

GHOST: Hierarchical Sub-Goal Policies for Generalizing Robot Manipulation

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<https://ghost-human-demo.github.io/>

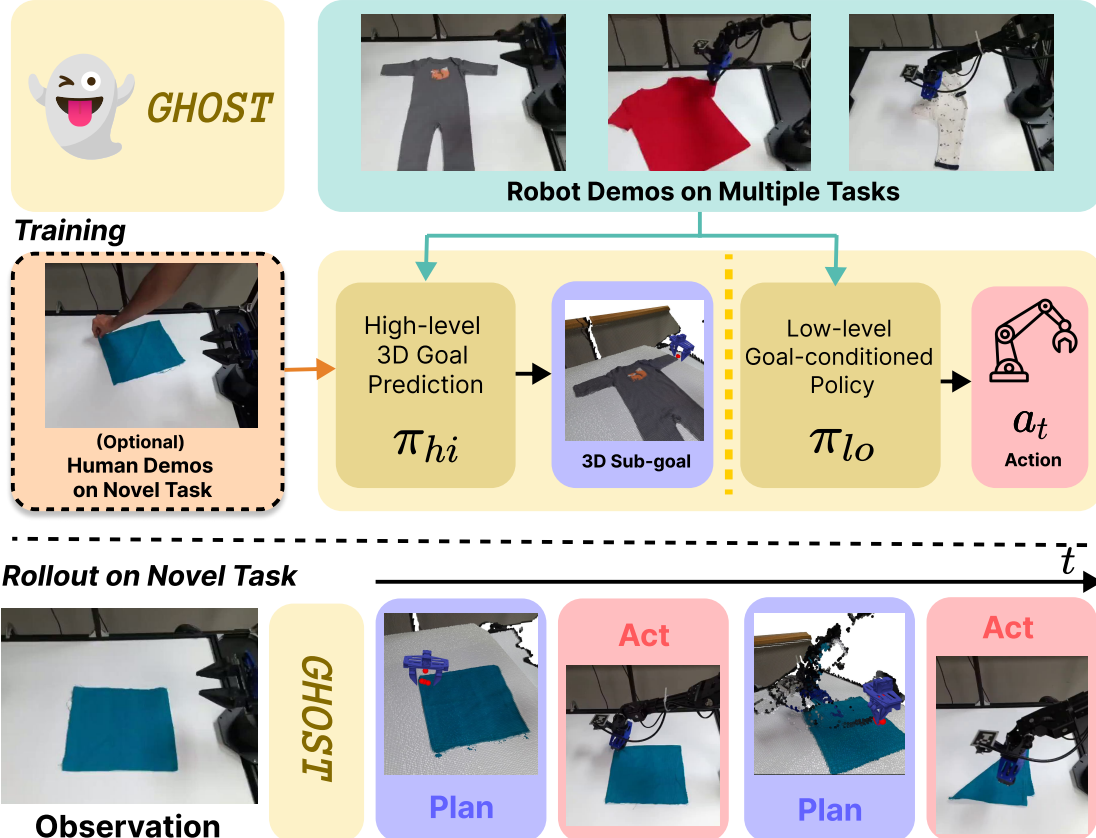


Fig. 1: GHOST learns skills from robot teleoperation data and optionally uses human demonstrations to generalize to novel tasks. We train a hierarchical policy that decouples embodiment-agnostic goal prediction (π_{hi}) from embodiment-specific action execution (π_{lo}). By training π_{hi} on both robot and human data and π_{lo} purely on robot data, GHOST transfers learned manipulation skills to out-of-distribution tasks with third person human video demonstrations.

Abstract—We present GHOST, a framework for learning visuomotor manipulation policies that *generalize* beyond the training distribution. GHOST factorizes control into (i) a high-level policy that predicts the next sub-goal as a *distribution* over 3D end-effector poses from multi-view RGB-D observations, and (ii) a low-level goal-conditioned controller that executes embodiment-specific actions. To condition image-based policies on 3D goals, we introduce a simple spatial interface that projects predicted goals into the image plane and represents them as *end-effector heatmaps*. Across a suite of manipulation tasks, this hierarchical factorization consistently improves performance and robustness compared to a flat Diffusion Policy.

Further, we show that this hierarchical interface also makes it easy to incorporate human demonstrations without relying on

(noisy) action retargeting. As sub-goals are largely embodiment-agnostic, we train the high-level policy on human video to specify how learned skills should be applied and composed, while keeping the low-level policy trained purely on robot data. This hierarchy enables adaptation to novel objects and task variations using a small number of human demonstrations.

I. INTRODUCTION

The dominant paradigm today for teaching robot policies to manipulate their environment is imitation learning (IL). Given a sufficiently large number of demonstration trajectories, imitation learning algorithms can learn precise, complex behaviors [4, 34]. However, to generalize to novel objects and

environments, they require massive amounts of data, typically collected through *teleoperation*, where a human operator controls a robot to complete a given task [2, 14, 26]. This recipe, while simple, is expensive and labor-intensive to scale.

In this work we focus on an alternate lever: *hierarchy*. Many manipulation tasks are naturally organized into phases - *e.g.*, a pick-and-place task may be decomposed into grasp, transport, and place phases. We argue that explicitly modeling this hierarchy improves robustness and data efficiency by separating *sub-goal selection* from *low-level execution*. Concretely, we define sub-goals as end-effector poses at phase boundaries, which provide a compact interface for composing skills and extending behavior over long horizons.

Based on this perspective, we propose a hierarchical policy that factorizes control into two modules. (i) A high-level policy π_{hi} predicts the next sub-goal from visual observations and a language instruction, and (ii) a low-level policy π_{lo} conditioned on the predicted goal to produce embodiment-specific actions. To connect these modules while retaining the benefits of image-based policies, we introduce a spatial goal representation that projects 3D sub-goals into the image plane and represents them as *end-effector heatmaps*, enabling effective goal-conditioning of image-based policies.

This hierarchy yields two practical benefits. First, even when trained only on robot demonstrations, our hierarchical factorization significantly improves success rates compared to a flat Diffusion Policy [4]. Second, our insight is that this sub-goal interface is largely embodiment-agnostic, making it a convenient point to incorporate additional supervision. As a secondary contribution, we show that we can use human videos to train the high-level policy for novel task variants, without requiring retargeted action labels, enabling out-of-distribution generalization.

Thus, we present **GHOST**: Generalizing manipulation via Hierarchical end-effectOr Sub-goals for Skill Transfer. GHOST is a hierarchical framework for training visuomotor policies that can generalize skills through human demonstrations. GHOST features: a) a 3D high-level goal prediction network that takes in RGB-D images to predict a distribution of sub-goal end-effector poses, and b) a low-level policy conditioned on goals represented as heatmap projections of the predicted end-effector sub-goals.

Our contributions are as follows:

- A hierarchical framework for training policies with 3D end-effector keypoint sub-goals and heatmap-based goal-conditioning that consistently improves in-distribution performance over flat policies.
- A demonstration that this factorization naturally enables cross-embodiment transfer from human video without action retargeting, by training π_{hi} on heterogeneous human and robot data while keeping π_{lo} grounded in robot demonstrations.

II. RELATED WORK

A. Hierarchical Imitation Learning

Hierarchical Imitation Learning factorizes the policy into a high-level “planner” and a low-level “control” policy. Previous work has primarily focused on learning high- and low-level policies from robot data [17, 30, 16]. This structure is particularly attractive for manipulation, where tasks often decompose into phases and where long-horizon behaviors can be expressed as sequences of sub-goals. Recent work has shown that representing sub-goals directly in end-effector space can yield strong generalization for articulated manipulation [28]. In parallel, goal-conditioning has been explored through images and language, often by predicting intermediate targets and conditioning a controller on them [1, 29, 6]. Our work is most closely related to hierarchical approaches that use explicit spatial sub-goals. We differ in two ways: (i) we predict 3D end-effector sub-goals from multi-view RGB-D, and (ii) we introduce an *end-effector heatmap* interface that makes goal-conditioning compatible with image-based policies.

B. Learning from human demonstrations

Large-scale robot teleoperation datasets have enabled impressive generalization in visuomotor policies [14, 18, 3, 2]. However, collecting robot demonstrations remains expensive, motivating complementary sources of supervision such as human video [8, 9, 15]. One line of work attempts to directly learn robot actions from human demonstrations by estimating hand pose and retargeting to a robot end-effector [19, 21, 13, 22, 10, 15]. These approaches can suffer from noisy pose estimates and an embodiment mismatch. By restricting human supervision to embodiment-agnostic sub-goals, we avoid action retargeting and keep low-level control grounded in robot demonstrations. Another line of work learns higher-level representations or latent dynamics from video corpora and maps them to robot actions with additional robot data [31, 27]. Most similar to our work is MimicPlay [27], which learns a latent distribution over hand trajectories collected through play data. However, this approach relies on a video prompt of the task being provided at test-time, whereas we only require a language goal. In contrast, we treat human demonstrations as *optional* supervision for the high-level planner in a hierarchy.

III. PROBLEM STATEMENT AND ASSUMPTIONS

We consider manipulation tasks that can be naturally decomposed into a sequence of sub-goal states $\{g_i\}_{i \in [1 \dots M]}$, such that the task is completed when each sub-goal state is reached. We denote a *skill* $\pi(\cdot|l)$ as a reusable manipulation capability described by a language instruction l (*e.g.*, ‘grasping’, ‘placing’, ‘folding’) that can be instantiated across different objects and contexts [3]. We make the assumption that for every sub-goal transition $g_i \rightarrow g_{i+1}$ in a task, there exists a reusable language-conditioned skill $\pi(\cdot|l_{i+1})$ which can achieve the next desired sub-goal state (*e.g.*, a pick-and-place task would be decomposed into sub-goals {‘pick’, ‘place’}, with corresponding reusable skills to accomplish each transition). In this work, we are concerned with how to both learn representations

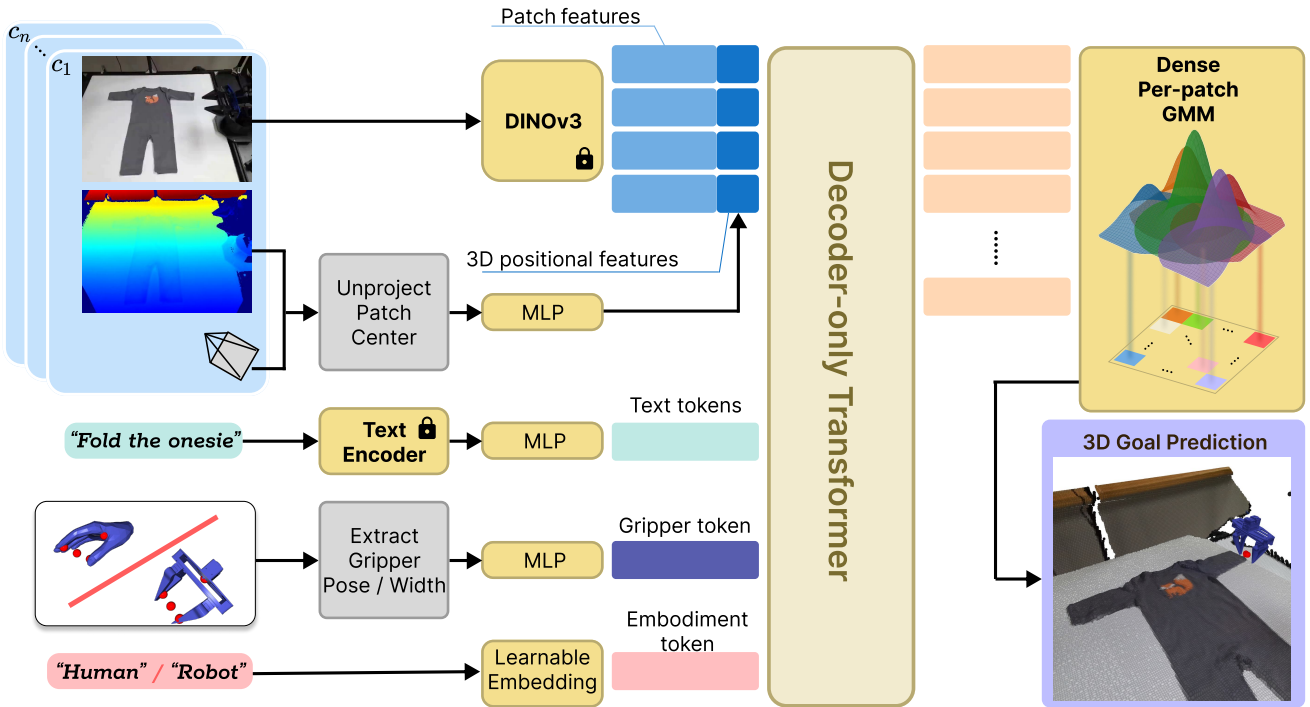


Fig. 2: **GHOST** High-level sub-goal prediction architecture: RGB-D observations from multiple cameras are processed with a DINOv3 encoder, with patch tokens augmented by 3D coordinates. Additional context (gripper state, language embedding, embodiment name) is encoded via separate MLPs. A decoder-only transformer processes all tokens, with each patch predicting the GMM parameters of a 3D sub-goal distribution over end-effector keypoints.

of these sub-goals g_i , and learn language-conditioned skills $\pi(\cdot|l_i)$ from demonstrations, such that agents can generalize to novel task variations.

Training data. We assume access to robot teleoperation demonstrations $\mathcal{D}_{robot} = \{(o_t, aux_t, a_t, e_t, g)\}$ - workspace cameras o_t , auxiliary robot observations aux_t (e.g., wrist cameras, proprioception), actions a_t , end-effector poses e_t and a language goal g , where t denotes the timestep of the observation.

Optional human data. We optionally allow an additional dataset of human videos $\mathcal{D}_{human} = \{(o_t, \hat{e}_t, g)\}$, where $\hat{e}_t$ is an estimated hand pose from an off-the-shelf tracker [21, 32]. Human demonstrations do not provide action labels, so we use them only to train or adapt our high level policy π_{hi} on estimated end-effector poses $\hat{e}_t$, keeping the low-level policy π_{lo} trained purely on robot data.

Assumptions. We assume calibrated RGB-D workspace cameras for goal prediction, and that demonstrations contain sufficient visual cues to localize the hand near sub-goal boundaries. In addition, we assume that human demonstrations use similar grasp types as the robot gripper to minimize the embodiment gap. Full hardware configuration and per-task data collection details are provided in Appendix B and Appendix C respectively.

IV. GHOST

A. Overview

The GHOST framework learns a hierarchy over *sub-goal end-effector poses*. During training, sub-goal boundaries provide supervision for the high-level planner π_{hi} , while the full robot trajectories provide action supervision for the low-level controller π_{lo} . At test time, π_{hi} predicts the next end-effector sub-goal (as a distribution) from workspace observations and language, and π_{lo} executes goal-conditioned control toward that sub-goal. This separation isolates long-horizon reasoning in π_{hi} and maintains precise, embodiment-specific control in π_{lo} .

B. Data Collection and Preprocessing

Robot Data. We collect demonstrations through teleoperation across multiple task variants, each demonstrating the same skill (e.g., pick-and-place). When possible, we extract sub-goals $s \in \mathcal{S}$ automatically by identifying the timesteps where the gripper state changes from open $\rightarrow$ close and vice versa.

Human Data. We optionally collect human demonstrations of the *same skill* in a novel setting, using either new objects or novel applications of the skill. We track 3D hand poses H_t using off-the-shelf hand pose estimators [21, 32]. We resolve the weak-perspective scale ambiguity of the detection by segmenting the hand using Grounded-SAM [23] and scaling the detection with the observed depth of the hand. We manually annotate sub-goals at the timesteps where a sub-goal

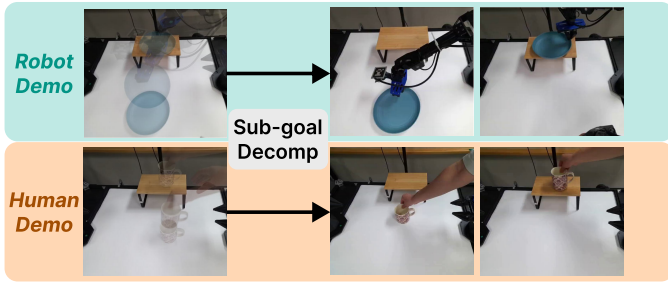


Fig. 3: Sub-goal decomposition for robot and human demonstrations. **Top:** Robot teleop demonstrations with sub-goals automatically extracted at gripper state transitions. **Bottom:** Human demonstrations with manually annotated sub-goals. Each sub-goal represents a semantically meaningful transition in the skill execution.

terminates. We treat sub-goal boundaries as supervision rather than discovering them; we discuss automated discovery as future work in Sec. VI. Figure 3 shows an example of our sub-goal decomposition for both robot and human demonstrations.

Representing the end-effector pose: Following prior work [28], we represent the end-effector pose as a sparse set of 3D points instead of a position and $SO(3)$ rotation. For robot data, we sample a point cloud P_R from the gripper mesh at each time-step and represent the end-effector pose e_t as a set of 4 3D points from P_R , located at the base of the gripper, the tips of the two gripper fingers and the grasping center. Similarly, for human data, we extract hand point clouds P_H from the MANO [24] mesh of the hand pose H_t and select 4 3D points - corresponding to points on the palm, tips of the thumb and index finger, and the grasping center. Figure 4 illustrates the keypoint locations for both gripper types. Thus, we extract a unified 3D end-effector representation for both human and robot data.

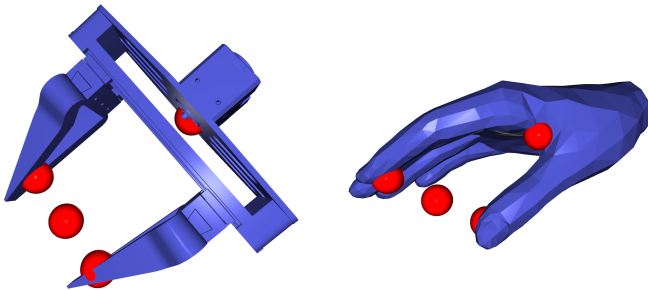


Fig. 4: End-effector representations for robot and human demonstrations. Instead of representing the gripper pose as a translation and $SO(3)$ rotation, we represent the gripper pose as a set of 3D keypoints (red spheres): gripper base, fingertip locations, and grasping center. **Left:** Parallel-jaw gripper. **Right:** MANO hand.

C. Policy Learning

1) *High-Level Goal Prediction Policy:* The high-level policy π_{hi} predicts a distribution over the end-effector pose e_s at

sub-goal timestep s . We parameterize π_{hi} as a decoder-only transformer [12] operating on RGB-D observations from C cameras. The architecture is shown in Figure 2. Each RGB-D image is processed independently with a frozen DINOv3 [25] encoder, producing $K \times C$ patch tokens (K per camera). Each patch token is augmented with the features of the 3D coordinate $[x, y, z]$ of the patch center, processed with an MLP. Additional tokens encode the current gripper pose and the task language embedding with Flan-T5 [5]. We also include a learnable token specifying whether the demonstration is from a human or robot. All tokens are projected to the transformer’s feature dimension through separate MLPs. We also add register tokens [7], as they have been shown to improve performance on dense prediction tasks without any change in training objective.

To handle the multimodality inherent in the demonstration data, we model the goal distributions as a dense per-patch Gaussian Mixture Model (GMM). Each patch token predicts: (1) a mixing weight w_i , and (2) four 3D residual vectors $\{\delta_{i,1}, \delta_{i,2}, \delta_{i,3}, \delta_{i,4}\}$ relative to the patch center p_i . These residual vectors are trained to predict the 3D points of the gripper. The global goal distribution is a mixture of $K \times C$ isotropic Gaussians (one per patch) with fixed variance σ^{21} . We do not claim the Dense GMM as a novel contribution in this paper, though we believe that this paper is the first to apply the idea of a Dense GMM in this per-patch manner (as opposed to using a Dense GMM over point clouds and predicting a Gaussian per-point).

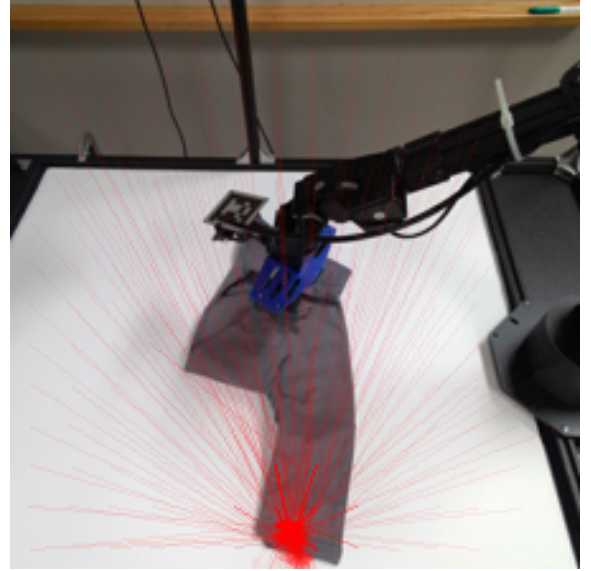


Fig. 5: High-level policy GMM predictions at inference. We visualize the mixture components of the GMM, with the opacity encoding mixing weight w_i and arrows showing projections of 3D residuals δ_i from patch centers p_i .

Training. We train π_{hi} by minimizing the negative log-

¹In practice we sum NLL losses over a small set of fixed variances to capture sub-goal distributions at multiple scales; see Appendix A.1.

Task	Data Source	# Demos	Generalization Type
<i>Pick-and-Place</i>			
plate-on-table	Robot	20	—
plate-in-bin	Robot	20	—
mug-in-bin	Robot	20	—
mug-on-table	Human	20	Object combination
<i>Cloth Folding</i>			
fold-onesie	Robot	33	—
fold-shirt	Robot	50	—
fold-onesie-ood	Human	17	Object instance
fold-towel	Human	50	Object category + Skill composition
<i>Hammer Pin</i>			
hammer-pin	Human+Robot	100	—

TABLE I: Overview of tasks. **Blue**: In-distribution (ID) tasks. **Orange**: Out-of-distribution (OOD) tasks requiring generalization.

likelihood on sub-goal transitions from a dataset of both human and robot data $\mathcal{D}' = \mathcal{D}_{robot} \cup \mathcal{D}_{human}$ that consists of observations o_t for each timestep t and end-effector poses e_s at the end of each sub-goal s :

$$\mathcal{L}_{hi} = \mathbb{E}_{(o_t, e_s) \sim \mathcal{D}'} \left[-\log \left(\sum_{i=1}^{K \times C} w_i \mathcal{N}(e_s; \mu_i, \sigma^2) \right) \right]$$

where μ_i is the predicted goal, given by the patch center + each of the residuals for patch i : $\mu_i = p_i + \delta_i$. Full architecture and training hyperparameters are listed in Appendix A.1.

Inference. During inference, we sample a patch i from the categorical distribution on mixing weights $\{w_i\}$. We then use the corresponding mean prediction $\mu_i = p_i + \delta_i$ to obtain the predicted end-effector pose. Figure 5 visualizes the components of the GMM, depicting the spatial distribution over the predicted residuals for a single keypoint in a single camera view.

2) *Low-Level Goal Conditioned Policy*: We instantiate π_{lo} as a Diffusion Policy [4], which generates action chunks $\{a_t, \dots, a_{t+H}\}$ by denoising conditioned on observations.

Goal Conditioning. Each point in the 3D goal e_s is projected onto the image plane of each camera using the camera parameters, yielding sparse 2D coordinates $\mathbf{p}_i \in \mathbb{R}^2$ for $i \in \{1 \dots C\}$. These are converted to dense *end-effector heatmaps* H where each channel c encodes the pixel distance field from keypoint $\mathbf{p}_c$: $H_{xy}^{(c)} = \sqrt{\frac{\|\mathbf{x}_{xy} - \mathbf{p}_c\|_2}{d_{\max}}}$ where $\mathbf{x}_{xy}$ denotes the pixel coordinates, $d_{\max} = \sqrt{h^2 + w^2}$ normalizes by the image diagonal, and we use the square root for steeper gradients near the targets. We denote the resulting heatmap tensor as $\text{heatmap}(e_s) := H \in \mathbb{R}^{3 \times h \times w}$, where $\mathbf{x}_{xy}$ denotes the pixel coordinates. We use heatmaps rather than single-pixel binary masks as goal representations, empirically we find them to yield better performance; we hypothesize this is due to the denser supervisory signal. For practical implementation reasons, we select three of the heatmap channels corresponding

to non-collinear points in the goal², and pass these channels through standard 3-channel image encoder networks before incorporating into the policy network. This preserves spatial structure while densifying the sparse goal representation. This process is illustrated in Figure 7, and the architecture of the low-level goal conditioned policy is shown in Figure 6.

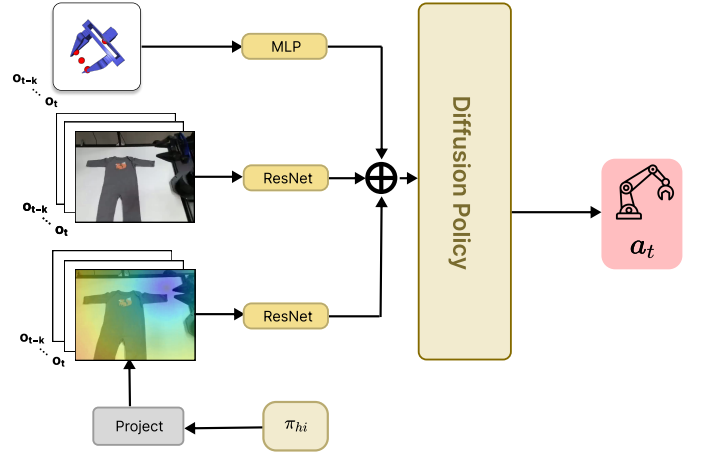


Fig. 6: **GHOST** Low-level goal-conditioned policy architecture. Images from each camera and the projected end-effector heatmap images are processed independently with ResNet [11] encoders and concatenated along with the proprioceptive input into a global conditioning vector for the Diffusion Policy.

Training. We use the standard diffusion loss, training on the robot-only data $\mathcal{D}_{robot}$:

$$\mathcal{L}_{lo} = \mathbb{E}_{\mathcal{D}_{robot}, \epsilon} \left[\|\epsilon - \epsilon_{\theta}(a_t^{\text{noisy}}, o_t, \text{aux}_t, \text{heatmap}(e_s))\|^2 \right]$$

where aux_t are auxiliary robot observations (e.g., wrist cameras, proprioception), a_t are low-level robot actions, a_t^{noisy} denotes the action corrupted according to the forward diffusion process and e_s is the gripper pose extracted from the robot

²We choose a point on the gripper wrist, as well as a point on each finger. Because of the rigid structure of the gripper, this minimal representation is sufficient to capture the state of the gripper, so discarding channels does not have a major effect on the policy.

demonstrations. We train π_{hi} and π_{lo} independently. Full hyperparameters for π_{lo} are listed in Appendix A.2.

Inference. At deployment, we execute π_{hi} and π_{lo} sequentially, where π_{hi} predicts a sub-goal conditioned on the current observation and π_{lo} predicts one action chunk conditioned on the heatmap representation of the sub-goal prediction.

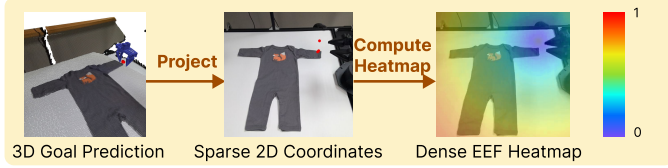


Fig. 7: End-effector heatmap generation for goal conditioning. Predicted 3D keypoints are projected to 2D coordinates, and then converted to dense distance field heatmaps that encode spatial proximity to each keypoint.

V. EXPERIMENTS AND RESULTS

We evaluate whether our hierarchical policy learning approach improves performance and enables skill generalization. Concretely, our experiments test two questions: **(Q1) In-distribution performance:** Do hierarchical policies improve in-distribution performance even without human data? **(Q2) Generalization:** Do human demonstrations enable transferring learned skills to novel object instances, categories, and contexts?

A. Tasks and Evaluation Protocol

Table I summarizes our evaluation tasks. We collect robot demonstrations on **in-distribution (ID)** tasks to train both π_{hi} and π_{lo} , and human demonstrations on **out-of-distribution (OOD)** variations to train only π_{hi} . For all experiments, we conduct $n = 30$ trials per method with randomized object configurations, reporting mean success rate $\pm$ half-width of the 95% percentile bootstrap CI (clipped to $[0, 100]$).

- **Pick-and-Place:** Grasp a specified object (plate, mug) and place on a target (table, bin). Robot demos include placing plates on a table/bin and placing a mug in the bin; human demos provide OOD (out of distribution) object-target combinations (see Table I). The OOD task **mug-on-table** evaluates whether models can demonstrate *compositional* generalization on a novel combination of objects. The task is considered a success if the object is placed stably on the target; objects placed successfully but knocked off during reset are given a score of 0.5.
- **Cloth Folding:** Long-horizon deformable manipulation requiring multiple sequential folds. Robot demos on folding onesies and shirts; human demos on novel instances (**fold-onesie-ood**) and applying the skill on entirely novel categories (**fold-towel**). k -step success indicates first k folds completed successfully.
- **Hammer Pin:** Pick up a hammer and strike a target pin. The blue, purple, red, and pink pins are initially raised.

Robot demos include hammering the blue pin or the pink pin; human demos on novel target pin (purple pin). This task is considered a success if the target pin is fully driven in using the hammer.

B. Baselines

We evaluate GHOST against two baselines: (1) **Diffusion Policy (DP)** [4], a flat policy trained on robot data, and (2) **MimicPlay** [27], a hierarchical approach that learns a latent trajectory representation from human play data. For fair comparison, we train our high-level policy architecture with MimicPlay’s representation and training objective, appending a CLS token to the input sequence as the latent plan with a separate MLP as the GMM decoder. This ensures that we measure the differences that stem from the goal representation rather than policy architecture. We also evaluate **GHOST (Robot Only)**, our method trained without human demonstrations, to isolate the benefit of hierarchy from the benefit of human data.

C. Implementation Details

We train a single multi-task policy with language conditioning for each method. Complete hyperparameters for both π_{hi} and π_{lo} , our hardware setup, and per-task data collection details are provided in Appendix A, Appendix B, and Appendix C respectively. For the Diffusion Policy baseline, we add language conditioning by appending the text embedding to the global conditioning vector. For hierarchical methods, language conditioning is only provided for the high-level policy. We train all DP variants for 300k steps with color jitter and random crop augmentations. The high-level policy is trained for 100 epochs with additional augmentations: adding noise to the gripper pose, blur, grayscale, and token dropout augmentations. At inference, we synchronously execute π_{hi} and π_{lo} , *i.e.*, the low-level predicts action chunks that fully execute before the next high-level inference step, enabling reactive replanning to changes in environment.

D. Results

Do hierarchical policies improve in-distribution performance even without human data? For **plate-on-table** (Table II) we see that nearly all methods saturate in performance, as the task is simple and sufficient training data is available. However, for a long-horizon complex task, we see a significant increase in the performance of “GHOST (Ours - Robot Only)” compared to “DP”. As shown in Table III, on **fold-onesie** performance increases from 10% to 80% final success, showing large benefits from the hierarchical decomposition. Similarly, in **hammer-pin**, a task requiring precise grasping of the hammer tool and striking the correct pin, we see that performance significantly improves from DP (16.7%) to “GHOST (Ours - Robot Only)” (50%) (Table V). Appendix D further isolates the contribution of the DINOv3 backbone via an ablation with a tiny ViT trained from scratch; the hierarchy alone (with no pre-trained encoder) already substantially outperforms flat DP, while DINOv3 provides additional gains on long-horizon tasks.

Method	Success Rate (%) $\uparrow$	
	plate-on-table	mug-on-table
DP	80.0 $\pm$ 15.0	13.3 $\pm$ 9.2
MimicPlay	65.0 $\pm$ 15.0	28.3 $\pm$ 12.5
GHOST (Ours - Robot Only)	83.3 $\pm$ 10.8	55.0 $\pm$ 15.0
GHOST (Ours)	98.3 $\pm$ 2.5	63.3 $\pm$ 13.3

TABLE II: Pick-and-place success rates. Best: **shaded**, second-best: underline.

Task	Method	Success Rate (%) $\uparrow$				
		1-step	2-step	3-step	4-step	Final
fold-onesie	DP	90.0	<u>76.7</u>	53.3	40.0	10.0 $\pm$ 11.7
	MimicPlay	<u>93.3</u>	<u>76.7</u>	70.0	70.0	46.7 $\pm$ 16.7
	GHOST (Ours - Robot Only)	100.0	100.0	<u>96.7</u>	<u>86.7</u>	80.0 $\pm$ 15.0
	GHOST (Ours)	100.0	100.0	100.0	90.0	83.3 $\pm$ 13.3
fold-onesie-ood (Novel Object Instance)	DP	<u>76.7</u>	<u>60.0</u>	46.7	26.7	10.0 $\pm$ 10.0
	MimicPlay	63.3	36.7	30.0	20.0	0.0 $\pm$ 0.0
	GHOST (Ours - Robot Only)	100.0	100.0	<u>73.3</u>	60.0	43.3 $\pm$ 16.7
	GHOST (Ours)	100.0	100.0	93.3	86.7	56.7 $\pm$ 16.7

TABLE III: Onesie-folding success rates. k -step = first k folds completed. Final = all 5 folds completed. Best: **shaded**, second-best: underline.

Method	Success Rate (%) $\uparrow$
MimicPlay	16.7 $\pm$ 13.3
GHOST (Ours)	36.7 $\pm$ 16.7

TABLE IV: **fold-towel** (Novel Object Category + Skill Composition) success rates. Best: **shaded**.

Method	Success Rate (%) $\uparrow$
DP	16.7 $\pm$ 13.3
MimicPlay	33.3 $\pm$ 16.7
GHOST (Ours - Robot Only)	50.0 $\pm$ 16.7
GHOST (Ours)	70.0 $\pm$ 16.7

TABLE V: **hammer-pin** success rates. Best: **shaded**, second-best: underline.

Do human demonstrations enable transferring learned skills to novel object instances, categories, and contexts? As shown in Table II, Table III and Table IV human demonstrations unlock meaningful OOD transfer of learned skills to novel objects and novel skill compositions. GHOST achieves 63.3% success on **mug-on-table**, a task featuring a combination of objects unseen in robot demonstrations. On **fold-onesie-ood**, GHOST achieves 56.7% final success vs 43.3% for “GHOST (Ours - Robot Only)” and 0% for MimicPlay (Table III). Finally, on the hardest task of generalizing a policy to a novel object category and skill combination (**fold-towel**), GHOST achieves 36.7% success as compared to 16.7% with the MimicPlay baseline.

VI. LIMITATIONS AND FUTURE WORK

Although GHOST shows significant gains in performance through a hierarchical framework, and promising results in generalizing learned skills across multiple axes, it is not without limitations. Like other methods that use hand pose estimators on human demonstrations [15, 22], our approach is limited by the quality of the estimated hand pose, and suffers in situations where hand pose estimation has errors. We extract sub-goals through heuristics (gripper open/close), which may not be optimal or even valid for tasks requiring continuous manipulation skills (pouring, stirring, or hammering), and through annotation on human demonstrations, which imposes an additional cost on the collection of demonstrations. Related work on automatic sub-goal discovery [20, 33] is an interesting direction for future research on mining sub-goals from collected human and robot demonstrations.

While GHOST generalizes to novel object instances and composes learned skills in novel sequences, we observe a steep drop in performance as the task horizon lengthens, which we attribute to the visual domain gap between human and robot observations in π_{hi} . To verify this, we conduct an oracle ablation (Appendix E): when π_{hi} is trained on a small set of robot demonstrations of **fold-towel** instead of human demonstrations—while π_{lo} remains identical and has never seen towel-folding data—final success increases from 40% to 90%. This indicates that π_{lo} generalizes zero-shot to novel object categories when given accurate sub-goals, and that the principal bottleneck for OOD generalization is the high-level visual domain gap rather than the low-level controller. Existing work on embodiment-invariant visual representations [27, 22] aims to close precisely this gap and represents an important direction for future work.

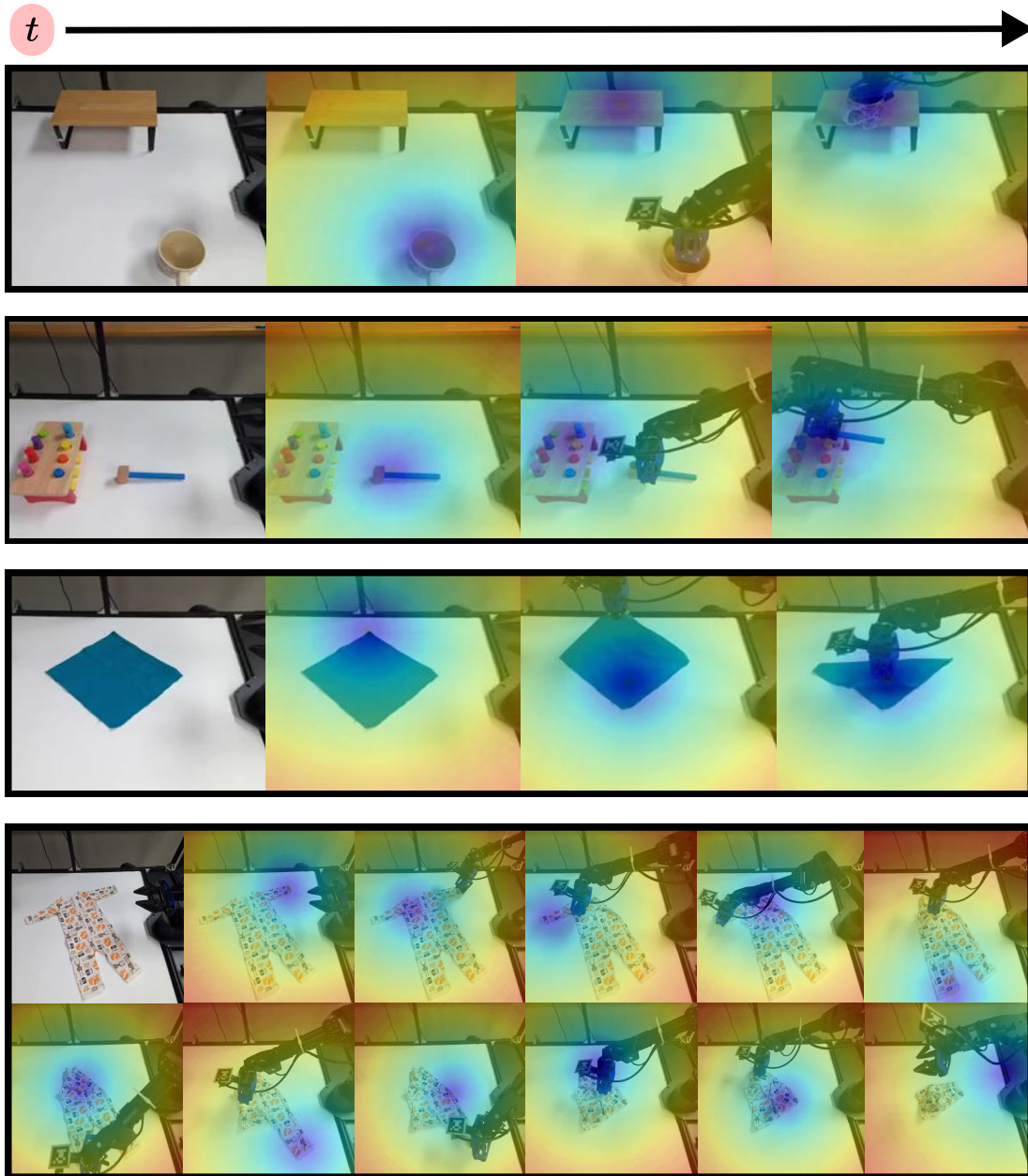


Fig. 8: We visualize qualitative results on various tasks with the **GHOST** framework. **Row 1: mug-on-table** (novel object combination). **Row 2: hammer-pin**. **Row 3: fold-towel** (novel category + skill composition). **Row 4: fold-onesie-ood** (novel instance). We visualize rollouts by overlaying a colormap on the projection of π_{hi} 's goal predictions at each timestep.

VII. CONCLUSION

We present GHOST, a hierarchical imitation learning framework that decouples embodiment-agnostic goal prediction from embodiment-specific action execution. This factorization enables two key benefits: improved in-distribution performance through explicit sub-goal modeling, and out-of-distribution generalization via human demonstrations.

We introduce a 3D goal prediction architecture that processes multi-view RGB-D observations to predict dense per-patch Gaussian mixture models over end-effector poses. We

condition the low-level policy through 2D projections of 3D goals, represented as end-effector heatmaps. This representation bridges the gap between human and robot demonstrations without requiring explicit action retargeting. By training a high-level policy on heterogeneous human and robot data and a low-level policy purely on robot demonstrations, we generalize learned skills across novel object-context combinations and compositional skill generalization.

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