Unsupervised Reinforcement Learning for Transferable Manipulation Skill Discovery

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Abstract—Current reinforcement learning (RL) in robotics often experiences difficulty in generalizing to new downstream tasks due to the innate task-specific training paradigm. To alleviate it, unsupervised RL, a framework that pre-trains the agent in a task-agnostic manner without access to the task-specific reward, leverages active exploration for distilling diverse experience into essential skills or reusable knowledge. For exploiting such benefits also in robotic manipulation, we propose an unsupervised method for transferable manipulation skill discovery that ties structured exploration toward interacting behavior and transferable skill learning. It not only enables the agent to learn interaction behavior, the key aspect of the robotic manipulation learning, without access to the environment reward, but also to generalize to arbitrary downstream manipulation tasks with the learned task-agnostic skills. Through comparative experiments, we show that our approach achieves the most diverse interacting behavior and significantly improves sample efficiency in downstream tasks including the extension to multi-object, multitask problems.

I. INTRODUCTION

While deep reinforcement learning has shown considerable progress toward solving complex robotic control tasks in the presence of extrinsic rewards [1] [2], these advances produced agents that are unable to generalize to new downstream tasks beyond the one they were trained to solve. Humans, on the other hand, are able to acquire skills with minimal supervision and apply them to solve a variety of downstream tasks. Inspired by human’s flexible capability, recently, unsupervised RL, a framework that trains the agent without access to the environment reward supervision, has emerged as a promising paradigm for developing RL agent that can generalize to new downstream tasks.

In the unsupervised RL setting, the agent is first pre-trained in a downstream-task-agnostic environment without access to the environment reward supervision, and then transferred to the various tasks with the environment rewards. As the goal of unsupervised pre-training is to have data-efficient adaptation for some downstream tasks, some prior works [3], [4] address the pre-training problem by leveraging the skill learning method. However, such skill-based techniques are only applicable within the variation of the objectives in the same environment, and these cannot be transferred into the task variation in totally different environments due to the limited flexibility of the learned skills.

More fundamental challenge is that in the context of the unsupervised RL, skill learning is intimately connected to the efficient exploration of the given environment and vice-versa. That is, the skills discovered by the agent depend on the regions of the state space covered during exploration. If exploration is ineffective, the learned skills cannot properly characterize meaningful parts of the state space in the environment, degrading the performance for downstream tasks. Even though some exploration methods are proposed for obtaining diverse data distribution [5]–[7], most of these methods are still limited to exploration based on the novelty of the proprioceptive states rather than encouraging exploration towards the interaction behavior, which is a key aspect of the robotic manipulation skill learning. Conversely, efficient exploration cannot be performed without proper skills since no practical exploration method would be able to exhaustively explore all possible states. Thus, we argue that the development of algorithms specialized to simultaneously address such proper skill learning and diverse, effective exploration for manipulation tasks is of paramount importance to benefit from unsupervised pre-training.

In this work, we address the challenges described above through a framework for the unsupervised training on robot manipulation that learns interactive behaviors without access to task-specific rewards. Specifically, we consider the mutual information-based two-phase approach with specialized policy network design, which enables addressing the diverse-exploration challenge, but also distilling the generated experience in the form of reusable task-agnostic skills. In the first phase, the agent explores the environment without prior knowledge of downstream tasks, while learning task-agnostic, interactive skills through intrinsic rewards based on mutual information. Then in the second phase, given the

Fig. 1: Task-agnostic skills naturally emerged by interaction-oriented exploration can significantly improve the sample efficiency in learning diverse downstream manipulation tasks.
skills trained in the first phase, the agent is transferred to solve various downstream tasks with as few environment interactions as possible. Such a setup evaluates the agent’s ability to adapt to new tasks after pre-trained only once in an unsupervised manner.

To summarize, our work makes the following contributions.

- To the best of the author’s knowledge, this is the first work on an unsupervised method for transferable manipulation skill discovery, which generates task-agnostic skills for transferring to a wide range of robot manipulation tasks.
- The proposed method achieves the most diverse, interactive exploration for unsupervised pre-training compared to other baselines.
- After pre-training only once with the proposed method, 2-5 times improvements in sample efficient training have been achieved in various downstream tasks including the extension to multi-object, multitask problems.

II. RELATED WORKS

A fundamental problem in RL is exploring the state space, especially in cases where the reward is sparse. For tackling this problem, task-agnostic approaches or exploiting various inductive biases that correlate positively with structured, efficient exploration are proposed. Prior works include state-visitiation counts [7] [8], eigendecomposition-based exploration [9], curiosity/similarity-driven exploration [5] [10], mutual information-based exploration [4] [12] [13]. In contrast, our work, aiming at robot manipulation learning, is different in the aspect of drawing motivation from interaction-oriented exploration and distilling the experience into reusable skills rather than just trying to discover unseen, new states.

To enable sample efficient RL for various downstream tasks, several researchers have taken inspiration from skill transfer or multiple-task learning. They have shown that utilizing different modules across different tasks reduces the interference on each module [14] [15]. But pre-defined skills or sub-policies need human engineering for effectiveness in specific tasks, while our work enables the agent to learn and transfer skills in a task-agnostic way. A different set of approaches are learning the single integrated policy by addressing the entire tasks all at once with a carefully designed network [16] [17], or improving the optimization technique [18] [19]. Instead of distilling the multitaskable knowledge into a policy by experiencing all tasks, our approach could be considered as learning necessary backbone features for downstream tasks, which allows a significant margin in data efficiency and flexibility of the learned skills.

III. PRELIMINARY

In this study, we consider a latent augmented Markov Decision Process (MDP) defined by a state space $\mathcal{S}$, action space $\mathcal{A}$, discount factor $\gamma$, reward function $R$, transition probability $p(s'|s, a)$, and latent space $Z$. The objective is to obtain a policy $\pi(a|s, z)$ to maximize the expected sum of rewards $\mathbb{E}[\sum_{t=0}^{T} R(s_t, a_t, z_t)]$, where the latent variable $z$ is sampled from some distribution $p(z)$, and states are sampled according to initial state distribution $p(s_0)$, $a_t \sim \pi(a_t|s_t, z_t)$.

All of the latent $z$ in these definitions could be replaced with the goal $g$ in goal space $\mathcal{G}$ when we consider the goal-conditioned MDP.

One of the important quantities in the following training process is mutual information (MI) $I(X; Y) = \int_X \int_Y p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \, dx \, dy$, which can be equivalently expressed as $\mathcal{H}(X) - \mathcal{H}(X|Y)$, where $\mathcal{H}$ is entropy. It is a measure of the mutual dependence between the two variables $X, Y$. If $X, Y$ is independent, $I(X; Y)$ is 0, and otherwise, it has a positive value. This mutual information could be used as an intrinsic reward to induce the interacting behavior of the robot.

Another quantity is a compositional policy network structure, called multiplicative compositional policies (MCP) [20]. It represents the policy by multiplication of some primitives and gating network, and it is expressed as follows,

$$
\pi(a|s, z) = \frac{1}{Z(s, z)} \prod_{i=1}^{N} \pi_i(a|s)^{W_i(s, z)} \quad W_i(s, z) \geq 0 \quad (1)
$$

where $\pi_i$ is the $i$th primitive, and $W_i$ is a positive gating weight for $\pi_i$, and $Z$ is a partition function that ensures the output action distribution is normalized. In this study, we use $N = 8$ and the latent variable $z$ is augmented to the MCP, and it will be explained in section IV-A. With the assumption of Gaussian distribution $\pi_i$, the output of the MCP could be represented by Gaussian distribution as follows,

$$
\mu^i(s, z) = \frac{1}{\sum_{i=1}^{N} W_i(s, z)} \sum_{i=1}^{N} \frac{W_i(s, z)}{\sigma^2_i(s, z)} \mu^i(s, z) \quad (2)
$$

$$
\sigma^2(s, z) = \left( \frac{\sum_{i=1}^{N} W_i(s, z)}{\sigma^2_i(s, z)} \right)^{-1}
$$

where $\mu^i, \sigma^2_i$ is the $j$th element of the $\pi_i$’s mean and variance. Unlike other compositional policy architecture such as an additive policy which consists of the weighted sum of primitive policies, MCP could be effective when the effect of each primitive’s action should be in a non-zero-sum way. That is, simultaneous activation of each primitive could be more effective and could represent more complex expression and concurrent behavior.

IV. METHOD

A. How to induce interaction-oriented exploration

To learn interaction-oriented exploration behaviors without any external task reward, some intrinsic reward that implicitly induces interacting behavior is needed. One of the possible approaches is utilizing mutual information (MI) $I(S_o; S_r)$ as an intrinsic reward, where $S_o$ is the object’s position, $S_r$ is the robot’s gripper position. Then, by definition of $I(S_o; S_r) = h(S_o) - h(S_o|S_r)$, the policy maximizes
the uncertainty of the object’s state while minimizing the uncertainty of the object’s state when given the gripper’s state. By using this MI as a reward, the robot is intrinsically motivated to interact with an object. That is, the robot should grasp an object and place it in other states here and there.

As MI between the two variables from unknown distribution is generally not tractable, we propose to use Jensen-Shannon Divergence (JSD)-based mutual information estimation [21], which is expressed as follows,

\[
I(S_o; S_r) = D_{\text{JSD}}(P||Q), (P : P_{S_oS_r}, Q : P_{S_r})
\]

\[
= \int_X q(x) \sup_{t \in dom_f, \psi_1} \left\{ \frac{p(x)}{q(x)} - f^*(t) \right\} dx
\]

\[
\geq \sup_{T \in T} \left( \int_X p(x)T(x) dx - \int_X q(x)f^*(T(x)) dx \right) \quad (3)
\]

\[
= \sup_{\psi_1 \in \Psi} E_{x \sim P}[T_{\psi_1}(x)] - E_{x \sim Q}[f^*(T_{\psi_1}(x))]
\]

\[
= I_{\psi_1}(S_o; S_r)
\]

where the distribution \( P \) is a joint distribution between \( S_o \) and \( S_r \), and \( Q \) is a product of marginal distribution of each \( S_o \) and \( S_r \). The first and second equalities hold from the definition of \( f \)-divergence [21], and inequality holds from the Jensen’s inequality when swapping the integration and supremum operations. Following the [21], we substituted the \( T(x) = \log(2) - \log(1 + e^{-\psi_1(x)}) \), where \( g_{\psi_1} \) is a neural network parameterized by \( \psi_1 \), and \( f^*(x) = -\log(2 - e^{x^2}) \). By maximizing the lower bound of (3), where the expectation is over the data collected by the policy, we could train the MI estimator \( I_{\psi_1} \).

However, we empirically found that the estimated \( I(S_o, S_r) \) alone makes some interactive behavior of the agent, but does not induce the most diverse behavior. It could be due to the exploitation of the approximated lower bound rather than the true MI value. To incentivize more diverse behaviors when interacting with an object, we propose to use a additional diversity-driven component, referred from DADS [12]. It introduces an information-theoretic objective as follows,

\[
I(s' ; z|s) = \int \int p(s' , z|s) \left[ \log \frac{p(s', z|s)}{p(s'|z)p(z|s)} \right] ds' dz ds
\]

\[
= E_{z,s,s' \sim P(z,s,s')} \left[ \log \frac{p(s'|z)p(z|s)}{p(s'|z)} \right]
\]

\[
= E_{z,s,s' \sim P(z,s,s')} \left[ \log q_{\psi_2}(s'|z)p(z|s) \right]
\]

\[
+ E_{z,s \sim P(z,s)} [D_{\text{KL}}(p(s'|z)p(z|s)||q_{\psi_2}(s'|z,p(z|s)))]
\]

\[
\geq E_{z,s,s' \sim P(z,s,s')} \left[ \log \frac{q_{\psi_2}(s'|z)p(z|s)}{p(s'|z)} \right] = I_{\psi_2}(s'|z|s)
\]

where the first equality holds by the definition of conditional mutual information, and the inequality holds by non-negativity of KL-divergence. \( I(s'|z|s) \) can be decomposed into \( H(s'|z) - H(s'|z, s) \), and it encourages the agent to make the next state \( s' \) as diverse as possible given the current state \( s \), while reducing the uncertainty of \( s' \) when given \( s \) and latent \( z \) sampled from the prior uniform distribution \( p(z) \). So \( z \) could mean ‘skill’ that discriminates state distribution followed by some policy that maximizes the reward \( I(s'|z|s) \).

That is, each different \( z \) induces each different trajectory while maintaining low variance of trajectory when the same \( z \) is given, and \( q_{\psi_2} \) is called ‘skill dynamics’ due to this property. The output distribution of the \( q_{\psi_2} \) is modeled as a mixture of Gaussian distributions with the parameterized neural network, and the MI estimator \( I_{\psi_2} \) could be trained by maximizing the lower bound of (4), where the expectation is over the data collected by the policy.

By substituting the state \( s \) with \( S_o \), the two MI estimations could be combined together as an intrinsic reward,

\[
\hat{r} = I_{\psi_1}(S_o; S_r) + I_{\psi_2}(S'_o; z|S_o)
\]

and by maximizing (5) through RL, we could expect that the robot is naturally induced to perform interaction-oriented exploration, while learning skills. All of these intrinsic rewards are formulated in an unsupervised way, and there is no external task reward signal for manipulation behavior. As the reward is represented by MI that contains the latent \( z \), the overall MDP is augmented with \( z \), and the policy is represented as in (1).

B. Transfer to goal-conditioned reinforcement learning

Through the unsupervised pre-training phase in TV-X, the agent is encouraged to learn interaction-oriented exploration behavior, and it leads the policy \( \pi(a|s, z) \) to be trained to have skill-agnostic primitives \( \pi_i \) and gating network \( W_i \) that regularizes the activation of each primitive. Then, we can say that the primitives \( \pi_i \) implicitly contain the necessary information about interaction; which action distribution is most frequently used when interacting with an object, and which combination of action distribution is enough to represent the possible action outputs that cover the state space where the interaction behavior occurred. That is, the primitives \( \pi_i \) can be a backbone of the policy for any kind of task that needs interaction with something.
Train the agent with SAC [22].

For deploying such properties of the learned primitives $\pi_i$, we can transfer them to the goal-conditioned reinforcement learning (GCRL) by retraining only the gating network while replacing the latent $z$ in (1) with goal $g$, and freezing the weights of the $\pi_i$ to maintain the primitives as they are. Then, the policy can be expressed as follows.

$$\pi(a|s, g) = \frac{1}{Z(s, g)} \prod_{i=1}^{N} \pi_i(a|s)W_i(s, g), \quad W_i(s, g) \geq 0 \quad (6)$$

which can be used for any type of GCRL problems.

C. Extension to multiple objects

To extend the idea into multi-object setting, the agent should know how to deal with the variable number of objects which can be used for any type of GCRL problems.

D. Extension to multitask learning

Given the learned primitives that implicitly represent the interacting behavior $[\text{IV-A}]$, we can leverage these properties to perform the multitask reinforcement learning (MTRL) efficiently. MTRL considers the standard RL algorithm (SAC [22] in this work) except that it is conditioned on task distribution $p(T)$, where $T$ is in task space $T$, and it could be expressed as follows,

$$\max_\pi \mathbb{E}_{T_j \sim p(T)} \left[ \mathbb{E}_{\tau_j \sim p^\pi(\tau_j|T_j)} \left[ \sum_{t=0}^{t_{\text{max}}} r(s, a) + \alpha H(\pi) \right] \right] \quad (7)$$

where $T_j$ is one-hot embedding vector for the $j$th task, and $\tau_j$ is trajectory sampled from $T_j$. By optimizing the (7), the policy $\pi$ is trained to perform well on multiple tasks. We can use the same transfer process like in $[\text{IV-A}]$ and $[\text{IV-B}]$ except that the gating network’s inputs are augmented with the task embedding $T$ when transferred to MTRL. That is, the policy is represented as $\pi(a|s, g, T) = \frac{1}{Z(s, g, T)} \prod_{i=1}^{N} \pi_i(a|s, g, T)W_i(s, g, T)$, where $\pi_i$ is learned primitives $[\text{IV-A}]$ with fixed weights. MTRL process is summarized in Algorithm 2.
V. Experiments

In this study, the Fetch environment in the openAI gym is used to compare the mutual-information-based intrinsic reward's effectiveness, and custom UR3 with end-effector position and gripper control (20Hz, 4-dimensional action) environment is used for evaluation of the GCRL in multi-object, multitask, real-world experiments.

A. Analysis of the learned exploration behavior

To verify the effectiveness of the proposed method in terms of the interaction-oriented exploration behavior, we compare each different combination of mutual information-based unsupervised RL methods, where each method has the following properties,

- **MISC [13]**: It uses Donsker-Varadhan (DV) representation to estimate \( I(S_o; S_r) \) and only uses it as an intrinsic reward for exploration. It is the first and only work that shows success in stably picking an object without any external task reward.
- **DIAYN [4]**: It encourages the agent to explore as diverse as possible by maximizing \( I(s; z) \). It suggests that the skill \( z \) should control which states the agent visits, thus the agent is rewarded by visiting each different state space according to each different skill.
- **Proposed (JSD+DADS)**: Described in IV-A

For comparison, 2000 trajectories (50 steps per trajectory) are gathered by \( \pi(a|s, z) \) with multiple random seeds and latent \( z \). Some of the collected trajectories and object’s states are visualized in Fig 3 and our proposed method shows more desirable interaction-oriented exploration behavior compared to other MI-based baselines.

MISC uses Donsker-Varadhan (DV) representation to estimate \( I(S_o; S_r) \), but this representation is known to be numerically unstable in estimating MI, which is verified on benchmark tests [25]. Furthermore, it has a tendency to overestimate the MI (Fig 4). As the agent exploits these properties, it collapses to almost the same behaviors once after grasping the object rather than diverse interaction behavior after grasping the object (Fig 3).

Even though adding DIAYN is proposed in [13], it frequently leads to missing the object. It is due to the different rewarding mechanisms for diversity. DIAYN rewards the occupation of different state distributions according to the intrinsic reward proportional to \( \log q(z|s) \), where \( q(z|s) \) is skill discriminator. Thus, even though the object is not moving in a specific region, the agent can receive the reward for diversity (e.g. pushing away the object out of the table). This property of DIAYN limits the utility of learned interaction primitives. However, DADS rewards according to the predictability of the next state (equation 4), which encourages the agent to keep moving with the object. Thus, the agent does not receive the reward for diversity if the object is not moved.

To analyze the visualized results numerically, we compare each MI objective with 2 criteria; 1) the number of grasping among the states in trajectories for comparing the interaction ratio, 2) entropy of the object’s states for comparing diversity. The number of grasping is computed by counting the number of states where the distance between the gripper and object is within a threshold (5 cm). The entropy is computed approximately by discretizing the 3D space into 3D bins and treating the ratio of the number of states in each bin as a probability. The values normalized by the total number of states and maximum entropy (uniform distribution) are shown in Fig 5-a.

As expected by visualization results, the proposed one shows a higher grasping ratio and object’s state entropy compared to other baselines. While DIAYN brings higher entropy when added to MISC, the robot frequently pushes the object away rather than grasping (Fig 3). DADS helps to increase the entropy while maintaining grasping because it optimizes the policy not only for diversity but also for predictability of the skill dynamics \( q_{\phi_2} \). Furthermore, using Jensen Shannon Divergence (JSD) instead of DV representation (MISC) shows higher entropy and less failure in grasping due to the more stable, conservative estimation as the JSD-based estimation’s value and variance are bounded [26]. These properties could be indirectly supported by looking into Fig 4.

B. Analysis of the learned primitives

Another factor that we look into is the distribution of each primitive. Collapse to similar primitives is not a desirable feature for transfer because the primitives not only should represent the backbone feature of interactive motions but also should be diverse to cover the possible action distributions that may be needed in the transferred downstream tasks.
This could be explored through the local approximation to the perturbation sensitivity of $\pi$ by using the approximated Fisher Information.

While the Fisher matrix is typically computed with respect to the model parameters, we compute the modified diagonal Fisher $\tilde{F}$ of the policy $\pi$, which is motivated by [27], with respect to other representation $h^{(i)}$ such as gating weights $W_i$ and primitive’s mean $\mu_i$. We define the diagonal matrix $\tilde{F}$ with diagonal elements $\tilde{F}(m, m)$, and derive the Average Fisher Sensitivity (AFS) of feature $m$ in the $i$th primitive as:

$$\tilde{F}^{(i)} = \mathbb{E}_{\rho^\pi(s,a)} \left[ \frac{\partial \log \pi}{\partial h^{(i)}} \frac{\partial \log \pi}{\partial h^{(i)}}^T \right], \quad AFS(i, m) = \frac{\tilde{F}^{(i)}(m,m)}{\sum_i \tilde{F}^{(i)}(m,m)}$$

(8)

where the expectation is over the joint state-action distribution $\rho^\pi(s,a)$ induced by the policy $\pi$. In practice, it is often useful to consider the AFS score per primitive $AFS(i) = \sum_m AFS(i, m)$, i.e. summing over all features in the $i$th primitive. AFS thus estimates how much the policy relies on each primitive to compute the output.

As AFS is computed along with each primitive (Fig 5c,d), we use the normalized value of AFS as a pseudo categorical probability (Just for comparison. It is not probability by definition) to compute the AFS’ pseudo entropy for comparing the distribution of the sensitivity along with each primitive (Fig 5b). The desirable feature of the primitives is low sensitivity (high entropy of AFS) as it means each primitive performs its own role rather than collapsing to similar distributions with a few different ones. Further verified by t-sne visualization in Fig 5a. If collapse occurs, the sensitivity of a few primitives will surge like in MISC case in Fig 5c,d.

For minor ablation, there could be a question about whether the learned primitives $\pi_i$ really represent the interaction behavior implicitly. To validate it, 2000 trajectories are collected by the policy, $\pi(a|s) = \frac{1}{Z(s)} \prod_{i=1}^{N} \pi_i(a|s)^{W_i(s)}$, with the primitives $\pi_i$ trained by each MI objective, and randomly initialized gating network $W_i(s)$ (Fig 7a). Then, the interaction ratio is computed by checking whether the number of states where the distance between object and gripper is within a threshold (5 cm) is more than 60% in a trajectory. The proposed method shows the highest interaction ratio, and we can say that implicit representation of the interaction behavior in $\pi_i$ is a reasonable conjecture and it is helpful for interaction-oriented exploration in the transferred downstream tasks.

C. Transfer to GCRL

To compare the effectiveness of the primitives learned by the proposed unsupervised pre-training method, we compare the UR3 pick&place tasks with other MI-based unsupervised baselines and supervised RL baselines. Over the all experiments, a sparse reward that indicates whether the task is succeeded or not is used with the goal relabeling technique, HER [28]. In multi-object setting, the learned primitives are transferred to GCRL where the sparse reward is given only when the agent performs the given task with the object corresponding to $w$. As the attention based feature $\phi(s, w)$ is used instead of state $s$ in the multi-object setting, we could transfer the learned primitives $\pi_i$ without constraint on the number of objects. Thus, the learned primitives in the 4 objects setting are transferred to 6 & 8-object setting.

Over the all different number of objects, the proposed method achieves the large sample efficiency margins in transferred downstream tasks, even with the multiple distractor objects in inputs. Most of the other mutual information-based baselines show slow convergence or failures within 1M steps (Fig 6) due to the lack of primitive’s expressivity stems from not enough exploration and skill discovery in the pre-training phase.

For ablation, in a single-object setting, we also compare with standard supervised RL baselines (Fig 7b) to validate the advantage of the unsupervised pre-training. The proposed method shows a significant improvement in sample efficiency than SAC (vanilla RL with Gaussian policy), and MCP [20] (SAC with the policy structure in [6]), Composable SAC [15] (SAC with attention-based additive policy rather than
Comparison with others

The most attention to the object that corresponds to \( w \) rather than collapsed to a few primitives. Also, the robot has weights are regularized to combine each primitive properly.

When the robot has to change its behavior, the gating order of red, green, blue, orange. We could verify that every is asked to arrange 4 objects into each goal state in the sequential tasks in real-world experiments (Fig 8). The robot

...vector where high-level policy's output corresponds to intention problems like hierarchical reinforcement learning (HRL), the trained policy can be used in solving sequential task together rather than a few ones working across all timesteps, ...As our study is not about HRL, we just assume that \( w \) is specified by a scripted rule at every step, and evaluate some success in simulation are due to the safety constraint of the UR3 hardware, which limits the joint from moving any further when the inputs into the robot arm produce too much agile movement. We suspect that the primitives with higher AFS entropy effectively regularizes the action outputs as the low perturbation sensitivity means a slower change in action probability when inputs are changed, and it could lead to the less agile movement.

To test whether the entire primitives are properly combined together rather than a few ones working across all timesteps, the trained policy can be used in solving sequential task problems like hierarchical reinforcement learning (HRL), where high-level policy’s output corresponds to intention vector \( w \). As our study is not about HRL, we just assume that \( w \) is specified by a scripted rule at every step, and evaluate sequential tasks in real-world experiments (Fig 8). The robot is asked to arrange 4 objects into each goal state in the order of red, green, blue, orange. We could verify that every moment that the robot has to change its behavior, the gating weights are regularized to combine each primitive properly rather than collapsed to a few primitives. Also, the robot has the most attention to the object that corresponds to \( w \) at that timestep. Further experimental results can be found in the supplementary video.

D. Transfer to MTRL

We evaluate our method in the environments including pick&place with/without obstacle, pushing, drawer & door open/close, button press, where all tasks need interaction with the robot’s gripper. These are chosen from the meta-world environment [16] developed for meta/multitask RL for robotics control. Building on top of these tasks, we further extend the tasks to be randomly generated goal-conditioned tasks, unlike fixed goals in the original metaworld, and modify the shaped reward into a sparse reward to make the training process more difficult. We also propose to learn the temperature \( \alpha \) in SAC for adjusting the entropy of the policy on a per-task basis, i.e. using a parameterized model to represent \( \alpha_j \sim f_c(T_j) \). Without the learnable \( \alpha \), the agent may stop exploring once all easier tasks are solved.

The proposed method is compared with other frequently referred baselines with SAC: 1) MT-SAC where task embedding \( T \) is concatenated in policy & critic. 2) MHMT-SAC built upon MT-SAC with independent heads for tasks. Both baselines are proposed in [16]. 3) PCGrad [18] which uses similar architecture like in MT-SAC, but projects the conflicting task gradient into other task’s normal plane to avoid a local optimum due to the gradient conflict. The conflict means negative cosine similarity between task gradients in PCGrad.

As shown in Fig 9, the proposed method achieves better sample efficiency and success rate in all of the tasks, even showing a higher initial success rate in a drawer, door environment due to the interactive property of the transferred primitives. Smaller performance gaps in the pushing task are due to the mismatch of action distribution as the gripper action is ignored to stay closed by default in this task. PCGrad is slower than other baselines, and it might be due to the assumption that there is a large enough conflict between tasks and large curvature in parameter space. But as we selectively choose the tasks that need interaction with an object and exclude the tasks such as reaching where no interaction is needed, there might be smaller gradient conflict than the metaworld environment. Other baselines MT-SAC and MHMT-SAC show better performance than PCGrad, but...
there are still large sample efficiency margins in the initial training process compared to the proposed one.

**VI. CONCLUSION AND FUTURE WORK**

In this work, we firstly present the unsupervised transferable manipulation skill discovery method for efficient adaptation to downstream tasks. We show that our method not only enables the agent to solve diverse, interaction-oriented exploration challenge without any external task reward but also distill the generated experience in the form of reusable task-agnostic skills. It brings significant improvement in sample efficiency when the skills are transferred to MTRL and GCRL even with multiple distractor objects. For future work, we would like to extend the idea into a reset-free or offline RL setting for developing more practical, real-world applicable algorithms.

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