
Chain-of-Action: Trajectory Autoregressive Modeling for Robotic Manipulation

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Project page: <https://chain-of-action.github.io/>

Code: <https://github.com/ByteDance-Seed/Chain-of-Action>

Abstract

We present **Chain-of-Action (CoA)**, a novel visuomotor policy paradigm built upon *Trajectory Autoregressive Modeling*. Unlike conventional approaches that predict next step action(s) *forward*, CoA generates an entire trajectory by explicit *backward* reasoning with task-specific goals through an action-level Chain-of-Thought (CoT) process. This process is unified within a single autoregressive structure: (1) the first token corresponds to a stable keyframe action that encodes the task-specific goals; and (2) subsequent action tokens are generated autoregressively, conditioned on the initial keyframe and previously predicted actions. This backward action reasoning enforces a global-to-local structure, allowing each local action to be tightly constrained by the final goal. To further realize the action reasoning structure, CoA incorporates four complementary designs: continuous action token representation; dynamic stopping for variable-length trajectory generation; reverse temporal ensemble; and multi-token prediction to balance action chunk modeling with global structure. As a result, CoA gives strong spatial generalization capabilities while preserving the flexibility and simplicity of a visuomotor policy. Empirically, we observe that CoA outperforms representative imitation learning algorithms such as ACT and Diffusion Policy across 60 RLBench tasks and 8 real-world tasks.

1 Introduction

visuomotor policies have made substantial progress in enabling robots to perform complex manipulation tasks from raw sensory observations. With the rise of large-scale demonstrations [5, 19, 37] and powerful neural architectures [36, 11], recent methods have increasingly focused on end-to-end learning from visual inputs to low-level control [15, 2].

To better model multi-modal action distributions and mitigate compounding errors, various modeling paradigms have been proposed [3, 45]. For instance, ACT [45] employs a conditional variational autoencoder to learn action distributions and introduces action chunking to reduce compounding errors. Diffusion Policy [3] formulates action generation as a denoising process, capturing complex, multi-modal behaviors more effectively. Many subsequent developments have explored enhancements in multiple directions, including enriched sensory inputs [41, 40], improved network architecture [4, 24], expanded datasets [5], and scaled model capacity, represented by trend of VLA (vision-language-action) model [21, 28, 25, 1].

Despite a wide range of these improvements, most of methods still follow a forward prediction paradigm, as illustrated in Figure 1. While this formulation is intuitive and widely adopted, it suffers from a critical limitation: the accumulation of *compounding errors* [32, 18, 22, 30] during execution. The root cause lies in the training objective: these models are optimized to predict the next-step action based on current observation, rather than to ensure successful completion of tasks with long-horizon [32]. While techniques such as action chunking and image goal conditioned behavioral cloning [28, 37] have been introduced to alleviate compounding errors, they primarily address the symptoms rather than the root cause, which lies in the inherently myopic nature of forward prediction.

We approach the problem from the *opposite end*, both conceptually and practically, by reversing the action generation process. While the change in direction may appear simple, it reflects a fundamental shift in how we conceptualize action generation. Instead of predicting actions in a forward, step-wise manner, we propose to construct action sequences in reverse, forming a *chain of actions* that starts from the a keyframe action [13, 34, 9, 8], and backward towards the initial state. Our insight is that the keyframe action encodes the task-specific goal, which provides a strong structural prior to guide the entire action sequence. By explicitly generating actions from the goal backward, our method enforces a global-to-local consistency [26, 39] that significantly mitigates compounding errors and enhances generalization under distribution shifts.

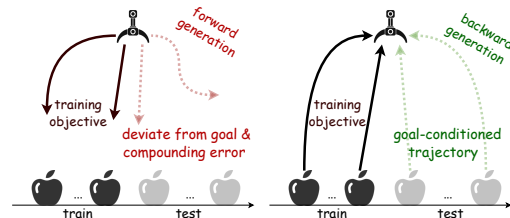


Figure 1: Comparison between a conventional visuomotor policy (left) and our proposed Chain-of-Action (right). The former is optimized to predict step-wise actions based on current observations, rather than long-term goals, often leading to misaligned behaviors during execution. In contrast, Chain-of-Action adopts a backward generation paradigm, producing goal-conditioned trajectories that reliably execute toward the intended target.

To realize this backward reasoning paradigm while maintaining scalability potential [16, 35] for end-to-end training, we unify the entire reverse generation process into a single autoregressive framework. While the formulation is theoretically effective, its practical viability depends on four extra specific designs. These are not optional improvements, but necessary for stable training and reliable closed-loop execution. (1) Continuous action representation: Discretizing actions into finite bins introduces resolution loss [20, 31, 23], which becomes particularly problematic in long-horizon autoregressive generation. In our backward generation setup, even small quantization errors can accumulate from the goal backward, leading to significant deviations in earlier steps. To preserve fine-grained structure and trajectory fidelity, we adopt a continuous action representation. (2) Local action modeling: While the backward autoregressive structure effectively propagates high-level intent from the goal, it does not explicitly model local action dependencies [20, 45, 3] within a sub-trajectory. To address this, we adopt a multi-token prediction strategy [7, 43] during training, which encourages the model to jointly predict short action chunks. This enhances local coherence and stabilizes training. (3) Dynamic stop: Closed-loop execution [27] requires our generation stop at right point. However, in continuous action spaces, there is no discrete end-of-sequence (EOS) token to indicate termination [43]. We thus design a distance-based stop mechanism that enables the model to determine when to stop based on proximity to the goal, reducing over-generation and improving execution efficiency. (4) Reverse temporal ensemble: Original ensemble strategies [45], used in ACT, are designed under forward temporal assumptions and are not directly applicable to our backward generation setting. To address this, we develop a reverse-compatible variant that ensembles multiple backward rollouts, mitigating temporal misalignment and reducing variance during closed-loop execution.

Chain-of-Action (CoA), which integrates these four essential components into a single autoregressive framework, achieves strong performance in both simulation and real-world settings. CoA outperforms ACT by 16% and Diffusion Policy by 23% across 60 RLBench tasks, the most comprehensive evaluation conducted on this benchmark to date, and surpasses ACT by 15% in real-world robotic manipulation. Crucially, CoA adopts comparable architectures and training setups to ACT, underscoring that the performance gains stem from a principled shift in the modeling paradigm. These results position our trajectory autoregressive modeling as a competitive alternative for visuomotor policy learning.

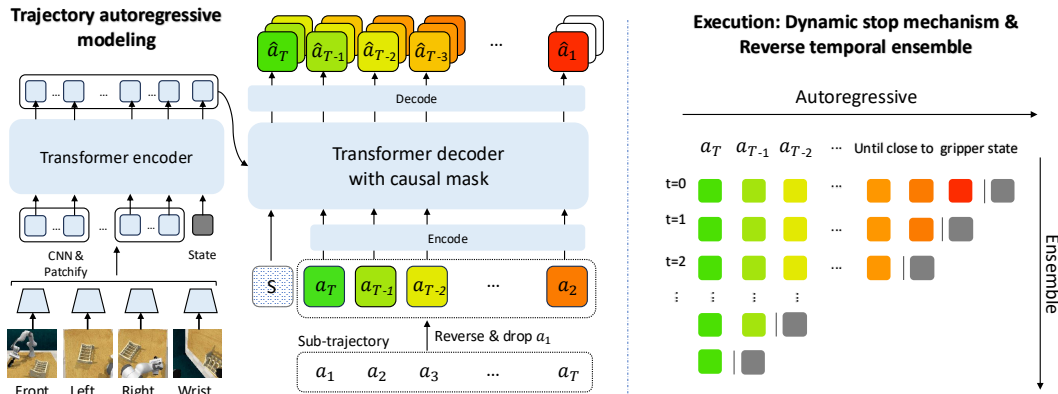


Figure 2: **Chain-of-Action built on trajectory autoregressive modeling.** The left part illustrates the network architecture where notation is for the training stage, and the right part illustrates the execution process. The model encodes visual and proprioceptive observations and generates actions in reverse order from a predicted keyframe action by an autoregressive decoder. *For clarity, the keyframe action a_T is shown in green, and subsequent steps are visualized with a gradual color transition.*

2 Related work

Hierarchical modeling in robotic manipulation A widely adopted strategy in robotic manipulation is to first identify high-level keyframes, and then rely on predefined controllers to handle the low-level execution. This paradigm is exemplified by C2F-ARM [13] and extended by methods such as Per-Act [34], RVT [9], RVT-2 [8]. Recent works like ChainedDiffuser [39] and HDP [26] propose neural planners to replace traditional optimization-based planners. Despite these advances, such methods still operate in an open-loop manner [39, 26] between keyframes and struggle to adapt to dynamic environments. Our method also builds on the notion of keyframes, but differs fundamentally in its formulation. By unifying keyframe detection and trajectory generation within a single autoregressive framework, it enables efficient environment-aware action prediction and closed-loop execution, where the model can continuously refine its actions based on feedback. As a result, our method no longer relies on high-fidelity 3D inputs for one-shot accurate predictions, which are commonly required by those hierarchical approaches.

CoT-style methods in robotic manipulation A separate line of research explores CoT-style VLA agents [44, 6, 38, 46], which introduce intermediate semantic representations—such as imagined image goal, visual trace, bounding boxes, or gripper pose, as guidance for subsequent action generation. Orthogonal to these directions, our work focuses on modeling the reasoning process directly between actions without relying on extra modalities as intermediate representations. This design makes our method broadly compatible with different sensory inputs and policy architectures.

3 Chain-of-Action for robotic manipulation

Formulation The core idea of Chain-of-Action is to model trajectory generation in reverse: starting from a task-specific goal and predicting actions backward in an autoregressive manner. This reverse formulation imposes a global-to-local structure, anchoring the rollout to the final intent and mitigating compounding errors. An overview of the CoA pipeline is shown on the left of Figure 2. We adopt the definition of keyframe originally from C2F-ARM [13], where a keyframe is identified as a time step at which the gripper state changes or the joint velocities approach zero. This simple yet effective heuristic captures transitions between semantically meaningful phases, such as grasp completion or object placement, and can be interpreted as a task-specific goal. Representing the goal as an action allows it to share the same embedding space with all other actions, enabling seamless backward generation. For each training sample, CoA learns to model the action sequence in reverse order using an autoregressive decoder. *This formulation enforces a reverse causal dependency among actions, yielding a goal-conditioned reasoning chain. Such backward chaining lies at the heart of the our framework, which models the trajectory distribution as:*

$$p(a_{1:T} | O) = \underbrace{p(a_T | O)}_{\text{Keyframe Action}} \cdot \underbrace{p(a_{T-1} | a_T, O) \dots p(a_2 | a_{3:T}, O)}_{\text{Reverse Reasoning Actions}} \cdot \underbrace{p(a_1 | a_{2:T}, O)}_{\text{Executed Action}} \quad (1)$$

where $\mathbf{a}_T$ denotes the keyframe action, and $\mathbf{O}$ denotes the observation context, including visual input $\mathbf{I}$ and proprioceptive state $\mathbf{S}$. To make the meaning of $\mathbf{a}_{1:T}$ explicit, we clarify how each training sample is constructed. A sub-trajectory is sampled from an expert demonstration by selecting a segment that starts at a random time step and ends at the next first keyframe action. The observation $\mathbf{O}$ is taken from the initial step, and $\mathbf{a}_{1:T}$ denotes the sequence of actions from the current step up to (and including) the keyframe. Each pair $(\mathbf{O}, \mathbf{a}_{1:T})$ forms an independent training example.

Algorithm 1: Training Phase

1 **Inputs:** dataset $\mathcal{D}$
2 **Modules:**
• Action encoder $f_{\text{enc}}: a_t \mapsto x_t$
• Action decoder $f_{\text{dec}}: x_t \mapsto a_t$
• Transformer F_θ : encoder-decoder model
Parameters: learned token x_{SOS} , loss weight λ
for iteration $n = 1, 2, \dots$ **do**
 Sample $(\mathbf{I}, \mathbf{S}, \tau = (a_1, \dots, a_T))$ from $\mathcal{D}$ based on keyframe heuristic
 $x_{1:T} \leftarrow \text{REVERSE}(f_{\text{enc}}(a_{1:T}))$
 $H \leftarrow \text{CONCAT}(x_{\text{SOS}}, x_{1:T-1})$
 $\hat{x}_{1:T} \leftarrow F_\theta(H | \mathbf{I}, \mathbf{S})$
 $\hat{a}_{1:T} \leftarrow \text{REVERSE}(f_{\text{dec}}(\hat{x}_{1:T}))$
 $\mathcal{L}_{\text{reg}} \leftarrow \sum_{t=1}^T \mathcal{L}_{\text{action}}(\hat{a}_t, a_t)$
 $\mathcal{L}_{\text{latent}} \leftarrow \sum_{t=1}^T \mathcal{L}_{\text{latent}}(\hat{x}_t, f_{\text{enc}}(a_t))$
 $\mathcal{L}_{\text{total}} \leftarrow \mathcal{L}_{\text{reg}} + \lambda \cdot \mathcal{L}_{\text{latent}}$
 Update θ, x_{SOS} via backprop on $\mathcal{L}_{\text{total}}$

Algorithm 2: Inference Phase

1 **Inputs:** image $\mathbf{I}$, proprioceptive state $\mathbf{S}$
2 **Modules:**
• Action encoder $f_{\text{enc}}: a_t \mapsto x_t$
• Action decoder $f_{\text{dec}}: x_t \mapsto a_t$
• Transformer F_θ : encoder-decoder model
Parameters: learned token x_{SOS} , max length T_{max}
Initialize $H \leftarrow [x_{\text{SOS}}]$
for $t = 1$ **to** T_{max} **do**
 $\hat{x}_t \leftarrow F_\theta(H | \mathbf{I}, \mathbf{S})$
 Append $\hat{x}_t$ to H
 if $\text{STOP}(f_{\text{dec}}(\hat{x}_t), \mathbf{S})$ **then**
 break
Remove x_{SOS} : $H' \leftarrow H[1:]$
 $\hat{a}_{1:T} \leftarrow \text{REVERSE}(f_{\text{dec}}(H'))$
Return: action sequence $\hat{a}_{1:T}$

Continuous action token representation CoA adopts continuous action token representation. However, directly training with continuous latent tokens introduces its own challenge. Unlike discrete token embeddings [21] that are fixed indices supervised by a softmax classifier, our latent actions are generated through a learned encoder. In this setting, imposing loss directly on the action space fails to constrain the latent space to exhibit temporal consistency during autoregressive decoding. As a result, the latent space lacks meaningful regularization, allowing encoding errors to propagate and amplify through the autoregressive process. To address this, we introduce a latent consistency loss to regularize latent action space: $\mathcal{L}_{\text{consistency}} = \|\hat{x}_t - f_{\text{enc}}(\mathbf{a}_t)\|$, where $f_{\text{enc}}(\mathbf{a}_t) = W_{\text{enc}}\mathbf{a}_t + b_{\text{enc}}$. Here, $\hat{x}_t$ denotes the predicted latent from the previous timestep, and $f_{\text{enc}}(\mathbf{a}_t)$ is the encoded latent of the ground-truth action. This loss acts as an inductive bias to align the latent space with temporal dynamics, improving the quality of autoregressive generation.

Locality modeling Multi token prediction (MTP) [7] can serve as a regularization for action locality modeling. We assign the last K layers of the transformer decoder to produce predictions for different future steps. Concretely, layer k predicts token $\hat{x}_{t+k}$, where $k = 1, \dots, K$, making the model aware of the mutual dependencies across the next K steps in a single forward pass. This design introduces temporal locality into the decoding process, enhancing stability in long-horizon generation while maintaining our global-to-local chain-like structure. Importantly, this regularization is applied only during training and is removed at inference.

Dynamic stop To enable flexible-length trajectory generation in continuous action space, we introduce a distance-based stop criterion. The core idea is to terminate decoding once the predicted action sufficiently approximates the current execution state, indicating that the backward-generated trajectory has successfully reached the present, as shown in bottom-right in Figure 2. This stop mechanism is agnostic to the specific action representation and can be readily applied to delta actions or joint-space control by adjusting the reference point accordingly.

Reverse temporal ensemble We introduce a reverse temporal ensembling strategy tailored for CoA. As shown in the bottom-right corner of Figure 2, our approach aligns multiple reversed sub-trajectories by their predicted keyframe action a_T , which serves as the anchor point for autoregressive decoding. This design offers a unique advantage in CoA: since each trajectory is decoded in reverse from the keyframe, the compounding error is inherently constrained by the accuracy of the keyframe

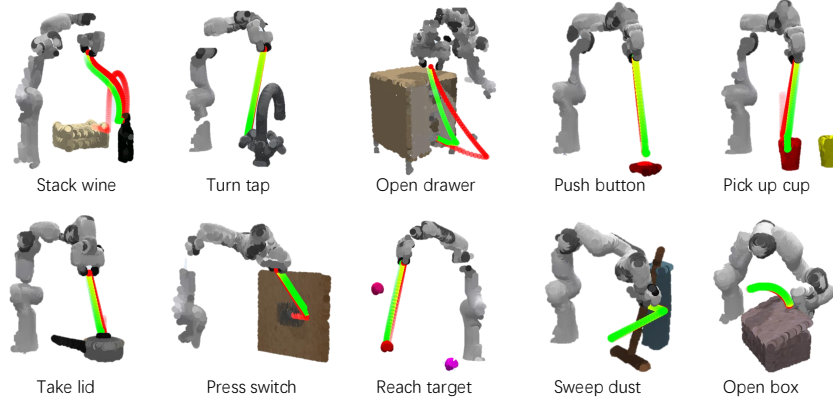


Figure 3: Visualization of predicted sub-trajectories across 10 widely used tasks. Detail refers to Table 1. Red waypoints represent ground-truth trajectories, and green waypoints denote model predictions. Each predicted trajectory is generated backward from a keyframe action to the current gripper state, enabling consistent goal-conditioned trajectory generation. The model successfully handles both straight and curved motion patterns.

action. By further improving the accuracy of the keyframe action through ensembling, we tighten this constraint even more.

4 Implementation details

Network architecture Our network follows a similar overall architecture to ACT [45], consisting of a 4-layer Transformer encoder and a 7-layer Transformer decoder. However, unlike ACT, our model does not include the conditional variational autoencoder (CVAE) module. The final decoder layer contains multiple parallel heads for multi-token prediction (MTP), which are only used during training. The observations consist of multi-view RGB images and corresponding robot states, which are encoded as follows: each image view is processed by a ResNet-18 vision encoder to extract visual tokens. The gripper state is projected via a learnable linear layer into a token representation. All tokens are concatenated and passed through the Transformer encoder to produce contextual features for decoding. Autoregressive action generation is performed by the Transformer decoder, which is initialized with a learnable start-of-sequence (SOS) token. This token serves as a query for the first prediction, corresponding to the keyframe action. The decoder iteratively predicts previous actions until the generated action becomes sufficiently close to the current gripper state, where the dynamic stopping criterion is applied. Actions are encoded and decoded into a shared latent embedding space via linear projection layers, which are regularized by the latent consistency loss as described earlier. Additionally, sinusoidal positional embeddings are added to the action tokens to preserve temporal ordering cues.

Training For each training sample, we apply two loss terms: a regression loss in the action space and a consistency loss in the latent space. Both are computed with the MTP regularization, where the model predicts a chunk of K actions at each decoding step. The total loss is defined as:

$$\mathcal{L}_{\text{total}} = \sum_{t=1}^T \sum_{k=1}^K \left\| \hat{\mathbf{a}}_{t+k-1}^k - \mathbf{a}_{t+k-1} \right\| + \lambda_1 \left\| \hat{\mathbf{x}}_{t+k-1}^k - f_{\text{enc}}(\mathbf{a}_{t+k-1}) \right\|, \quad (2)$$

where $\hat{\mathbf{a}}_{t+k-1}^k$ and $\hat{\mathbf{x}}_{t+k-1}^k$ are the predicted action and its latent embedding from k -th head of MTP layer at step t , and $f_{\text{enc}}(\cdot)$ is the action encoder network. Note that for decoding steps where $t+k-1 > T$, the corresponding terms are masked out and do not contribute to the loss. This ensures that predictions beyond the trajectory horizon are excluded from supervision. For parallel training with a batch of samples, we set T_{max} as the maximum sub-trajectory length (practically the longest in the dataset), and zero-pad all shorter sequences accordingly. The loss for padded steps is masked out to avoid affecting gradient updates.

Execution For each inference, CoA generates an entire trajectory segment, which can be executed in either open-loop or closed-loop mode. We generally adopt closed-loop control, as it allows

reverse temporal ensembling to continuously refine the predicted actions during execution. Under the dynamic stopping setting, we compute the Euclidean distance between the predicted action and the current end-effector pose. This termination criterion is well-suited for our continuous end-effector pose action space.

5 Experiments

In Sec. 5.1, we introduce our experiment settings, including simulation environment, train, evaluation settings and metrics. Then we show detailed results of the overall comparison in Section 5.2. To dive into the spatial generalization and obtain better understanding of how CoA work, more specific evaluation is shown in Section 5.3. Ablation studies of each components in CoA are shown in Section 5.4. Finally, the real-world robot evaluations are shown in Section 5.5

5.1 Simulation experiment settings

Simulation setup We conduct simulation experiments using RL Bench [14], a widely-used benchmark built on CoppeliaSim and interfaced via PyRep. The robot is a 7-DoF Franka Emika Panda mounted behind a tabletop workspace. Observations are collected from four RGB cameras (front, left shoulder, right shoulder, and wrist). Images are rendered at a resolution of 128×128 .

Baseline We compare our method against representative approaches from three categories: (1) training visuomotor policies from scratch, including ACT and Diffusion Policy (DP); (2) finetuned generalist robotic policies, represented by Octo [28]; (3) 3D-based hierarchical methods, including PerAct [34], 3D Diffuser Actor [17], and RVT-2 [8]. We note 3D-based hierarchical methods fundamentally differ from our approach by relying on 3D inputs and motion planners to generate trajectories. We provide additional discussion on these differences in Appendix A.

Training and evaluation protocol To ensure broad and representative evaluation, our main benchmark is conducted on a tailored set of 60 RL Bench tasks, where CoA is compared with ACT and DP. Each method is trained on 100 demonstrations and evaluated on 25 demonstrations per task. For ACT and DP, we follow the RL Bench training protocol introduced in [33], which is detailed in Appendix D. To better demonstrate the effectiveness of our modeling paradigm, we align our base architecture with ACT and introduce modifications primarily in the transformer decoder, as detailed in Section 4. The strong performance of these baselines—such as perfect success rates on tasks like *Sweep Dust* and competitive results on others (Table 1)—confirms that all reference models are properly trained. For comparison with Octo, we adopt the evaluation subset RL Bench-10 proposed in [42] and use the reported results. This subset is also used for our ablation studies for convenience. To facilitate comparison with 3D-based hierarchical methods, we evaluate on the RL Bench-18 split [34], using reported results from prior work [8]. Note that our RL Bench-18 setup is not strictly identical to the PerAct protocol: we train single-task policies and use only variation 0 for both training and evaluation. Hence, the RL Bench-18 results are reported as contextual reference rather than a fully protocol-matched comparison.

5.2 Overall comparisons

The overall results are presented in Figure 4, with task-wise averages summarized in the accompanying wrapped table. To better assess the effectiveness of our method, we report task-level improvements over both ACT and DP. Compared to ACT, our method achieves higher success rates on 81.7% of the tasks, with an average improvement of 16.3%. Relative to DP, our method improves performance on 80.0% of the tasks, with an average gain of 23.2%. These improvements are especially pronounced in tasks involving significant variation in object position and pose, indicating stronger spatial generalization. As ACT and CoA share a consistent Transformer encoder-decoder architecture and are trained on the same setting, the observed gains highlight the effectiveness of our modeling paradigm.

Table 1: Success rate across 10 widely-used tasks in RL Bench.

Task	CoA	ACT	DP	Octo
Stack Wine	0.80	0.56	0.56	0.52
Turn Tap	0.56	0.36	0.32	0.28
Open Drawer	0.88	0.52	0.44	0.84
Push Button	0.76	0.08	0.12	0.76
Pick Up Cup	0.80	0.20	0.00	0.44
Take Lid	0.80	0.40	0.60	0.76
Press Switch	0.44	0.52	0.56	0.44
Reach Target	0.84	0.88	0.08	0.60
Sweep Dust	0.92	1.00	1.00	0.80
Open Box	0.76	0.36	0.48	0.96
Avg.	0.756	0.488	0.416	0.644

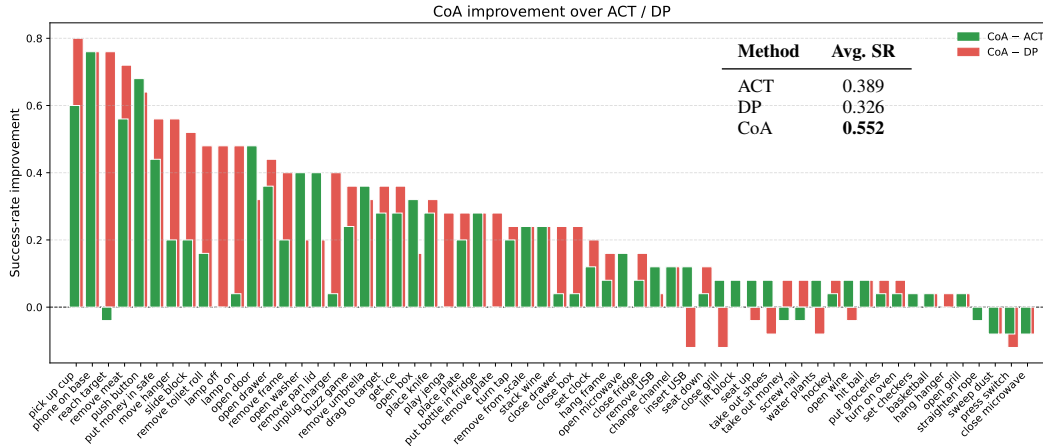


Figure 4: Success rate improvement on RLbench-60, sorted by improvement from high to low. The average success rate over all tasks is shown in the inset on the right.

Table 2: Comparison on the RLbench-18. 3D-based hierarchical methods use 3D point clouds and motion planners, while image-based visuomotor policies operate directly on RGB inputs.

Task	3D-based hierarchical methods			Image-based visuomotor policies				
	PerAct	3D Diffuser Actor	RVT-2	Image-BC (CNN)	Image-BC (ViT)	DP	ACT	CoA
Close Jar	55.2 ± 4.7	96.0 ± 2.5	100.0 ± 0.0	0	0	0	0	0
Drag Stick	89.6 ± 4.1	100.0 ± 0.0	99.0 ± 1.7	0	0	0	0	0
Insert Peg	5.6 ± 4.1	65.6 ± 4.1	40.0 ± 0.0	0	0	0	0	0
Meat off Grill	70.4 ± 2.0	96.8 ± 1.6	99.0 ± 1.7	0	0	16	32	88
Open Drawer	88.0 ± 5.7	89.6 ± 4.1	74.0 ± 11.8	4	0	44	52	88
Place Cups	2.4 ± 3.2	24.0 ± 7.6	38.0 ± 4.5	0	0	0	0	0
Place Wine	44.8 ± 7.8	93.6 ± 4.8	95.0 ± 3.3	0	0	56	56	80
Push Buttons	92.8 ± 3.0	98.4 ± 2.0	100.0 ± 0.0	0	0	0	32	28
Put in Cupboard	28.0 ± 4.4	85.6 ± 4.1	66.0 ± 4.5	0	0	0	0	8
Put in Drawer	51.2 ± 4.7	96.0 ± 3.6	96.0 ± 0.0	8	0	40	60	88
Put in Safe	84.0 ± 3.6	97.6 ± 2.0	96.0 ± 2.8	4	0	24	36	80
Screw Bulb	17.6 ± 2.0	82.4 ± 2.0	88.0 ± 4.9	0	0	0	0	0
Slide Block	74.0 ± 13.0	97.6 ± 3.2	92.0 ± 2.8	0	0	0	36	64
Sort Shape	16.8 ± 4.7	44.0 ± 4.4	35.0 ± 7.1	0	0	0	0	0
Stack Blocks	26.4 ± 3.2	68.3 ± 3.3	80.0 ± 2.8	0	0	0	0	0
Stack Cups	2.4 ± 2.0	47.2 ± 8.5	69.0 ± 5.9	0	0	0	0	0
Sweep to Dustpan	52.0 ± 0.0	84.0 ± 4.4	100.0 ± 0.0	0	0	100	100	92
Turn Tap	88.0 ± 4.4	99.2 ± 1.6	99.0 ± 1.7	8	16	32	36	56
Average	48.7	81.3	81.4	1.33	0.89	17.33	24.44	37.33

The results suggest that a principled change in how action sequences are represented and generated can lead to substantially better performance under distribution shifts. The detailed per-task results are in Appendix B. In addition, the comparison with Octo and detailed results with ACT and DP over 10 selected tasks are shown in Table 1. Results on the RLbench-18 benchmark are reported in Tab 2. We observe that, in these settings, CoA outperforms the finetuned generalist robot policy Octo, while a substantial performance gap remains compared to the 3D-based hierarchical methods.

5.3 Dive into spatial generalization

Although CoA significantly outperforms ACT and DP on the overall benchmark, it remains crucial to understand *why* such improvements emerge. To this end, we investigate the spatial generalization behavior of our model from three complementary perspectives.

First, in the *Interpolation vs. Extrapolation case study*, we analyze CoA’s performance under controlled spatial distributions within a single representative task. This study reveals that CoA not only achieves higher success rates under in-distribution (interpolation) configurations, but also demonstrates a substantially larger advantage in out-of-distribution (extrapolation) settings, indicating stronger spatial generalization.

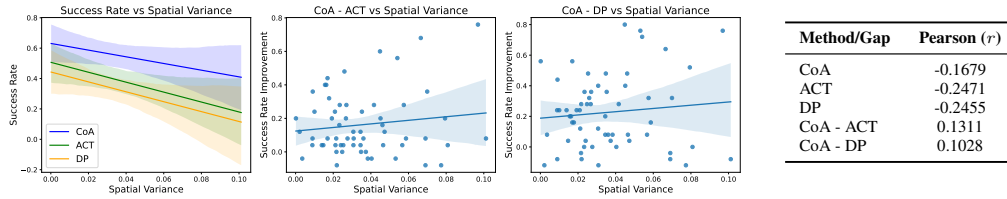


Figure 5: Correlation between success rate and spatial variance. Left image: Overall success rate decreases as object spatial variance increases. Middle and right image: CoA consistently outperforms ACT and DP across varying spatial generalization levels, with larger advantages in more challenging (higher variance) settings. Table: Pearson correlations highlight CoA's robustness to spatial perturbations.

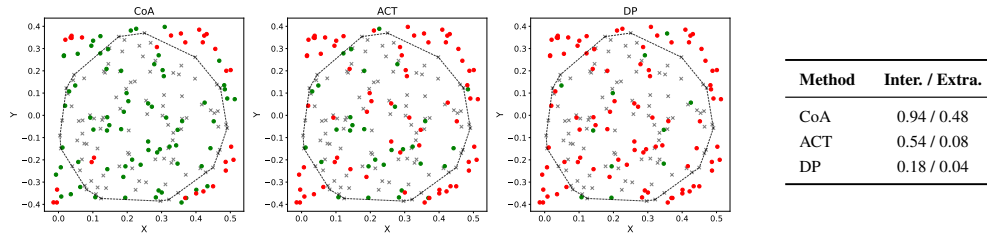


Figure 6: Interpolate vs. extrapolate performance. Success rate comparison on interpolation (in-distribution) and extrapolation (out-of-distribution) subsets for the *Push Button* task. CoA maintains stronger performance across both regimes, with a notably smaller degradation under extrapolation. The gray dashed line denotes the 2D convex hull computed from the training samples. Cross markers represent training data, while circular markers denote evaluation samples, where green circles indicate successful executions and red circles indicate failures.

Second, in *Correlation with spatial distribution*, we quantitatively examine how task performance correlates with spatial variation difficulty across the 60 RL Bench tasks. The results show that CoA consistently improves over ACT and DP across all spatial variance levels, and that the performance gap widens as spatial generalization becomes more challenging.

Finally, in *Attention-based analysis of action chain*, we visualize the attention maps between action tokens in the Transformer decoder. The attention patterns clearly reveal structured dependencies along the predicted action sequence, supporting the hypothesis that CoA performs chain-like global-to-local reasoning throughout the trajectory generation process.

Interpolation vs. Extrapolation case study We conduct qualitative analyses on *Push button* task to contrast model behavior under interpolated (in-distribution) versus extrapolated (out-of-distribution) spatial configurations. For this analysis, we choose the *Push Button* task due to its large spatial variation and its frequent use in prior works. Unlike the standard benchmark setting, we randomly sample 200 demonstrations from the full dataset and project the button target positions onto the (x, y) workspace plane. We then compute the centroid of all sampled positions and select the 150 samples closest to this centroid based on Euclidean distance, which are used to form a 2D convex hull. Within this convex hull, we randomly assign 100 samples for training and 50 samples for *interpolation* testing, while the remaining 50 samples lying outside the convex hull are used as *extrapolation* testing data. This protocol ensures a controlled and reproducible evaluation of spatial generalization, where extrapolation explicitly corresponds to goal configurations beyond the spatial support of the training distribution.

Correlation with spatial distribution We examine the relationship between success rate and the spatial distribution of objects in the evaluation set, aiming to quantify each model's spatial generalization ability. We use the variance of object coordinates to measure how widely objects are spread in the workspace. As shown in the left plot of Figure 5, all methods exhibit a clear trend: success rate decreases as spatial variance increases. This indicates that there spatial generalization becomes more difficult when object placement is more diverse. The improvement plots in the Figure 5 reveal more details. Compared to ACT and DP, our method consistently outperforms across all levels of spatial variance, and its advantage becomes more pronounced as task difficulty increases. This trend is further supported by quantitative Pearson correlation.

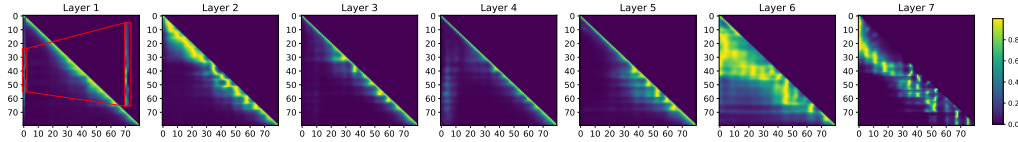


Figure 7: **Attention-based analysis of action chains.** Self-attention maps reveal two key patterns: (1) chain-like dependencies, where each action token attends to recent predecessors, and (2) long-range dependencies (highlighted in the red box in Layer 1), where some tokens directly attend to the initial keyframe action.

As shown in Figure 6, our method outperforms both ACT and DP under both interpolation and extrapolation conditions. Interestingly, while the success rate of CoA in extrapolated settings is about half of that in interpolation, ACT and DP suffer from significantly steeper drops. This highlights the particular difficulty of spatial extrapolation for forward modeling approaches, and suggests that the reverse autoregressive modeling in CoA provides more robust generalization under spatial distribution shifts.

Attention-based analysis of action chain Figure 7 presents the self-attention maps among action tokens across all decoder layers in our model. The horizontal and vertical indices correspond to the autoregressive decoding order of action tokens, where index 0 denotes keyframe action. We observe two distinct attention patterns: (1) a dominant local chain-like structure, where each action token primarily attends to a recent window of preceding tokens, directly reflecting modeling of CoA; and (2) occasional long-range dependencies (e.g., red box in layer 1 and most of tokens in layer 6), where later tokens exhibit strong attention to initial tokens. This behavior suggests the model leverages the goal-conditioned actions to anchor and guide the full trajectory generation.

5.4 Ablation on architectural components

We summarize how each architectural component contributes to performance across 10 representative RL Bench tasks (selected consistently with Table 1). The average success rate of each variants are provided in Table 3.

Modeling paradigm. CoA’s modeling incorporates two core designs: (1) chain-style autoregressive generation, and (2) goal anchoring via a keyframe action. To assess the necessity of each component, we compare *Reverse* ordering of CoA against two ablated variants:

Forward ordering retains the autoregressive structure but removes goal anchoring, starting from the current state and predicting actions forward. Compared to CoA, its lower success rate (0.668 vs. 0.756) highlights the importance of reverse ordering, the core of our proposed modeling. On the other hand, it significantly outperforms ACT (0.668 vs. 0.488), which also uses a autoregressive architecture but predicts fixed-length action chunks. This contrast underscores the advantage of modeling the joint distribution over the entire trajectory, rather than treating it as separated chunks.

Hybrid ordering retains goal anchoring but drops chain-style reasoning. It initializes from the keyframe action but switches to forward action generation, removing backward generation process between actions. As a result, the local continuity of autoregressive is lost, and performance drops greatly to 0.600.

These results confirm that trajectory autoregressive modeling is essential for effective robotic manipulation. Furthermore, reverse autoregressive ordering further enhances performance by anchoring the generation process to the a task-specific goal, providing global guidance throughout the rollout.

Table 3: Ablation study on individual components by replacing them with alternative settings. The **bold** indicates the best setting adopted by our final model.

Components	Setting	Avg. SR
Modeling Paradigm	Reverse	0.756
	Forward	0.668
	Hybrid	0.600
Embedding Loss	Action consistency	0.212
	Latent consistency	0.756
Execution	Non-ensemble	0.66
	Reverse ensemble	0.756
Num. of MTP head	1	0.710
	2	0.704
	4	0.720
	5	0.756
	8	0.672
	10	0.660



Figure 8: Real-world experiments on 8 kitchen tasks.

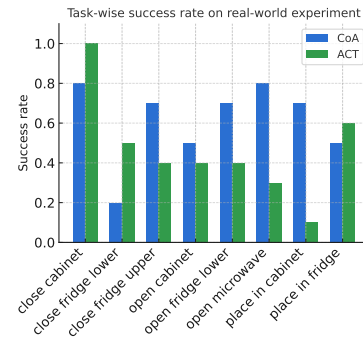


Figure 9: Real-world experimental results.

Number of MTP heads Multi-token prediction regularization enables the model to capture local action chunks while preserving global causality. Allocating too few heads underutilizes this local context, whereas allocating too many heads disrupts the causal structure. A moderate configuration of 5 heads strikes an effective balance, achieving the highest overall score 0.752.

Latent consistency loss We ablate the latent consistency loss by replacing it with a direct action reconstruction loss, which supervises the action encoder and action decoder to reproduce the input action. This substitution leads to a significant performance drop from 0.752 to 0.212, and results in unstable trajectories with unnatural curling. In contrast, enforcing latent consistency yields a well-structured representation and substantially improves task success.

Reverse temporal ensemble We evaluate the impact of reverse temporal ensemble by comparing it with a non-ensemble baseline. Without ensembling, the model achieves 0.660. Applying our reverse-compatible ensemble strategy improves performance to 0.756, highlighting the benefit of aggregating multiple backward rollouts during inference.

5.5 Real-world experiments

We deploy our method on a Fetch robot featuring a 7-DoF arm and a mobile base for real-world validation. For each task, the robot navigates to a predefined location using its built-in 2D LiDAR-based localization system. Observations are captured from a single RGB camera at 640×480 resolution and resized to 224×224 for policy input. Execution is command by absolute end effector poses. To execute commands, we implement a PD controller that calculates the difference between current and desired end effector poses, projects this error into joint space via the Jacobian, and sends velocity commands to the robot. The neural policy operates at 10Hz on a laptop with a 4070 GPU, while the PD controller runs locally on the robot at 1000Hz, with communication handled through ROS for both image data and control commands. As shown in Figure 8, we evaluated CoA and ACT on 8 kitchen tasks, with the number of expert demonstrations ranging from 35 to 81 per task. Each task was evaluated over 10 trials. The results, summarized in Figure 9, show that CoA achieves an average success rate of 0.613, outperforming ACT, which achieves 0.463, by a margin of 15%. The detailed results are in Appendix C.

6 Conclusion

We present **Chain-of-Action**, an action-level reasoning model built upon trajectory autoregressive modeling. By decomposing the joint distribution of the trajectory in reverse, starting from a keyframe and progressing backward to the initial gripper state, our formulation imposes a *global-to-local* structure that enforces consistency between local actions and global task goal. To enable stable training and execution under this backward autoregressive framework, we introduce four necessary design components. Overall, our proposed visuomotor modeling paradigm significantly improves spatial generalization, and we hope it offers a compelling alternative for future visuomotor policy design. However, the current modeling paradigm relies on keyframe heuristics to split the trajectory, which may not generalize well to diverse task types. Future work can explore learning keyframe structures in an unsupervised manner.

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A Comparison on RL Bench-18

The RL Bench-18 subset was originally introduced by PerAct [34] and later became the standard comparison benchmark for 3D hierarchical methods. The results are detailed in Table 2. To clarify the fundamental difference between these two categories of approaches, Table 4 summarizes their methodological distinctions. 3D-based hierarchical methods typically rely on 3D perception and motion planning, whereas image-based visuomotor policies operate directly on raw RGB observations and learn end-to-end trajectory generation without explicit planners. We observe that, for RGB-only policies, several tasks in RL Bench-18 are challenging and frequently result in zero success rates, which limits their discriminative power. This observation motivates our use of the proposed RL Bench-60 evaluation split.

Table 4: Key differences between 3D-based hierarchical methods and image-based visuomotor policies.

Aspect	3D-based Hierarchical Methods	Image-based Visuomotor Policies
Typical Methods	PerAct, RVT, RVT-2, 3D Diffuser Actor	ACT, Diffusion Policy, CoA
Input Modality	3D point cloud / RGB-D	RGB-only
Pipeline	Two-stage: keyframe action detection + motion planning	End-to-end trajectory prediction without explicit planning
Execution Mode	Open-loop execution between keyframes	Closed-loop prediction and control

B Per-task success rates on RL Bench-60

To complement the summary figure in the main paper, which visualizes the performance gap between CoA and baseline methods, we provide the full success rates on all 60 RL Bench tasks in Table 5. This table lists the per-task success rate of CoA, ACT, and DP, along with the gap of baselines over CoA. Tasks are ordered by the maximum improvement CoA achieves over either baseline, highlighting where our method provides the most substantial gains.

Table 5: Detailed results of the overall comparison on RL Bench. The simplified names used in Figure 4 are matched with their corresponding original task names. The success gap between ACT, DP and CoA is shown as superscripts.

Simplified name	Original name	CoA	ACT	DP
pick up cup	pick_up_cup	0.80	0.20 ^{-0.60}	0.00 ^{-0.80}
phone on base	phone_on_base	0.80	0.04 ^{-0.76}	0.04 ^{-0.76}
reach target	reach_target	0.84	0.88 ^{+0.04}	0.08 ^{-0.76}
remove meat	meat_off_grill	0.88	0.32 ^{-0.56}	0.16 ^{-0.72}
push button	push_button	0.76	0.08 ^{-0.68}	0.12 ^{-0.64}
put money in safe	put_money_in_safe	0.80	0.36 ^{-0.44}	0.24 ^{-0.56}
move hanger	move_hanger	0.88	0.68 ^{-0.20}	0.32 ^{-0.56}
slide block	slide_block_to_target	0.52	0.32 ^{-0.20}	0.00 ^{-0.52}
remove toilet roll	take_toilet_roll_off_stand	0.56	0.40 ^{-0.16}	0.08 ^{-0.48}
lamp off	lamp_off	0.68	0.68 ^{-0.00}	0.20 ^{-0.48}
lamp on	lamp_on	0.48	0.44 ^{-0.04}	0.00 ^{-0.48}
open door	open_door	0.92	0.44 ^{-0.48}	0.60 ^{-0.32}
open drawer	open_drawer	0.88	0.52 ^{-0.36}	0.44 ^{-0.44}
remove frame	take_frame_off_hanger	0.64	0.44 ^{-0.20}	0.24 ^{-0.40}

Continued on next page

Simplified name	Original name	CoA	ACT	DP
open washer	open_washing_machine	0.76	0.44 ^{-0.32}	0.60 ^{-0.16}
remove pan lid	take_lid_off_saucepan	0.80	0.40 ^{-0.40}	0.60 ^{-0.20}
unplug charger	unplug_charger	0.60	0.56 ^{-0.04}	0.20 ^{-0.40}
buzz game	beat_the_buzz	0.36	0.12 ^{-0.24}	0.00 ^{-0.36}
remove umbrella	take_umbrella_out_of_umbrella_stand	0.52	0.16 ^{-0.36}	0.20 ^{-0.32}
drag to target	reach_and_drag	0.64	0.36 ^{-0.28}	0.28 ^{-0.36}
get ice	get_ice_from_fridge	0.60	0.32 ^{-0.28}	0.24 ^{-0.36}
open box	open_box	0.32	0.16 ^{-0.16}	0.32 ^{-0.00}
place knife	place_knife_on_chopping_board	0.04	0.04 ^{-0.00}	0.00 ^{-0.04}
play jenga	play_jenga	1.00	1.00 ^{-0.00}	0.72 ^{-0.28}
place plate	put_plate_in_colored_dish_rack	0.32	0.12 ^{-0.20}	0.04 ^{-0.28}
put bottle in fridge	put_bottle_in_fridge	0.28	0.00 ^{-0.28}	0.00 ^{-0.28}
remove plate	take_plate_off_colored_dish_rack	0.40	0.40 ^{-0.00}	0.12 ^{-0.28}
turn tap	turn_tap	0.56	0.36 ^{-0.20}	0.32 ^{-0.24}
remove from scale	take_off_weighing_scales	0.84	0.44 ^{-0.40}	0.64 ^{-0.20}
stack wine	stack_wine	0.80	0.56 ^{-0.24}	0.56 ^{-0.24}
close drawer	close_drawer	1.00	0.96 ^{-0.04}	0.76 ^{-0.24}
close box	close_box	1.00	0.96 ^{-0.04}	0.76 ^{-0.24}
set clock	change_clock	0.40	0.28 ^{-0.12}	0.20 ^{-0.20}
hang frame	hang_frame_on_wall	0.16	0.08 ^{-0.08}	0.00 ^{-0.16}
open microwave	open_microwave	0.44	0.40 ^{-0.04}	0.40 ^{-0.04}
close fridge	close_fridge	0.92	0.84 ^{-0.08}	0.76 ^{-0.16}
remove USB	take_usb_out_of_computer	0.60	0.48 ^{-0.12}	0.72 ^{+0.12}
change channel	change_channel	0.12	0.00 ^{-0.12}	0.00 ^{-0.12}
insert USB	insert_usb_in_computer	0.92	0.80 ^{-0.12}	0.88 ^{-0.04}
seat down	toilet_seat_down	1.00	0.96 ^{-0.04}	0.88 ^{-0.12}
close grill	close_grill	0.56	0.48 ^{-0.08}	0.68 ^{+0.12}
lift block	lift_numbered_block	0.08	0.00 ^{-0.08}	0.08 ^{-0.00}
seat up	toilet_seat_up	0.84	0.76 ^{-0.08}	0.88 ^{+0.04}
take out shoes	take_shoes_out_of_box	0.08	0.00 ^{-0.08}	0.16 ^{+0.08}
take out money	take_money_out_safe	0.76	0.80 ^{+0.04}	0.68 ^{-0.08}
screw nail	screw_nail	0.08	0.12 ^{+0.04}	0.00 ^{-0.08}
water plants	water_plants	0.48	0.40 ^{-0.08}	0.56 ^{+0.08}
hockey	hockey	0.08	0.04 ^{-0.04}	0.00 ^{-0.08}
open wine	open_wine_bottle	0.36	0.28 ^{-0.08}	0.40 ^{+0.04}
hit ball	hit_ball_with_cue	0.08	0.00 ^{-0.08}	0.00 ^{-0.08}
put groceries	put_groceries_in_cupboard	0.08	0.04 ^{-0.04}	0.00 ^{-0.08}
turn on oven	turn_oven_on	0.36	0.32 ^{-0.04}	0.28 ^{-0.08}
set checkers	setup_checkers	0.04	0.00 ^{-0.04}	0.04 ^{-0.00}
basketball	basketball_in_hoop	0.76	0.72 ^{-0.04}	0.72 ^{-0.04}
hang hanger	place_hanger_on_rack	0.32	0.04 ^{-0.28}	0.00 ^{-0.32}
open grill	open_grill	0.24	0.00 ^{-0.24}	0.00 ^{-0.24}
straighten rope	straighten_rope	0.00	0.04 ^{+0.04}	0.00 ^{-0.00}
sweep dust	sweep_to_dustpan	0.92	1.00 ^{+0.08}	1.00 ^{+0.08}
press switch	press_switch	0.44	0.52 ^{+0.08}	0.56 ^{+0.12}
close microwave	close_microwave	0.72	0.80 ^{+0.08}	0.80 ^{+0.08}

C Supplementary real-world results

Table 6 reports the per-task success rates of CoA, ACT, and DP across 8 real-world kitchen manipulation tasks. CoA consistently achieves the highest average performance.

Table 6: Per-task success rate in real-world experiments.

Task	CoA	ACT	DP
close cabinet	0.80	1.00	0.90
close fridge lower	0.20	0.50	0.60
close fridge upper	0.70	0.40	0.80
open cabinet	0.50	0.40	0.10
open fridge lower	0.70	0.40	0.00
open microwave	0.80	0.30	0.50
place in cabinet	0.70	0.10	0.00
place in fridge	0.50	0.60	0.00
Avg.	0.613	0.463	0.363

D Hyperparameters for RL Bench

We provide the training and evaluation hyperparameters for CoA and all baseline methods used in the simulation experiments. To ensure a fair comparison, the hyperparameters for ACT are largely aligned with those of CoA, allowing us to isolate and assess the impact of our proposed modeling paradigm. For DP, we observe slower convergence relative to CoA and ACT, and thus extend its training duration to 100,000 iterations. In addition, we incorporate temporal ensembling into DP following the implementation in ACT. Octo converges substantially faster, and we find that 2,000 training iterations are sufficient. Given that Octo is primarily pretrained on single-camera data, we finetune it using only the front camera, while increasing the image resolution to enhance visual fidelity. All models are trained on a single NVIDIA H100 GPU per task.

Table 7: Hyperparameters for CoA

Backbone	ImageNet-trained ResNet18 [10]
Action dimension	8 (3 position + 4 quaternion + 1 gripper)
Cameras	wrist, front, right shoulder, left shoulder
Learning rate	$1e^{-4}$
Weight decay	$1e^{-4}$
Image size	128×128
Execution horizon	1
Observation horizon	1
# encoder layers	4
# decoder layers	7 (6 + 1 multi-token prediction layer)
# heads	8
Feedforward dimension	3200
Hidden dimension	512
Dropout	0.1
Iteration	20000
Batch size	128
Temporal ensembling	true (reverse temporal ensemble)
Action normalization	$[-1, 1]$

Table 8: Hyperparameters for ACT

Backbone	ImageNet-trained ResNet18 [10]
Action dimension	8 (3 position + 4 quaternion + 1 gripper)
Cameras	wrist, front, right shoulder, left shoulder
Learning rate	$1e^{-4}$
Weight decay	$1e^{-4}$
Image size	128×128
Action sequence	20
Execution horizon	1
Observation horizon	1
# encoder layers	4
# decoder layers	7
# heads	8
Feedforward dimension	3200
Hidden dimension	512
Dropout	0.1
Iteration	20000
Batch size	128
Temporal ensembling	true
Action normalization	$[-1, 1]$

Table 9: Hyperparameters for DP

Backbone	ImageNet-trained ResNet18 [10]
Noise predictor	UNet [29]
Action dimension	8 (3 position + 4 quaternion + 1 gripper)
Cameras	wrist, front, right shoulder, left shoulder
Learning rate	$1e^{-4}$
Weight decay	$1e^{-6}$
Image size	128×128
Observation horizon	1
Action sequence	20
Execution horizon	1
Train, test diffusion steps	50, 50
Hidden dimension	512
Iteration	100000
Batch size	128
Temporal ensembling	true (following ACT's)
Scheduler	DDPM [12]
Action normalization	$[-1, 1]$

Table 10: Hyperparameters for Octo

Pretrained model	Octo-small [28]
Action dimension	8 (7 delta joints + 1 gripper)
Cameras	front
Learning rate	$3e^{-4}$
Weight decay	$1e^{-2}$
Image size	256×256
Observation horizon	1
Action sequence	4
Execution horizon	1
Iteration	2000
Batch size	128
Temporal ensembling	false
Action normalization	mean 0, std 1
Finetuning head	linear head
Image augmentation	resized crop, brightness, contrast, saturation, hue

E ACT variant with keyframe action

To further examine the impact of keyframe action on action sequence modeling, we conduct an additional ablation by modifying the ACT baseline. Specifically, we introduce a variant, ACT+KF, in which an extra keyframe action is appended to ACT’s original action chunk.

As shown in Table 11, ACT+KF achieves a higher average success rate (0.516) compared to the original ACT (0.488), indicating that injecting keyframe actions yields marginal improvements. However, the overall gain remains limited.

This result suggests that while keyframe actions may provide some global guidance, they do not substantially improve the final action quality when introduced in this manner. A similar trend is observed in the poor performance of *Hybrid* (Table 3), a variant of CoA that incorporates both keyframe supervision and causal decoding but lacks trajectory continuity. The limited effectiveness of both ACT+KF and Hybrid underscores a key insight: merely injecting keyframe signals and enforcing an autoregressive structure is not sufficient. Instead, it is crucial to model the entire trajectory holistically with temporal continuity, which is explicitly realized in our CoA formulation.

Table 11: Comparison of ACT vs. ACT+KF (with keyframe action) on 10 RLBench tasks.

Task	ACT	ACT+KF
Stack Wine	0.56	0.56
Turn Tap	0.36	0.32
Open Drawer	0.52	0.76
Push Button	0.08	0.16
Pick Up Cup	0.20	0.36
Take Lid	0.40	0.40
Press Switch	0.52	0.28
Reach Target	0.88	0.72
Sweep Dust	1.00	0.96
Open Box	0.36	0.64
Avg.	0.488	0.516

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