can be applied to existing VLA architectures without modification. By directly encoding the empirical hierarchy revealed in our preliminary studies, MAPS strikes an effective balance between retaining essential pretrained priors and adapting to new action domains.

5. Experiments

We evaluate MAPS through three guiding questions. **(RQ1)** How well does it generalize across ID and OOD tasks? To test this, we use three diverse benchmarks – SimplerEnv

[20] (Sec. 5.2), CALVIN [21] (Sec. 5.3), and LIBERO [22] (Sec. 5.4) – that span semantic, environmental, and visual shifts, providing a comprehensive measure of robustness. **(RQ2)** Are MAPS’ gains consistent across architectures? We evaluate five state-of-the-art VLA backbones – MiniVLA-VQ, MiniVLA-OFT, VLA-Adapter, OpenVLA-OFT, and NORA – to test architecture-agnostic benefits. **(RQ3)** Does the robustness afforded by MAPS transfer to real-world deployment? We assess real-world transfer by deploying MAPS on a Franka Emika Panda manipulator (Sec. 5.1). Importantly, across all benchmarks, *we evaluate MAPS by fine-tuning the base VLM weights directly*. In other words, we initialize each VLA backbone from its pretrained VLM and train it from scratch using MAPS.

Backbones. Because MAPS does not rely on architecture-specific hyperparameters, it can be dropped into models with any visual encoder, language model, or action tokenization strategy. To demonstrate this flexibility, we instantiate MAPS across four widely used VLA backbones: MiniVLA-VQ [17], MiniVLA-OFT, OpenVLA-OFT [19], and VLA-Adapter [53]. To demonstrate generalizability beyond the OpenVLA family, we also evaluate MAPS on the NORA [54] backbone in Appendix Sec. 10. For details about these backbones, please see Appendix Sec. 7.

5.1. Performance on Franka Emika Panda

Experimental setting. We conduct real-world tabletop manipulation experiments using a single Franka Emika Panda robotic arm. Our task suite consists of 4 paired ID and OOD tasks, which includes: (1) Grab coke can; (2) Stack blocks; (3) Stack cups; and (4) Close laptop. We form a pretraining corpora of 150 demonstrations per task following [55], and train MiniVLA-OFT (directly updating the VLM weights) using our self-collected demonstration dataset with both vanilla finetuning and MAPS. We provide our quantitative results below. Details on our task suite, extended fine-grained task analysis, qualitative results, rollout visualizations, setup details, and an in-depth results discussion along with observed success and failure modes can be found in Appendix Sec. 8.

Evaluation results. Table 3 presents the success rates for each task together with the overall average performance. MAPS yields substantial gains over MiniVLA-OFT on both ID and OOD tasks. On the ID tasks, MAPS raises average performance from 40.0% to 72.5%, demonstrating much stronger policy learning from limited demonstrations. MAPS also improves generalization under distribution shift, boosting average OOD success from 22.5% to 52.5%. Overall, MAPS enhances both robustness and task success across diverse manipulation scenarios, showing clear benefits for real-world policy training (RQ3).

Table 3. **Franka Results.**

Model	ID					OOD				
	T1: Coke	T2: Block	T3: Cup	T4: Laptop	Avg. ID	T1: Coke	T2: Block	T3: Cup	T4: Laptop	Avg. OOD
MiniVLA-OFT [†]	30.0	30.0	0.0	100.0	40.0	50.0	20.0	0.0	30.0	22.5
+MAPS (Ours)	50.0	70.0	80.0	90.0	72.5	100.0	30.0	20.0	60.0	52.5
Δ	+20.0	+40.0	+80.0	-10.0	+32.5	+50.0	+10.0	+20.0	+30.0	+30.0

Table 4. **SimplerEnv Results.** ID includes 4 tasks following SimplerEnv-Bridge setup. OOD evaluation suites include Visual, Novel Object, and Novel Category. * model checkpoints borrowed from original papers. [†] models pretrained from scratch on SimplerEnv.

Model	ID					OOD			
	T1: Spoon	T2: Carrot	T3: Stack	T4: Eggplant	Avg. ID	Visual	Novel Object	Novel Category	Avg. OOD
RT-1-X [2]	4.2	0.0	0.0	0.0	1.1	0.0	4.0	6.1	3.4
Octo [56, 57]	12.5	41.7	15.8	0.0	17.5	12.6	10.8	8.4	10.6
π_0 [4]	52.5	87.9	83.8	52.5	69.2	71.4	30.2	21.0	40.9
MiniVLA-VQ [†] [17]	52.0	24.0	42.0	58.0	44.0	37.3	34.0	27.3	32.9
+MAPS (Ours)	44.0	30.0	76.0	20.0	42.5	48.0	26.0	29.3	34.4
Δ	-8.0	+6.0	+34.0	-38.0	-1.5	+10.7	-8.0	+2.0	+1.5
MiniVLA-OFT [†]	22.0	30.0	0.0	2.0	13.5	12.7	2.0	12.0	8.9
+MAPS (Ours)	34.0	38.0	0.0	48.0	30.0	32.0	48.7	26.7	35.8
Δ	+12.0	+8.0	+0.0	+46.0	+16.5	+19.3	+46.7	+14.7	+26.9
OpenVLA-OFT [†] [19]	16.0	18.0	0.0	58.0	23.0	16.0	9.3	0.7	8.7
+MAPS (Ours)	2.0	16.0	0.0	74.0	23.0	18.7	20.0	12.7	17.1
Δ	-14.0	-2.0	+0.0	+16.0	+0.0	+2.7	+10.7	+12.0	+8.4

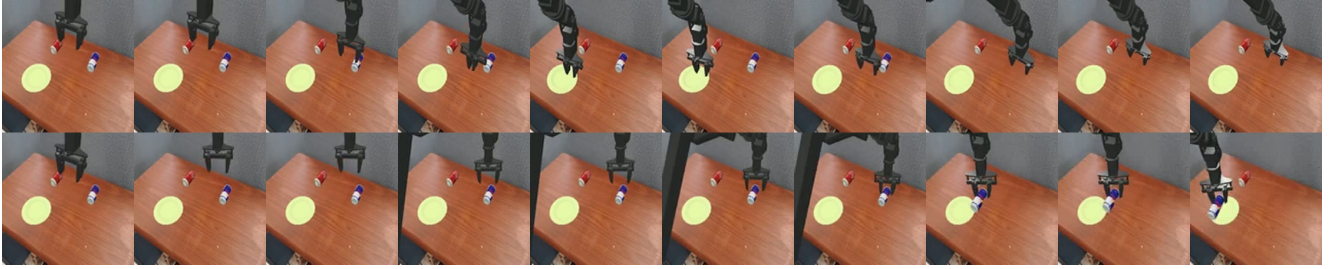


Figure 4. SimplerEnv qualitative example (new object: Red Bull can). Top: Full fine-tuning fails to complete the task. Bottom: MAPS successfully places the can on the plate.

5.2. Performance on SimplerEnv

Experimental setting. SimplerEnv is a lightweight simulation benchmark for efficient robotic manipulation evaluation. Because its tasks are originally text-only, we follow [57] to add visual observations and align it with the VLA setting. For ID evaluation, we use the standard WidowX BridgeData V2 Visual Matching setup and report performance on four tasks: spoon on towel, carrot on plate, stack cube, and put eggplant in basket. For OOD evaluation, we adopt the extended suite from [57], which includes: (1) Visual Generalization, placing three ID tasks in unseen environments; (2) Novel Object, introducing new instances from known categories; and (3) Novel Category, involving entirely new object types. We report success rates on both ID and OOD splits (Table 4).

Evaluation results. On MiniVLA-OFT, MAPS matches the ID performance of Vanilla finetuning, but demonstrates 10-20% improvement on OOD generalization. Notably, despite a substantially smaller pretraining corpora of just the

BridgeData V2 Visual Matching tasks, MAPS matches and even surpasses the OOD generalizability of much larger and much more extensively pretrained baselines such as RT-1-X, Octo and π_0 . On MiniVLA-VQ, MAPS maintains similar ID performance and offers a moderate increase in OOD performance. On OpenVLA-OFT, MAPS maintains similar ID performance and improves average OOD by 8.4%. Again, this suggests that MAPS scales effectively across a variety of backbone sizes and architectures (RQ2).

5.3. Performance on CALVIN

Experimental setting. CALVIN features long-horizon tabletop manipulation tasks in a real-to-sim setting, partitioned into the A, B, C, and D splits that increasingly withhold task–environment combinations. We follow the standard ABC→D protocol: models are trained on splits A–C and evaluated OOD on split D. During evaluation, agents must complete sequences of five instructions; each new instruction is provided only after the previous one is completed, with success defined by reaching the instruction’s

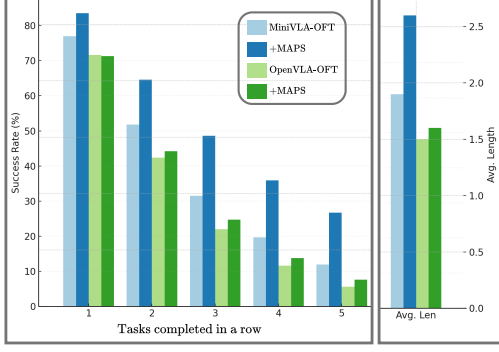


Figure 5. **CALVIN Results.** MAPS improves success rates across all action horizons (25% for MiniVLA-OFT and 3% for OpenVLA-OFT) and average length (+0.7 for MiniVLA-OFT and +0.1 for OpenVLA-OFT).

goal state. The benchmark reports two metrics: *tasks completed in a row*, the success rate for completing exactly k consecutive tasks ($k = 1-5$), and *average length* (*avg. len*), the mean number of tasks completed per five-instruction sequence across all episodes.

Evaluation results. As shown in Fig. 5, MAPS leads to a +0.7 gain in average sequence length and consistently improves success rates across all task horizons on MiniVLA-OFT. The largest gains are observed for longer horizons: MAPS improves the success rate of completing 2-, 3-, 4-, and 5-task sequences by roughly 15% each, while the 1-task success rate increases by 7%. MAPS demonstrates modest improvements over OpenVLA-OFT, boosting success rates by 2% across task horizons. Notably, MAPS demonstrates larger gains on stronger baselines, suggesting that it complements rather than replaces existing capabilities, and scales effectively with model quality (RQ2).

5.4. Performance on LIBERO

Experimental setting. The LIBERO benchmark consists of procedurally generated household manipulation tasks designed to evaluate generalization across task configurations, object appearances, and spatial layouts. It includes several predefined splits – LIBERO-90, LIBERO-Long, LIBERO-Goal, LIBERO-Spatial, and LIBERO-Object – each targeting a specific type of generalization, such as task diversity, long-horizon planning, unseen goals, spatial rearrangements, or novel objects. Previous works often rely on large-scale external pretraining – such as on Open X Embodiment – followed by fine-tuning separate model variants for each LIBERO split, and reporting results using these tailored models. In contrast, **our approach uses no external pretraining whatsoever**. Instead, we follow the more challenging protocol of [53]: we pre-train solely on the LIBERO-90 subset, and evaluate both ID performance on LIBERO-90 and OOD generalization on LIBERO-Spatial, LIBERO-Object, LIBERO-Goal, and LIBERO-Long. We

Table 5. **LIBERO Results.** * Results from [17]. † Pretrained from scratch on LIBERO-90. ‡ Finetuned on LIBERO-90.

Model	ID (%)	OOD (%)				
	LIBERO-90	-Spatial	-Object	-Goal	-Long	Avg. OOD
OpenVLA	62.0	-	-	-	-	-
miniVLA*	61.4	0.0	0.0	0.0	1.0	0.25
miniVLA-VQ*	77.0	0.0	0.0	3.0	1.0	1.0
miniVLA-hist.*	82.0	0.0	1.0	2.0	7.0	2.5
miniVLA-wrist*	82.1	0.0	0.0	0.0	0.0	0.0
SpatialVLA‡	46.2	0.0	0.0	0.67	1.33	0.5
MiniVLA-VQ†	79.0	0.0	0.0	0.0	0.0	0.0
+MAPS (Ours)	82.0	0.0	1.0	8.0	10.0	4.75
Δ	+3.0	+0.0	+1.0	+8.0	+10.0	+4.75
MiniVLA-OFT†	91.0	0.0	8.0	7.0	4.0	4.75
+MAPS (Ours)	91.0	6.0	14.0	0.0	8.0	7.0
Δ	+0.0	+6.0	+6.0	-7.0	+4.0	+2.25
VLA-Adapter†	83.0	2.0	5.0	1.0	2.0	2.5
+MAPS (Ours)	88.0	0.0	7.0	6.0	6.0	4.75
Δ	+5.0	-2.0	+2.0	+5.0	+4.0	+2.25
OpenVLA-OFT†	92.0	3.0	9.0	3.0	5.0	5.0
+MAPS (Ours)	90.0	0.0	11.0	1.0	10.0	5.5
Δ	-2.0	-3.0	+2.0	-2.0	+5.0	+0.5

report the success rates using 10 trials per task in Table 5. **Evaluation results.** MAPS delivers consistent improvements in OOD performance across all four model backbones, yielding an average gain of 1–5%. Notably, the base MiniVLA model shows no inherent OOD generalization capability; however, with MAPS, its performance increases by 8% on LIBERO-Goal and 10% on LIBERO-Long. For MiniVLA-OFT, MAPS enhances generalization on LIBERO-Spatial and LIBERO-Object by 6%. Similarly, MAPS improves the VLA-Adapter’s performance on LIBERO-Goal and LIBERO-Long by 5% and OpenVLA-OFT’s performance on LIBERO-Long by 5%. Beyond OOD gains, MAPS also provides moderate improvements on ID tasks, boosting MiniVLA-VQ performance by 3% and VLA-Adapter by 5%. This suggests that MAPS’ gains are indeed consistent across architectures and generalize well to different action tokenization schemes (RQ2). These results, in conjunction with results on the other benchmarks, also suggest that MAPS generalizes effectively across diverse ID and OOD tasks (RQ1).

6. Conclusion

We present Module-Wise Proximity Scheduling (MAPS), a robust finetuning framework designed specifically for adapting pretrained VLM backbones to action data. By uncovering a clear hierarchy in how different model components should be constrained, MAPS applies a linear schedule that selectively regularizes each module. This yields conservative updates for visual layers – preserving essential geometric priors – while allowing more flexible adaptation in language components. Across SOTA backbones and standard benchmarks, MAPS delivers consistent improvements, enhancing both ID and OOD performance. Our findings highlight guided proximity to pretrained VLMs as a simple yet powerful principle for scalable VLA adaptation.

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