# TRIVLA: A TRIPLE-SYSTEM-BASED UNIFIED VISION-LANGUAGE-ACTION MODEL FOR GENERAL ROBOT CONTROL

Zhenyang Liu<sup>1,2</sup> Yongchong Gu<sup>1,2</sup> Sixiao Zheng<sup>1,2</sup> Xiangyang Xue<sup>1†</sup> Yanwei Fu<sup>1,2†</sup>

lzyzjhz@163.com, yongchonggu22@m.fudan.edu.cn, {sxzheng18,xyxue,yanweifu}@fudan.edu.cn

# **ABSTRACT**

Recent advancements in vision-language models (VLMs) for common-sense reasoning have led to the development of vision-language-action (VLA) models, enabling robots to perform generalized manipulation. Although existing autoregressive VLA methods design a specific architecture like dual-system to leverage large-scale pretrained knowledge, they tend to capture static information, often neglecting the dynamic aspects vital for embodied tasks. To this end, we propose TriVLA, a unified Vision-Language-Action model with a triple-system architecture for general robot control. The vision-language module (System 2) interprets the environment through vision and language instructions. The dynamics perception module (System 3) inherently produces visual representations that encompass both current static information and predicted future dynamics, thereby providing valuable guidance for policy learning. TriVLA utilizes pre-trained VLM model and fine-tunes pre-trained video foundation model on robot datasets along with internet human manipulation data. The subsequent policy learning module (System 1) generates fluid motor actions in real time. Experimental evaluation demonstrates that TriVLA operates at approximately 36 Hz and surpasses state-of-the-art imitation learning baselines on standard simulation benchmarks as well as challenging real-world manipulation tasks.<sup>1</sup>

# 1 Introduction

Recent vision-language models (VLMs) Liu et al. (2024c); Alayrac et al. (2022); Li et al. (2023a); Zhang et al. (2023); Bai et al. (2023); Gao\* et al. (2023); Zhang et al. (2024b;a) have exhibited notable abilities in instruction following and commonsense reasoning. These advances are largely attributed to pretraining on extensive image-text datasets sourced from the internet. Building upon these advancements, recent works have proposed specialized architectures—including dual-system approaches—to augment VLMs into vision-language-action (VLA) models. These models facilitate action plan generationAhn et al. (2022); Driess et al. (2023); Huang et al. (2023); Belkhale et al. (2024) and SE(3) pose estimationBrohan et al. (2023); Kim et al. (2024); Li et al. (2024a). VLA models empower robots to interpret visual inputs and linguistic commands, thereby generating generalizable control actions. Existing VLMs for vision and language Li et al. (2024b) serve as foundational components for training robotic policies capable of generalizing to novel objects, environments, and tasks beyond the training distribution.

Although VLM-based VLA approaches Intelligence et al. (2025); Black et al. (2024); Brohan et al. (2023); Kim et al. (2024); Pertsch et al. (2025) have achieved success in embodied tasks, they predominantly focus on static information. This limitation arises because these methods typically utilize only one or two current sampled images, thereby underutilizing the dynamic information inherent in

<sup>&</sup>lt;sup>1</sup> Fudan University <sup>2</sup> Shanghai Innovation Institute

<sup>&</sup>lt;sup>T</sup>Corresponding authors

<sup>&</sup>lt;sup>1</sup>Project in https://zhenyangliu.github.io/TriVLA/

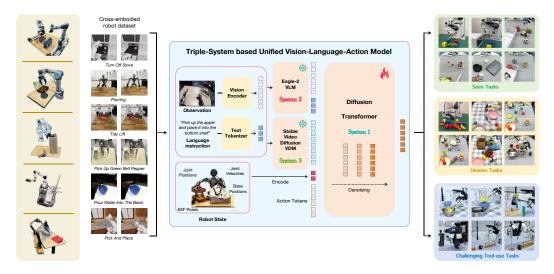


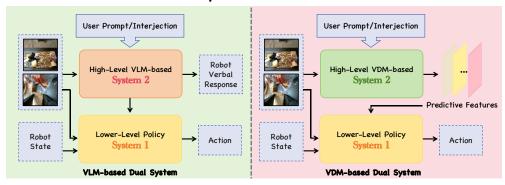
Figure 1: Our **TriVLA** is a Vision-Language-Action (VLA) system with a triple-system architecture. The TriVLA converts image observations and language instructions into token sequences, which are processed by the Vision-Language Model (VLM) for reasoning using common knowledge, and the Stable Video Diffusion Model (VDM) as the world model for both current and future predictions. The outputs of the VLM and VDM, along with robot state and action encodings, are fed into the policy learning module to generate motor actions. The TriVLA can be used directly to perform tasks based on prompts or fine-tuned with high-quality data to support complex multi-stage tasks.

sequential demonstrations. It is essential to leverage the intrinsic strengths of VLMs to develop VLA models capable of robust manipulation within dynamic environments. Recent advances in video diffusion models (VDMs) Blattmann et al. (2023a); Hong et al. (2022); Yang et al. (2024); Brooks et al. (2024) have demonstrated remarkable performance in video generation tasks. Unlike methods pretrained on single images or image pairs, VDMs model entire video sequences and predict future frames guided by current observations and instructions, thereby exhibiting strong comprehension of physical dynamics.

Inspired by the strong prediction and dynamic perception capabilities of VDMs, we introduce TriVLA, a unified Vision-Language-Action model to integrate the physical dynamics into general policy learning. As shown in Figure 2, TriVLA adopts a triple-system compositional architecture on the basis of the existing dual-system structure Bjorck et al. (2025); Shi et al. (2025). The System 2 vision-language module is a pre-trained Vision-Language Model (VLM) that processes the robot's visual perception and language instruction to interpret the environment and understand the task goal. The System 3 Dynamics Perception Module is a versatile video diffusion model fine-tuned on largescale human and robotic manipulation data collected from the internet Khazatsky et al. (2024); Jin et al. (2024); Lu et al. (2024). This module focuses on developing a controllable video generation model to enhance predictive accuracy within the manipulation domain. Consequently, the downstream policy can implicitly acquire the inverse dynamics model Min et al. (2023); Tian et al. (2024) by monitoring the robot's motions embedded in the predictive representation. This approach enables transfer of the video prediction model's generalization capabilities to robotic policies. Only a limited number of demonstrations are required to align the robot's action space with the visual domain. Subsequently, the System 1 policy learning module, trained via action flow-matching, cross-attends to output tokens from Systems 2 and 3. It utilizes embodiment-specific encoders and decoders to manage variable state and action dimensions during motion generation. Motivated by recent progress in robot learning, the System 1 policy learning module predicts action sequences (action chunking) instead of single actions at each timestep.

The primary contribution of this paper is the introduction of a triple-system compositional architecture. This innovative framework integrates Vision-Language Models (VLMs) and Video Diffusion Models (VDMs) to support both high-level reasoning based on common knowledge and dynamic predictive representation through a world model. As illustrated in Figure 1, the proposed unified framework allows robots to handle significantly more complex prompts and endows them with long-horizon task execution capabilities. Although individual components of the triple-system, including

#### Previous Dual System Structure-based VLA Model



#### Unified Triple System Structure-based VLA Model (Ours)

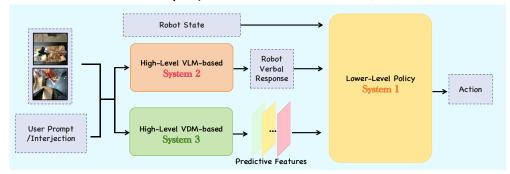


Figure 2: Comparison between previous dual-system architectures and our triple-system approach. Our TriVLA employs a unified triple-system compositional architecture that integrates world knowledge (System 2) and the world model (System 3), both critical for general policy learning. Prior dual-system methods typically addressed only one component, failing to unify both.

the VLM and VDM modules, have been explored in previous studies, their integration is novel and facilitates unique functionalities.

Experimental results demonstrate that the proposed TriVLA consistently outperforms baseline algorithms—including API-based VLMs and flat VLA policies—across three simulated Mees et al. (2022); Liu et al. (2024a); Yu et al. (2020) and three real-world environments. This highlights its effectiveness in aligning with human intent and achieving long-horizon task success. Notably, TriVLA attains improvements of 0.21, 0.11, and 0.13 on the Calvin ABC $\rightarrow$ D, LIBERO, and Meta-World benchmarks, respectively, compared to prior state-of-the-art methods.

The contributions of this paper are summarized:

- A Unified Vision-Language-Action Framework: We propose a unified Vision-Language-Action model to integrate the world knowledge and world model for general policy learning across multiple robot embodiments.
- *Triple-System Compositional Architecture*: The proposed TriVLA model designs a novel triple-system compositional architecture that possesses both high-level reasoning and dynamic predictive representation, enables a robot to process much more complex prompts and long-horizon manipulation tasks.
- *State-of-the-art performance*: TriVLA outperforms other baseline algorithms across simulated and real-world settings, including new combinations of skills seen during training, in the context of scenario. This demonstrates the effectiveness in both alignment with human intent and long-horizon task success.

# 2 RELATED WORK

**Vision-language-action models.** Previous works Ahn et al. (2022); Driess et al. (2023); Huang et al. (2023; 2024b) facilitate robotic understanding of language instructions and visual inputs to autonomously generate task plans. Concurrently, vision-language-action (VLA) models exploit the innate reasoning capacity of VLMs to predict low-level SE(3) poses. In particular, RT2 Brohan et al. (2023) discretizes 7-DoF actions into bins for autoregressive pose prediction. Extending this approach, ManipLLM Li et al. (2024a) integrates affordance priors via chain-of-thought reasoning, whereas OpenVLA Kim et al. (2024) conducts large-scale pretraining on the Open X-Embodiment dataset O'Neill et al. (2023), thereby improving generalization. FAST Pertsch et al. (2025) utilizes the discrete cosine transform to facilitate efficient and scalable training of autoregressive VLA models. The dual-system architectures of GR00T N1 Bjorck et al. (2025) and Hi Robot Shi et al. (2025), motivated by human cognition models, empower robots to reason about unfamiliar scenarios, robustly manage real-world variability, and accelerate learning of new tasks. Several VLA methods Liu et al. (2024d); Huang et al. (2024a); Li et al. (2023b); Wu et al. (2023) enable continuous action prediction by integrating policy heads like MLPs or LSTMs Graves & Graves (2012), and applying regression loss within imitation learning frameworks. Nevertheless, these approaches predominantly capture static information and insufficiently leverage dynamics present in sequential demonstrations, largely due to reliance on only one or two current sampled images. Therefore, exploiting the intrinsic strengths of VLMs to construct VLA models capable of robust manipulation in dynamic environments is imperative. Our proposed TriVLA employs a triple-system architecture to incorporate physical dynamics into policy learning.

**Future prediction in robotics.** Prior studies have investigated leveraging future prediction to improve policy learning Bharadhwaj et al. (2024); Chen et al. (2024); Ye et al. (2024); Guo et al. (2024). SuSIE Black et al. (2023) bases its control policy on a predicted future keyframe produced by InstructPix2Pix Brooks et al. (2023), whereas UniPi Du et al. (2024) models inverse dynamics across two generated frames. These approaches rely on a single-step future prediction to guide action selection, failing to fully capture the complexity of physical dynamics. Furthermore, denoising the final predicted image is time-consuming and results in reduced control frequency. GR-1 Wu et al. (2023) generates future frames and actions in an autoregressive manner. However, it produces only one image per forward pass, and its prediction quality trails behind diffusion-based techniques. Seer Tian et al. (2024) proposes an end-to-end framework that predicts actions by applying inverse dynamics models conditioned on forecasted visual states. VPP Hu et al. (2024) employs representations fine-tuned from video foundation models to build a generalist robotic policy. In contrast, our TriVLA incorporates a fine-tuned video foundation model as an additional System 3 within the dual-system VLM-based VLA architecture. This enables prediction of sequential future frames while maintaining high-level reasoning, thereby more effectively guiding policy learning.

#### 3 Preliminaries

**Vision-language-action model.** Robotic manipulation has long been a central focus within the robotics community. Vision-language-action (VLA) models are designed to iteratively determine the robot's subsequent action—specifically, the end-effector's pose—based on visual observations and human instructions that define the current task. Recently, high-capacity, pretrained vision-and-language models (VLMs) have demonstrated strong generalization capabilities across diverse language-conditioned manipulation tasks. Among these, recent VLM-based VLA methods adopt a dual-system compositional architecture inspired by human cognitive processing Kahneman (2011). This architecture facilitates higher-level reasoning to interpret complex long-horizon tasks and select appropriate action sequences. At each timestep t, The high-level system takes the captured image  $o_t$  by cameras from base and wrist mounted cameras and the open-ended instruction  $\mathbf{v}_t^{\text{in}}$  as input to generate reasoning tokens. The low-level policy uses these tokens, images, and robot states and outputs an action token sequence  $\mathbf{v}_t^{\text{out}} \in \mathcal{V}^n$ , where each action token represents a discrete bin of one dimension of the robot action space. The final robot action is extracted from this sequence using a post-processing function f, resulting in  $\mathbf{a}_t = f(\mathbf{v}_t^{\text{out}})$ .

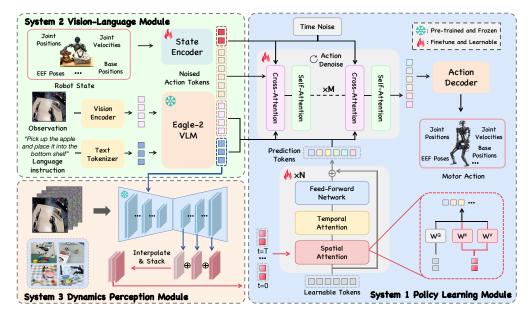


Figure 3: The pipeline of our TriVLA. Our TriVLA adopts a triple-system compositional architecture on the basis of the existing dual-system structure. The System 2 vision-language module employs a pre-trained Eagle-2 Vision-Language Model (VLM) to process the robot's visual inputs and language instructions, enabling environmental interpretation and task goal understanding. The System 3 dynamics perception module uses a general-purpose video diffusion model to capture entire video sequences and predict future frames based on current observations and task instructions. Subsequently, the System 1 policy learning module—trained using action flow-matching—cross-attends to the output tokens from Systems 2 and 3, and employs embodiment-specific encoders and decoders to handle variable state and action dimensions for generating motor actions.

## 4 OUR PROPOSED TRIVLA

This section outlines the triple-system learning procedure of TriVLA, as illustrated in Figure 3. Initially, the NVIDIA Eagle-2 VLM Li et al. (2025) is employed as the vision-language backbone to process visual perception and language instructions. Subsequently, a video diffusion model fine-tuned on diverse manipulation datasets is adopted to generate visual representations. TriVLA employs flow matching Lipman et al. (2022) to facilitate action generation via a diffusion transformer (DiT).

# 4.1 VISION-LANGUAGE MODULE (SYSTEM 2)

To encode vision and language inputs, TriVLA employs the Eagle-2 vision-language model (VLM) pretrained on large-scale internet data. Eagle-2 is fine-tuned from a SmolLM2 large language model (LLM) and a SigLIP-2 image encoder. Images are encoded at a resolution of 224 × 224 pixels, followed by pixel shuffle, producing 64 image token embeddings per frame. These embeddings are subsequently encoded jointly with textual input by the LLM component of the Eagle-2 VLM. The LLM and image encoder are aligned over a wide range of vision-language tasks according to a general training protocol. During policy training, task descriptions in text form, along with potentially multiple images, are input to the VLM using the chat format implemented during vision-language pretraining. Vision-language tokens, denoted as  $Q_{vl}$  with dimensions (batch size × sequence length × hidden dimension), are then extracted from the LLM. Empirically, using embeddings from the middle layers of the LLM rather than the final layer yields faster inference and improved downstream policy success rates. In TriVLA, representations are extracted specifically from the 12th LLM layer. To handle varying state dimensions across diverse robots, TriVLA employs an embodiment-specific MLP to project states into a shared embedding space, denoted as the state token  $Q_s$ .

#### 4.2 Dynamics Perception Module (System 3)

To incorporate extensive prior knowledge of dynamics into policy learning, we fine-tuned the open-source Stable Video Diffusion (SVD) model Blattmann et al. (2023a), which has 1.5 billion parameters, as the dynamics perception module for robot manipulation tasks. The fine-tuning utilized datasets including internet-sourced human manipulation data, internet robot manipulation data, and self-collected datasets. Then dynamics perception module  $V_{\theta}$  is trained with diffusion objective, reconstructing the full video sequence  $x_0 = s_{0:T}$  in dataset D from noised samples  $x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$ :

$$\mathcal{L}_D = \mathbb{E}_{x_0 \sim D, \epsilon, t} \|V_{\theta}(x_t, l_{emb}, s_0) - x_0\|^2$$

$$\tag{1}$$

where  $l_{emb}$  denotes the language feature from CLIP Radford et al. (2021). Then we froze the fine-tuned dynamics perception module in downstream action learning.

However, denoising a complete video sequence is computationally intensive and may cause open-loop control problems, as highlighted in Du et al. (2024). Furthermore, videos in raw pixel format frequently contain abundant irrelevant information that can hinder effective decision-making. To mitigate these challenges, we utilize the video diffusion model with a single forward pass. Our key insight is that the initial forward step, despite not producing a clear video, offers a coarse trajectory of future states and informative guidance. This observation is validated experimentally and illustrated in Figure 5. Specifically, we concatenate the current image  $s_0$  with the final noised latent  $q(x_{t'}|x_0)$  (typically white noise) and input this combination into the System 2. The latent features are then directly utilized. Previous work Xiang et al. (2023) emphasizes that up-sampling layers in diffusion models produce more effective feature representations. The feature at the  $m^{th}$  up-sampling layer, with width  $W_m$  and height  $H_m$ , is expressed as:

$$L_m = V_{\theta}(x_{t'}, l_{emb}, s_0)_{(m)}, L_m \in \mathbb{R}^{T \times C_m \times W_m \times H_m}$$
(2)

To efficiently integrate features from multiple up-sampling layers while eliminating manual layer selection, we propose an automatic feature aggregation approach across layers. First, each layer's feature map is linearly interpolated to a common height and width  $W_p \times H_p$ :

$$L'_{m} = Interpolation(L_{m}), L'_{m} \in \mathbb{R}^{T \times C_{m} \times W_{p} \times H_{p}}$$
(3)

Subsequently, the features are concatenated along the channel dimension. The final predictive visual representation  $F_p \in \mathbb{R}^{T \times (\sum_m C_m) \times W_p \times H_p}$  is given by:

$$F_p = \operatorname{concate}((L'_0, L'_1, \dots, L'_m), dim = 1)$$

For robots equipped with multiple camera perspectives, including third-person and wrist-mounted cameras, future states are predicted independently for each view, denoted as  $F_p^{static}$ ,  $F_p^{wrist}$ .

# 4.3 POLICY LEARNING MODULE (SYSTEM 1)

The predictive representations generated by the video diffusion model remain high-dimensional because they encode sequences of image features. To efficiently aggregate information across spatial, temporal, and multi-view dimensions, TriVLA compresses these representations into a fixed set of tokens. We initializes learnable tokens  $Q_{[0:T,0:L]}$  with fixed length  $T \times L$ , performing spatial-temporal attention Blattmann et al. (2023b) on each corresponding frame, followed by feed-forward layers. Formally, this branch can be expressed as follows where i is the index of frame:

$$Q' = \{ \text{Spat-Attn}(Q[i], (F_p^{static}[i], F_p^{wrist}[i])) \}_{i=0}^T$$
 
$$Q_p = \text{FFN}(\text{Temp-Attn}(Q'))$$
 (4)

After the vision-language module (System 2) extracts vision-language tokens  $Q_{vl}$ , and the dynamics perception module (System 3) aggregates future dynamic features into predictive tokens  $Q_p$ , a diffusion policy is employed as the action head to generate the action sequence  $a_0 \in A$  conditioned on  $Q_{vl}$  and  $Q_p$ . The aggregated tokens  $Q_{vl}$  and  $Q_p$  are integrated into the diffusion transformer blocks via cross-attention layers. The diffusion policy aims to reconstruct the original action  $a_0$  from the noised action  $a_k = \sqrt{\bar{\beta}_k} a_0 + \sqrt{1 - \bar{\beta}_k} \epsilon$ , where  $\epsilon$  denotes white noise and  $\bar{\beta}_k$  is the noise coefficient at step k. This process can be interpreted as learning a denoiser  $D_\psi$  to approximate the noise  $\epsilon$ . After the final DiT block, we apply an embodiment-specific action decoder  $A_d$ —a multi-layer perceptron (MLP)—to the final tokens to predict actions and minimize the following loss function:

$$\mathcal{L}_{\text{diff}}(\psi; A) = \mathbb{E}_{a_0, \epsilon, k} \| A_d(D_{\psi}(a_k, Q_{vl}, Q_p)) - a_0 \|^2$$

$$\tag{5}$$

Category	Method	Annotated Data	i <sup>th</sup> Task Success Rate					
Category	Methou	Amiotateu Data	1	2	3	4	5	Avg. Len↑
Direct Action Learning Method	RT-1	100%ABC	0.533	0.222	0.094	0.038	0.013	0.90
	Diffusion Policy	100%ABC	0.402	0.123	0.026	0.008	0.00	0.56
	Robo-Flamingo	100%ABC	0.824	0.619	0.466	0.331	0.235	2.47
	Uni-Pi	100%ABC	0.560	0.160	0.080	0.080	0.040	0.92
	MDT	100%ABC	0.631	0.429	0.247	0.151	0.091	1.55
Future Prediction	Susie	100%ABC	0.870	0.690	0.490	0.380	0.260	2.69
r didie r redietion	GR-1	100%ABC	0.854	0.712	0.596	0.497	0.401	3.06
Related Method	Vidman	100%ABC	0.915	0.764	0.682	0.592	0.467	3.42
	Seer	100%ABC	0.963	0.916	0.861	0.803	0.740	4.28
	VPP	100%ABC	0.965	0.909	0.866	0.820	0.769	4.33
3D Method	RoboUniview	100%ABC	0.942	0.842	0.734	0.622	0.507	3.65
Ours	TriVLA (ours)	100%ABC	0.968	0.924	0.868	0.832	0.818	4.37
Data Efficiency	GR-1	10%ABC	0.672	0.371	0.198	0.108	0.069	1.41
	VPP	10%ABC	0.878	0.746	0.632	0.540	0.453	3.25
	TriVLA (ours)	10%ABC	0.914	0.768	0.644	0.564	0.512	3.46

Table 1: **Zero-shot long-horizon evaluation on the Calvin ABC→D benchmark** where agent is asked to complete five chained tasks sequentially based on instructions. TriVLA demonstrates a significant improvement in the average task completion length (Avg. Len).

# 5 EXPERIMENTS

This section presents comprehensive experiments on both simulated and real-world robotic tasks to assess the performance of the proposed TriVLA. The simulation experiments utilize two distinct benchmarks specifically designed to systematically evaluate TriVLA's effectiveness across diverse robot embodiments and manipulation tasks. Real-world experiments examine the model's capabilities on a suite of tabletop manipulation tasks performed using Franka, Kinova, and Fair robots. These experiments are designed to demonstrate TriVLA's capacity to acquire novel skills from a limited set of human demonstrations.

### 5.1 SIMULATION SETUPS AND BASELINES

**CALVIN Simulation Benchmark.** CALVIN Mees et al. (2022) is a widely adopted benchmark developed to evaluate robotic policies' instruction-following ability in long-horizon manipulation tasks. This study concentrates on the challenging ABC→D scenario, in which the agent is trained within the ABC environment and tested in the previously unseen D environment. We adopt the same settings as GR1 Wu et al. (2023), employing only the language-annotated ABC datasets.

**LIBERO Simulation Benchmark.** We conduct evaluations on LIBERO Liu et al. (2024a), a simulation benchmark consisting of four distinct task suites: LIBERO-Spatial, LIBERO-Object, LIBERO-Goal, and LIBERO-Long. Each suite includes 10 diverse tasks, each accompanied by 50 human-teleoperated demonstrations, designed to assess the robot's understanding of spatial relationships, object interactions, and task-specific goals. We follow the same preprocessed pipeline as in Kim et al. (2024): (1) removing pause intervals from trajectories, (2) standardizing image resolution to 256×256 pixels, and (3) applying a 180-degree rotation to all images.

**MetaWorld Simulation Benchmark.** Metaworld Yu et al. (2020) employs a Sawyer robot to perform diverse manipulation tasks and serves as a widely adopted benchmark for assessing the precision and dexterity of robotic policies. It comprises 50 tasks encompassing a diverse set of objects with varying difficulty levels Radosavovic et al. (2023). We utilize the official Oracle policy to collect 50 trajectories per task, forming our dataset.

**Training Details.** As detailed in Section 4, we employ a triple-system architecture. The System 2 vision-language module utilizes the pretrained Eagle-2 VLM to process visual inputs and language instructions on an NVIDIA H100 GPU. Subsequently, we fine-tune a video foundation model to serve as a manipulation-focused dynamics perception module (System 3). The datasets used for fine-tuning comprise 193,690 human manipulation trajectories Goyal et al. (2017), 179,074 robotic manipulation trajectories O'Neill et al. (2023), and downstream task videos including the official Calvin ABC, MetaWorld, and real-world videos. Considering the varying scales and quality of these datasets, we apply distinct sampling ratios following the method described in Octo. Fine-tuning the

Method	Easy	Middle	Hard	Avg ↑
RT-1	0.603	0.030	0.014	0.331
Diffusion Policy	0.433	0.072	0.089	0.299
Susie	0.542	0.213	0.244	0.420
GR-1	0.695	0.337	0.448	0.582
VPP	0.822	0.507	0.519	0.679
TriVLA (ours)	0.857	0.528	0.563	0.714

Table 2: **Performance on the MetaWorld benchmark** by difficulty level (60 tasks total: 35 easy, 14 middle, 11 hard).

	Average (†)	Spatial (†)	Object (†)	Goal (†)	Long (†)
Diffusion Policy	$72.4\pm0.7\%$	$78.3 \pm 1.1\%$	$92.5 \pm 0.7\%$	$68.3 \pm 1.2\%$	$50.5 \pm 1.3\%$
Octo	$75.1 \pm 0.6\%$	$78.9 \pm 1.0\%$	$85.7 \pm 0.9\%$	$84.6\pm0.9\%$	$51.1 \pm 1.3\%$
OpenVLA	$76.5\pm0.6\%$	$84.7\pm0.9\%$	$88.4 \pm 0.8\%$	$79.2\pm1.0\%$	$53.7\pm1.3\%$
TriVLA (ours)	87.0 $\pm$ 0.7 %	$\textbf{91.2} \pm \textbf{0.8}\%$	$\textbf{93.8} \pm \textbf{0.7}\%$	$\textbf{89.8} \pm \textbf{0.9}\%$	$\textbf{73.2} \pm \textbf{0.5}\%$

Table 3: **LIBERO benchmark experimental results.** For each task suite (Spatial, Object, Goal, Long), we report the average success rate and standard error across 3 seeds with 500 episodes each. TriVLA achieves the best or competitive performance across all LIBERO benchmarks suites compared to baseline approaches. The bolded entries correspond to highest success rates.

video model requires 2–3 days on 8 NVIDIA H100 GPUs. Finally, a generalist policy (System 1) is trained using the training datasets, requiring approximately 5–9 hours on four NVIDIA H100 GPUs.

Roll-out Details. The System 2 vision-language module employs a pre-trained Eagle-2 VLM to extract vision-language tokens, operating at 36.36 Hz on an NVIDIA H100 GPU. Prior studies rely on denoising high-precision videos, a process that is time-consuming and leads to low control frequency Black et al. (2023) or even open-loop control issues Du et al. (2024). In contrast, our method employs the dynamics perception module's initial forward step, ensuring each observation passes through System 2 only once, requiring less than 85.9 ms per inference. Subsequently, the downstream policy generates an action chunk Chi et al. (2023) of 10 steps conditioned on vision-language and prediction tokens, further enhancing control frequency. This modification enables a substantially higher control frequency of 34–36 Hz on a consumer-level NVIDIA RTX H100 GPU.

**Comparison methods.** Generalist robot policies have been extensively investigated in prior research. In our experiments, we select a representative subset of prior methods for comparison, focusing on those that have achieved state-of-the-art performance or employ approaches similar to ours.

- RT-1 Brohan et al. (2022): A general action learning robot policy integrating semantic features via Efficient-Net with FiLM-conditioning, subsequently employing token learners.
- Diffusion Policy Chi et al. (2023): A action learning approach modeling the robot's visuomotor policy as a conditional denoising diffusion process enhanced with action diffusers.
- Robo-Flamingo Li et al. (2023b): A direct action learning policy leveraging a pre-trained LLM, integrating visual information into each layer following the Flamingo Alayrac et al. (2022).
- UniPi Du et al. (2024): Initiates by training a video prediction model for future sequence generation and concurrently learns an inverse kinematics model between frames to infer actions.
- MDT Reuss et al. (2024): Trains a diffusion transformer-based policy complemented by an auxiliary MAE loss to facilitate future state reconstruction.
- Susie Black et al. (2023): Employs a fine-tuned InstructPix2Pix Brooks et al. (2023) model
  to generate goal images and trains a downstream diffusion policy conditioned on these goal
  images.

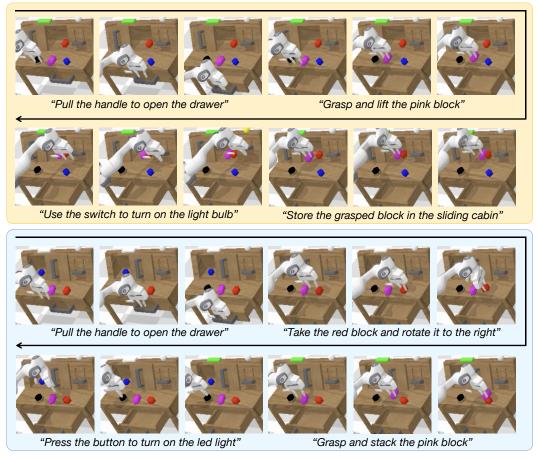


Figure 4: **Qualitative case study.** Our **TriVLA** performs exceptionally well in long-horizon missions. Taking the CALVIN simulation task as an example, TriVLA integrates world knowledge for intent understanding and leverages a world model for future prediction when given multiple sequential instructions, enabling effective execution of long-horizon tasks.

- GR-1 Wu et al. (2023): Models video and action sequences using an autoregressive transformer. During policy execution, GR-1 predicts one future frame followed by a action.
- Robo-Uniview Liu et al. (2024b): Develops a 3D-aware visual encoder supervised by a 3D occupancy loss for policy learning.
- Vidman Wen et al. (2024): Pre-trained on the Open X-Embodiment video dataset, it employs a self-attention adapter to convert video representations into policies. However, Vidman's performance is suboptimal due to the absence of fine-tuning the video model on downstream tasks.
- Seer Tian et al. (2024): Designs a novel end-to-end framework that leverages predictive inverse dynamics models to integrate vision and action for scalable robotic manipulation.
- VPP Hu et al. (2024): Leverages video diffusion models to generate visual representations, addressing the limitations of traditional vision encoders in capturing temporal aspects critical for robotic manipulation.

Quantitative Results. Comparisons on the Calvin benchmark are presented in Table 1. Experimental results for Robo-Flamingo, Susie, GR-1, and 3D Diffuser Actors are extracted from their respective original publications. MDT results are obtained from the official implementation. RT-1 and UniPi results are sourced from Li et al. (2023b) and Black et al. (2023), respectively. We additionally executed the Diffusion Policy using the official open-source codebase with CLIP language conditioning. Our proposed TriVLA significantly surpasses previous state-of-the-art results. Remarkably, despite training on only 10% of the annotated Calvin ABC dataset, our method achieved

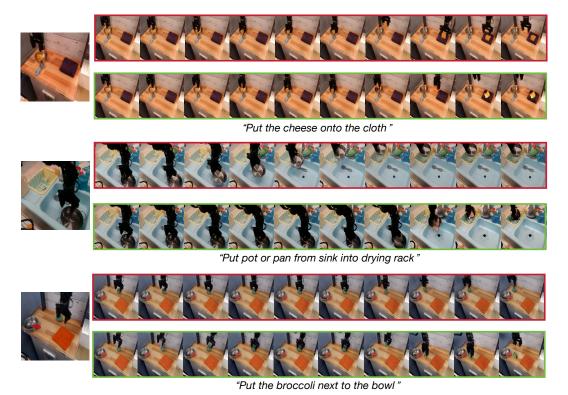


Figure 5: **Visualization of one-step visual representations of dynamics perception module.** We can observe that representation can provide valuable information on physical dynamics, although the textures and details are not precise enough.

an average task completion length of 3.46, outperforming related methods trained on the full dataset. Furthermore, TriVLA attained the highest performance on the MetaWorld benchmark comprising 60 tasks, as detailed in Table 2. It outperforms the strongest VPP baseline in average success rate. Quantitative results on the LIBERO benchmark are presented in Table 3, where each method is evaluated over 500 trials per task suite using 3 random seeds. The results demonstrate that TriVLA effectively adapts to LIBERO simulation tasks, achieving best or competitive performance relative to baseline methods.

Visualization of trajectories. We provide three qualitative examples of action sequences generated by TriVLA in Figure 4. Given multiple consecutive instructions—for instance, "Pull the handle to open the drawer," "Grasp and lift the pink block," "Use the switch to turn on the light bulb," and "Store the grasped block in the sliding cabin"—TriVLA demonstrates the ability to comprehend instructions, infer intent, and utilize predictive capabilities to accomplish long-horizon tasks. The results demonstrate that TriVLA employs VLMs and VDMs for both high-level reasoning based on common knowledge and dynamic predictive representation provided by a world model. TriVLA integrates world knowledge to enhance intent understanding and utilizes a world model for future state prediction when processing multiple sequential instructions, thereby enabling effective long-horizon task execution.

## 5.2 ABLATION STUDY

**Visualization of Dynamics Perception.** We employ a stable video diffusion model as the dynamics perception module, executing a single forward pass to obtain visual representations that encompass both current static information and predicted future dynamics. As illustrated in Figure 5, we present visualizations of ground-truth futures alongside single-step predictions on the Bridge benchmark Walke et al. (2023). The visualization results indicate that single-step representations convey critical information, including object and robot arm motion, thereby effectively supporting downstream action learning. The dynamics perception module models entire video sequences and

Results on Calvin Benchmark							
Sub-system			Performance				
VL-M	DP-M	PL-M	Avg. Length ↑	Latency ↓	Params ↓		
		/	3.68	29.29ms	0.53B		
	<b>✓</b>	/	4.06	115.19ms	1.87B		
<b>✓</b>	<b>✓</b>	<b>✓</b>	4.37	142.69ms	3.39B		

Table 4: **Sub-system ablation studies.** We report the average success length and latency on the CALVIN simulation benchmark. VL-M denotes the System 2 vision-language module, DP-M denotes the System 3 dynamics perception module, and PL-M denotes the System 1 policy learning module.

predicts future frames conditioned on current observations and instructions, demonstrating a sound understanding of physical dynamics.

**Effectiveness of Vision-Language Module.** The System 2 vision-language module (VL-M) of TriVLA is a pre-trained Vision-Language Model (VLM) responsible for processing the robot's visual perception and language instructions to interpret the environment and comprehend task goals. Experiments were conducted to evaluate the effectiveness of System 2. As summarized in Table 4, integration of the vision-language module improved performance from 4.06 to 4.37, with inference time increasing from 136 ms to 155 ms. These results suggest that integrating System 2 significantly enhances the accuracy of action generation.

Effectiveness of Dynamics Perception Module. The System 3 dynamics perception module (DP-M) is a general-purpose video diffusion model fine-tuned on internet-sourced human and robot manipulation datasets. This module is designed to develop a controllable video generation model enhancing predictive capabilities within the manipulation domain. To assess its effectiveness, we perform an ablation study by integrating the dynamics perception module into the proposed TriVLA framework. The results, summarized in Table 4, were obtained using a single NVIDIA H100 GPU. Notably, incorporation of the dynamics perception module results in a significant enhancement of robot control performance.

## 6 Conclusion

TriVLA presents a novel triple-system architecture that effectively integrates vision-language understanding with dynamic perception, enhancing the robot's capability to capture both static and future dynamic information. This integration enables more fluid and generalized control policies for robot manipulation. Experimental results demonstrate that TriVLA outperforms state-of-the-art imitation learning baselines on standard simulation benchmarks and challenging real-world tasks, highlighting its potential for broad applications in general robotic control.

# 7 ACKNOWLEDGMENTS

This work was supported by the Science and Technology Commission of Shanghai Municipality (No. 24511103100) and in part by NSFC Project (62176061), and Shanghai Technology Development and Entrepreneurship Platform for Neuromorphic and AI SoC.

#### REFERENCES

Michael Ahn, Anthony Brohan, Noah Brown, Yevgen Chebotar, Omar Cortes, Byron David, Chelsea Finn, Chuyuan Fu, Keerthana Gopalakrishnan, Karol Hausman, et al. Do as i can, not as i say: Grounding language in robotic affordances. *arXiv preprint arXiv:2204.01691*, 2022.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35:23716–23736, 2022.

- Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. Qwen-vl: A frontier large vision-language model with versatile abilities. arXiv preprint arXiv:2308.12966, 2023.
- Suneel Belkhale, Tianli Ding, Ted Xiao, Pierre Sermanet, Quon Vuong, Jonathan Tompson, Yevgen Chebotar, Debidatta Dwibedi, and Dorsa Sadigh. Rt-h: Action hierarchies using language. *arXiv* preprint arXiv:2403.01823, 2024.
- Homanga Bharadhwaj, Debidatta Dwibedi, Abhinav Gupta, Shubham Tulsiani, Carl Doersch, Ted Xiao, Dhruv Shah, Fei Xia, Dorsa Sadigh, and Sean Kirmani. Gen2act: Human video generation in novel scenarios enables generalizable robot manipulation. arXiv preprint arXiv:2409.16283, 2024.
- Johan Bjorck, Fernando Castañeda, Nikita Cherniadev, Xingye Da, Runyu Ding, Linxi Fan, Yu Fang, Dieter Fox, Fengyuan Hu, Spencer Huang, et al. Gr00t n1: An open foundation model for generalist humanoid robots. *arXiv preprint arXiv:2503.14734*, 2025.
- Kevin Black, Mitsuhiko Nakamoto, Pranav Atreya, Homer Walke, Chelsea Finn, Aviral Kumar, and Sergey Levine. Zero-shot robotic manipulation with pretrained image-editing diffusion models. *arXiv preprint arXiv:2310.10639*, 2023.
- Kevin Black, Noah Brown, Danny Driess, Adnan Esmail, Michael Equi, Chelsea Finn, Niccolo Fusai, Lachy Groom, Karol Hausman, Brian Ichter, Szymon Jakubczak, Tim Jones, Liyiming Ke, Sergey Levine, Adrian Li-Bell, Mohith Mothukuri, Suraj Nair, Karl Pertsch, Lucy Xiaoyang Shi, James Tanner, Quan Vuong, Anna Walling, Haohuan Wang, and Ury Zhilinsky. π<sub>0</sub>: A vision-language-action flow model for general robot control, 2024. URL https://arxiv.org/abs/2410.24164.
- Andreas Blattmann, Tim Dockhorn, Sumith Kulal, Daniel Mendelevitch, Maciej Kilian, Dominik Lorenz, Yam Levi, Zion English, Vikram Voleti, Adam Letts, et al. Stable video diffusion: Scaling latent video diffusion models to large datasets. *arXiv preprint arXiv:2311.15127*, 2023a.
- Andreas Blattmann, Robin Rombach, Huan Ling, Tim Dockhorn, Seung Wook Kim, Sanja Fidler, and Karsten Kreis. Align your latents: High-resolution video synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 22563–22575, 2023b.
- Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Joseph Dabis, Chelsea Finn, Keerthana Gopalakrishnan, Karol Hausman, Alex Herzog, Jasmine Hsu, et al. Rt-1: Robotics transformer for real-world control at scale. *arXiv preprint arXiv:2212.06817*, 2022.
- Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Xi Chen, Krzysztof Choromanski, Tianli Ding, Danny Driess, Avinava Dubey, Chelsea Finn, et al. Rt-2: Vision-language-action models transfer web knowledge to robotic control. *arXiv preprint arXiv:2307.15818*, 2023.
- Tim Brooks, Aleksander Holynski, and Alexei A Efros. Instructpix2pix: Learning to follow image editing instructions. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18392–18402, 2023.
- Tim Brooks, Bill Peebles, Connor Holmes, Will DePue, Yufei Guo, Li Jing, David Schnurr, Joe Taylor, Troy Luhman, Eric Luhman, Clarence Ng, Ricky Wang, and Aditya Ramesh. Video generation models as world simulators. 2024. URL https://openai.com/research/video-generation-models-as-world-simulators.
- Xiaoyu Chen, Junliang Guo, Tianyu He, Chuheng Zhang, Pushi Zhang, Derek Cathera Yang, Li Zhao, and Jiang Bian. Igor: Image-goal representations are the atomic control units for foundation models in embodied ai. *arXiv preprint arXiv:2411.00785*, 2024.
- Cheng Chi, Zhenjia Xu, Siyuan Feng, Eric Cousineau, Yilun Du, Benjamin Burchfiel, Russ Tedrake, and Shuran Song. Diffusion policy: Visuomotor policy learning via action diffusion. *The International Journal of Robotics Research*, pp. 02783649241273668, 2023.

- Danny Driess, Fei Xia, Mehdi SM Sajjadi, Corey Lynch, Aakanksha Chowdhery, Brian Ichter, Ayzaan Wahid, Jonathan Tompson, Quan Vuong, Tianhe Yu, et al. Palm-e: An embodied multimodal language model. *arXiv preprint arXiv:2303.03378*, 2023.
- Yilun Du, Sherry Yang, Bo Dai, Hanjun Dai, Ofir Nachum, Josh Tenenbaum, Dale Schuurmans, and Pieter Abbeel. Learning universal policies via text-guided video generation. *Advances in Neural Information Processing Systems*, 36, 2024.
- Peng Gao\*, Jiaming Han\*, Renrui Zhang\*, Ziyi Lin, Shijie Geng, Aojun Zhou, Wei Zhang, Pan Lu, Conghui He, Xiangyu Yue, et al. Llama-adapter v2: Parameter-efficient visual instruction model. arXiv preprint arXiv:2304.15010, 2023.
- Raghav Goyal, Samira Ebrahimi Kahou, Vincent Michalski, Joanna Materzynska, Susanne Westphal, Heuna Kim, Valentin Haenel, Ingo Fruend, Peter Yianilos, Moritz Mueller-Freitag, et al. The" something something" video database for learning and evaluating visual common sense. In *Proceedings of the IEEE international conference on computer vision*, pp. 5842–5850, 2017.
- Alex Graves and Alex Graves. Long short-term memory. Supervised sequence labelling with recurrent neural networks, pp. 37–45, 2012.
- Yanjiang Guo, Yucheng Hu, Jianke Zhang, Yen-Jen Wang, Xiaoyu Chen, Chaochao Lu, and Jianyu Chen. Prediction with action: Visual policy learning via joint denoising process. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024.
- Wenyi Hong, Ming Ding, Wendi Zheng, Xinghan Liu, and Jie Tang. Cogvideo: Large-scale pretraining for text-to-video generation via transformers. *arXiv preprint arXiv:2205.15868*, 2022.
- Yucheng Hu, Yanjiang Guo, Pengchao Wang, Xiaoyu Chen, Yen-Jen Wang, Jianke Zhang, Koushil Sreenath, Chaochao Lu, and Jianyu Chen. Video prediction policy: A generalist robot policy with predictive visual representations. *arXiv* preprint arXiv:2412.14803, 2024.
- Siyuan Huang, Iaroslav Ponomarenko, Zhengkai Jiang, Xiaoqi Li, Xiaobin Hu, Peng Gao, Hongsheng Li, and Hao Dong. Manipvqa: Injecting robotic affordance and physically grounded information into multi-modal large language models. *arXiv preprint arXiv:2403.11289*, 2024a.
- Wenlong Huang, Chen Wang, Ruohan Zhang, Yunzhu Li, Jiajun Wu, and Li Fei-Fei. Voxposer: Composable 3d value maps for robotic manipulation with language models. *arXiv* preprint arXiv:2307.05973, 2023.
- Wenlong Huang, Chen Wang, Yunzhu Li, Ruohan Zhang, and Li Fei-Fei. Rekep: Spatiotemporal reasoning of relational keypoint constraints for robotic manipulation. *arXiv* preprint arXiv:2409.01652, 2024b.
- Physical Intelligence, Kevin Black, Noah Brown, James Darpinian, Karan Dhabalia, Danny Driess, Adnan Esmail, Michael Equi, Chelsea Finn, Niccolo Fusai, Manuel Y. Galliker, Dibya Ghosh, Lachy Groom, Karol Hausman, Brian Ichter, Szymon Jakubczak, Tim Jones, Liyiming Ke, Devin LeBlanc, Sergey Levine, Adrian Li-Bell, Mohith Mothukuri, Suraj Nair, Karl Pertsch, Allen Z. Ren, Lucy Xiaoyang Shi, Laura Smith, Jost Tobias Springenberg, Kyle Stachowicz, James Tanner, Quan Vuong, Homer Walke, Anna Walling, Haohuan Wang, Lili Yu, and Ury Zhilinsky.  $\pi_{0.5}$ : a vision-language-action model with open-world generalization, 2025. URL https://arxiv.org/abs/2504.16054.
- Yixiang Jin, Dingzhe Li, Jun Shi, Peng Hao, Fuchun Sun, Jianwei Zhang, Bin Fang, et al. Robotgpt: Robot manipulation learning from chatgpt. *IEEE Robotics and Automation Letters*, 9(3):2543–2550, 2024.
- Daniel Kahneman. Thinking, fast and slow. macmillan, 2011.
- Alexander Khazatsky, Karl Pertsch, Suraj Nair, Ashwin Balakrishna, Sudeep Dasari, Siddharth Karamcheti, Soroush Nasiriany, Mohan Kumar Srirama, Lawrence Yunliang Chen, Kirsty Ellis, Peter David Fagan, Joey Hejna, Masha Itkina, Marion Lepert, Yecheng Jason Ma, Patrick Tree Miller, Jimmy Wu, Suneel Belkhale, Shivin Dass, Huy Ha, Arhan Jain, Abraham Lee, Youngwoon Lee, Marius Memmel, Sungjae Park, Ilija Radosavovic, Kaiyuan Wang, Albert Zhan, Kevin

- Black, Cheng Chi, Kyle Beltran Hatch, Shan Lin, Jingpei Lu, Jean Mercat, Abdul Rehman, Pannag R Sanketi, Archit Sharma, Cody Simpson, Quan Vuong, Homer Rich Walke, Blake Wulfe, Ted Xiao, Jonathan Heewon Yang, Arefeh Yavary, Tony Z. Zhao, Christopher Agia, Rohan Baijal, Mateo Guaman Castro, Daphne Chen, Qiuyu Chen, Trinity Chung, Jaimyn Drake, Ethan Paul Foster, Jensen Gao, David Antonio Herrera, Minho Heo, Kyle Hsu, Jiaheng Hu, Donovon Jackson, Charlotte Le, Yunshuang Li, Kevin Lin, Roy Lin, Zehan Ma, Abhiram Maddukuri, Suvir Mirchandani, Daniel Morton, Tony Nguyen, Abigail O'Neill, Rosario Scalise, Derick Seale, Victor Son, Stephen Tian, Emi Tran, Andrew E. Wang, Yilin Wu, Annie Xie, Jingyun Yang, Patrick Yin, Yunchu Zhang, Osbert Bastani, Glen Berseth, Jeannette Bohg, Ken Goldberg, Abhinav Gupta, Abhishek Gupta, Dinesh Jayaraman, Joseph J Lim, Jitendra Malik, Roberto Martín-Martín, Subramanian Ramamoorthy, Dorsa Sadigh, Shuran Song, Jiajun Wu, Michael C. Yip, Yuke Zhu, Thomas Kollar, Sergey Levine, and Chelsea Finn. Droid: A large-scale in-the-wild robot manipulation dataset. 2024.
- Moo Jin Kim, Karl Pertsch, Siddharth Karamcheti, Ted Xiao, Ashwin Balakrishna, Suraj Nair, Rafael Rafailov, Ethan Foster, Grace Lam, Pannag Sanketi, et al. Openvla: An open-source vision-language-action model. *arXiv preprint arXiv:2406.09246*, 2024.
- Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In *International conference on machine learning*, pp. 19730–19742. PMLR, 2023a.
- Xiaoqi Li, Mingxu Zhang, Yiran Geng, Haoran Geng, Yuxing Long, Yan Shen, Renrui Zhang, Jiaming Liu, and Hao Dong. Manipllm: Embodied multimodal large language model for object-centric robotic manipulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18061–18070, 2024a.
- Xinghang Li, Minghuan Liu, Hanbo Zhang, Cunjun Yu, Jie Xu, Hongtao Wu, Chilam Cheang, Ya Jing, Weinan Zhang, Huaping Liu, et al. Vision-language foundation models as effective robot imitators. *arXiv preprint arXiv:2311.01378*, 2023b.
- Xinghang Li, Peiyan Li, Minghuan Liu, Dong Wang, Jirong Liu, Bingyi Kang, Xiao Ma, Tao Kong, Hanbo Zhang, and Huaping Liu. Towards generalist robot policies: What matters in building vision-language-action models. *arXiv* preprint arXiv:2412.14058, 2024b.
- Zhiqi Li, Guo Chen, Shilong Liu, Shihao Wang, Vibashan VS, Yishen Ji, Shiyi Lan, Hao Zhang, Yilin Zhao, Subhashree Radhakrishnan, et al. Eagle 2: Building post-training data strategies from scratch for frontier vision-language models. *arXiv* preprint arXiv:2501.14818, 2025.
- Yaron Lipman, Ricky TQ Chen, Heli Ben-Hamu, Maximilian Nickel, and Matt Le. Flow matching for generative modeling. *arXiv preprint arXiv:2210.02747*, 2022.
- Bo Liu, Yifeng Zhu, Chongkai Gao, Yihao Feng, Qiang Liu, Yuke Zhu, and Peter Stone. Libero: Benchmarking knowledge transfer for lifelong robot learning. *Advances in Neural Information Processing Systems*, 36, 2024a.
- Fanfan Liu, Feng Yan, Liming Zheng, Chengjian Feng, Yiyang Huang, and Lin Ma. Robouniview: Visual-language model with unified view representation for robotic manipulation. *arXiv* preprint arXiv:2406.18977, 2024b.
- Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *Advances in neural information processing systems*, 36, 2024c.
- Jiaming Liu, Mengzhen Liu, Zhenyu Wang, Lily Lee, Kaichen Zhou, Pengju An, Senqiao Yang, Renrui Zhang, Yandong Guo, and Shanghang Zhang. Robomamba: Multimodal state space model for efficient robot reasoning and manipulation. *arXiv preprint arXiv:2406.04339*, 2024d.
- Guanxing Lu, Shiyi Zhang, Ziwei Wang, Changliu Liu, Jiwen Lu, and Yansong Tang. Manigaussian: Dynamic gaussian splatting for multi-task robotic manipulation. In *European Conference on Computer Vision*, pp. 349–366. Springer, 2024.
- Oier Mees, Lukas Hermann, Erick Rosete-Beas, and Wolfram Burgard. Calvin: A benchmark for language-conditioned policy learning for long-horizon robot manipulation tasks. *IEEE Robotics and Automation Letters (RA-L)*, 7(3):7327–7334, 2022.

- Chuan Min, Yongjun Pan, Wei Dai, Ibna Kawsar, Zhixiong Li, and Gengxiang Wang. Trajectory optimization of an electric vehicle with minimum energy consumption using inverse dynamics model and servo constraints. *Mechanism and Machine Theory*, 181:105185, 2023.
- Abby O'Neill, Abdul Rehman, Abhinav Gupta, Abhiram Maddukuri, Abhishek Gupta, Abhishek Padalkar, Abraham Lee, Acorn Pooley, Agrim Gupta, Ajay Mandlekar, et al. Open x-embodiment: Robotic learning datasets and rt-x models. arXiv preprint arXiv:2310.08864, 2023.
- Karl Pertsch, Kyle Stachowicz, Brian Ichter, Danny Driess, Suraj Nair, Quan Vuong, Oier Mees, Chelsea Finn, and Sergey Levine. Fast: Efficient action tokenization for vision-language-action models. arXiv preprint arXiv:2501.09747, 2025.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PMLR, 2021.
- Ilija Radosavovic, Tete Xiao, Stephen James, Pieter Abbeel, Jitendra Malik, and Trevor Darrell. Real-world robot learning with masked visual pre-training. In *Conference on Robot Learning*, pp. 416–426. PMLR, 2023.
- Moritz Reuss, Ömer Erdinç Yağmurlu, Fabian Wenzel, and Rudolf Lioutikov. Multimodal diffusion transformer: Learning versatile behavior from multimodal goals, 2024. URL https://arxiv.org/abs/2407.05996.
- Lucy Xiaoyang Shi, Brian Ichter, Michael Equi, Liyiming Ke, Karl Pertsch, Quan Vuong, James Tanner, Anna Walling, Haohuan Wang, Niccolo Fusai, et al. Hi robot: Open-ended instruction following with hierarchical vision-language-action models. *arXiv preprint arXiv:2502.19417*, 2025.
- Yang Tian, Sizhe Yang, Jia Zeng, Ping Wang, Dahua Lin, Hao Dong, and Jiangmiao Pang. Predictive inverse dynamics models are scalable learners for robotic manipulation. *arXiv* preprint *arXiv*:2412.15109, 2024.
- Homer Walke, Kevin Black, Abraham Lee, Moo Jin Kim, Max Du, Chongyi Zheng, Tony Zhao, Philippe Hansen-Estruch, Quan Vuong, Andre He, Vivek Myers, Kuan Fang, Chelsea Finn, and Sergey Levine. Bridgedata v2: A dataset for robot learning at scale, 2023.
- Youpeng Wen, Junfan Lin, Yi Zhu, Jianhua Han, Hang Xu, Shen Zhao, and Xiaodan Liang. Vidman: Exploiting implicit dynamics from video diffusion model for effective robot manipulation. Advances in Neural Information Processing Systems, 37:41051–41075, 2024.
- Hongtao Wu, Ya Jing, Chilam Cheang, Guangzeng Chen, Jiafeng Xu, Xinghang Li, Minghuan Liu, Hang Li, and Tao Kong. Unleashing large-scale video generative pre-training for visual robot manipulation. *arXiv preprint arXiv:2312.13139*, 2023.
- Weilai Xiang, Hongyu Yang, Di Huang, and Yunhong Wang. Denoising diffusion autoencoders are unified self-supervised learners. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 15802–15812, 2023.
- Zhuoyi Yang, Jiayan Teng, Wendi Zheng, Ming Ding, Shiyu Huang, Jiazheng Xu, Yuanming Yang, Wenyi Hong, Xiaohan Zhang, Guanyu Feng, et al. Cogvideox: Text-to-video diffusion models with an expert transformer. *arXiv preprint arXiv:2408.06072*, 2024.
- Seonghyeon Ye, Joel Jang, Byeongguk Jeon, Sejune Joo, Jianwei Yang, Baolin Peng, Ajay Mandlekar, Reuben Tan, Yu-Wei Chao, Bill Yuchen Lin, et al. Latent action pretraining from videos. *arXiv preprint arXiv:2410.11758*, 2024.
- Tianhe Yu, Deirdre Quillen, Zhanpeng He, Ryan Julian, Karol Hausman, Chelsea Finn, and Sergey Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. In *Conference on robot learning*, pp. 1094–1100. PMLR, 2020.

- Renrui Zhang, Jiaming Han, Chris Liu, Peng Gao, Aojun Zhou, Xiangfei Hu, Shilin Yan, Pan Lu, Hongsheng Li, and Yu Qiao. Llama-adapter: Efficient fine-tuning of language models with zero-init attention. *arXiv preprint arXiv:2303.16199*, 2023.
- Renrui Zhang, Dongzhi Jiang, Yichi Zhang, Haokun Lin, Ziyu Guo, Pengshuo Qiu, Aojun Zhou, Pan Lu, Kai-Wei Chang, Peng Gao, et al. Mathverse: Does your multi-modal llm truly see the diagrams in visual math problems? *ECCV* 2024, 2024a.
- Renrui Zhang, Xinyu Wei, Dongzhi Jiang, Ziyu Guo, Shicheng Li, Yichi Zhang, Chengzhuo Tong, Jiaming Liu, Aojun Zhou, Bin Wei, et al. Mavis: Mathematical visual instruction tuning with an automatic data engine. *arXiv preprint arXiv:2407.08739*, 2024b.