Learning from Symmetry: Meta-Reinforcement Learning with Symmetric Data and Language Instructions

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Abstract—Meta-reinforcement learning (meta-RL) is a promising approach that enables the agent to learn new tasks quickly. However, most meta-RL algorithms show poor generalization in multiple-task scenarios due to the insufficient task information provided only by rewards. Language-conditioned meta-RL improves the generalization by matching language instructions and the agent’s behaviors. Learning from symmetry is an important form of human learning, therefore, combining symmetry and language instructions into meta-RL can help improve the algorithm’s generalization and learning efficiency. We thus propose a dual-MDP meta-reinforcement learning method that enables learning new tasks efficiently with symmetric data and language instructions. We evaluate our method in multiple challenging manipulation tasks, and experimental results show our method can greatly improve the generalization and efficiency of meta-reinforcement learning.

I. INTRODUCTION

Meta-reinforcement learning (meta-RL) is a promising approach that is aligned with the nature of human learning in understanding and adapting to new knowledge, where the agent interacts intensely with the environments of meta-training tasks in individual Markov Decision Processes (MDPs) to learn the meta-training tasks and expects to be capable of readily generalizing to new tasks that were never experienced during the meta-training phase, but drawn from the same family of the meta-training tasks. Meta-RL enables the agent to learn new tasks quickly [1]–[3], but most agents perform poorly on a diverse set of tasks, such as Meta-World [4], since they only rely on rewards to bridge the agent to new tasks, which is not sufficiently informative for the agent to learn the new tasks from prior knowledge.

By applying natural language to meta-RL, language-conditioned meta-RL mimics the teaching process, i.e., iteratively describing tasks and correcting the inappropriate descriptions, to guide the agent to connect new tasks and prior knowledge, which shows good generalization in challenging task sets or complex scenarios [5], [6]. However, language-conditioned meta-RL is time-consuming and inefficient, because the agent needs to match the language instructions and behaviors through the trial-and-error process. To improve the generalization and efficiency of meta-RL, other forms of human learning are also considered, e.g., learning from symmetry. Symmetry is considered an important carrier of information, and humans have found that infants can distinguish symmetrical visual patterns [7], [8], which implies that learning from symmetry plays a key role in human learning. Being aware of this phenomenon, some studies take symmetry into account to accelerate the learning and improve the generalization of new tasks [9], [10], but they are applicable to simple tasks, such as the bandit problem [11], not to complex manipulation tasks.

Combining symmetry and language instructions might help improve the efficiency and generalization of meta-RL in complex manipulation tasks, which is similar to the human learning process. For example, when people learn to open a drawer with teachers’ guidance, they will naturally try to close the drawer at the same time without the instruction of closing the drawer, because the opening action and the closing action are symmetrical to each other [12]. In addition, people have the ability of spontaneous exploration with symmetry, thus it is easy for people to learn the closing action from the opening action. If the teacher tells them that the closing action corresponds to the drawer-close task, they will quickly learn the drawer-close task. However, few studies have focused on this issue in manipulation tasks problem at present. The reasons are twofold. Firstly, introducing symmetry or language instructions into meta-RL is rather a new topic, hence there is no general framework to deal with the problem. Secondly, most methods learn the symmetry knowledge of meta-training tasks, so as to learn new tasks by reshaping the reward function of the new tasks through the knowledge. This solution works in simple scenarios where the reward functions of new tasks and meta-training tasks are similar. However, in manipulation tasks, the reward functions of new tasks and meta-training tasks are totally different [4], thus it is difficult to directly reshape the new tasks’ reward function via the symmetry knowledge of meta-training tasks.

To investigate combining symmetry and language instructions into meta-RL in the manipulation tasks problem, this paper propose a dual-MDP meta-RL method. In particular, we focus on cooperating symmetric language instructions with the symmetric behaviors of meta-training tasks to learn meta-test tasks in manipulation tasks. The contributions of this work are summarized as follows:

• A novel concept that combines symmetry and language instructions into meta-RL is proposed, which can be easily used in on-policy meta-RL approaches to improve the adaptability and learning efficiency of meta-RL algorithms in manipulation tasks.
• Based on language-conditioned meta-RL, a dual-MDP meta-RL involves the concept is designed. The results prove that our method can improve the generalization and efficiency in learning new manipulation tasks.
II. RELATED WORK

Language-conditioned meta-reinforcement learning considers natural language instructions as a part of the task formulation [13]. For example, the task goal is specified by language instructions, and then the instructions are encoded into the observation space to drive the agent to interact with the environment according to the intention of the instructions, which is conducive for the agent to communicate with new tasks without enormous number of environment interactions so as to accelerate the learning of new tasks [5], [6].

Symmetry has been studied widely and with great success in computer vision. Most works capture images invariance transformations, such as rotation and symmetry, to augment data and reduce sample complexity to improve the algorithm [14]–[16], which is not always the case in RL. For example, if left-right symmetry is applied to the agent’s observation, the corresponding rewards for right and left actions will be reversed, which provides error signals to the agent [17]. Therefore, applying symmetry in RL requires specific rules.

Zinkevich et al. theoretically define symmetry in MDPs and propose that symmetry is conducive to accelerating learning [12]. Symmetry is introduced into the RL or meta-RL, which utilizes the symmetry in various ways [9], [10], [18]–[21]. A natural approach to explore symmetry is augmenting the training data with symmetry, e.g., Lin et al. augment the trajectories of manipulation tasks through symmetry transformation according to the prior knowledge of the training tasks [20], while this method is not applicable to the meta-RL problem. In addition, symmetries are considered during policy training, one way is to learn the data symmetry from sampled experience in the MDP to ensure sample efficiency [21]. Besides, other methods learn symmetry by customizing neural networks. Zhou et al. propose a method for meta-learning symmetries from image data by convolutional architectures searching [9]. Kirsch et al. introduce symmetries to a black-box meta-RL and show that symmetries do improve meta-generalization [10]. However, the above methods are confronted with a problem, that is, if the reward functions of the training tasks and new tasks are totally different, e.g., in the complex manipulation tasks, the above methods are confronted with a problem, that is, if the reward functions of the training tasks and new tasks are totally different, e.g., in the complex manipulation tasks, it is difficult for these methods to utilize the symmetry knowledge of meta-training tasks to learn new tasks well.

III. BACKGROUND

Meta-RL aims to train an agent on a meta-training set $D_{\text{train}}^T$ to quickly adapt to new unseen tasks from a meta-test set $D_{\text{test}}^T$, where the meta-training and the meta-test tasks are drawn from the same task distribution $p(T)$ [22]. This work proposes a dual-MDP method for learning new tasks from symmetric data generated by meta-training tasks based on language-conditioned meta-RL and adversarial inverse reinforcement learning. Therefore, the following sections provide a brief background on related methods.

A. Language-conditioned Meta-reinforcement Learning

Bing et al. proposes an on-policy meta-reinforcement learning algorithm, namely MILLION [6], that incorporates free-form language instructions and trial-and-error methods to improve the algorithm’s generalization, showing state-of-the-art performance on Meta-World benchmark [4]. In each episode, MILLION first interprets language instructions as instruction embedding and inserts the embedding into observation in the instruction phase, and then the agent performs the task’s MDP in the trial phase. If the agent successfully solves the task in the trial phase, the environment will be reset and a new trial phase will start immediately. In case of an unsuccessful trial phase, another instruction phase with new language instructions will start after the failure trail. MILLION forms the baseline of our proposed method.

B. Adversarial Inverse Reinforcement Learning

Adversarial inverse reinforcement learning (AIRL) [23] trains a policy against a discriminator that endeavors to distinguish the expert demonstrations from the policy generated demonstrations, thereby recovering a state-only reward function that is more generalized to changes in environment dynamics. A key focus in AIRL is on reversely learning rewards from expert demonstrations and yields the same optimal policy as the true rewards [24].

IV. METHODOLOGY

Our goal is to train an agent on a meta-training set $D_{\text{train}}^T$ and a symmetric task set $D_{\text{sym}}^T$, such that it can efficiently learn new tasks of $D_{\text{test}}^T$, where $D_{\text{sym}}^T$ is augmented from $D_{\text{train}}^T$ with symmetry, and the tasks of $D_{\text{sym}}^T$ resemble those of $D_{\text{test}}^T$, shown as Figure 1. Consequently, the agent performs the meta-training tasks’ MDPs and the symmetric tasks’ MDPs in the meta-training stage simultaneously. Then the agent adapts quickly to the new tasks of $D_{\text{test}}^T$ in the meta-test stage. The architecture of our method is shown in Figure 2.

The architecture consists of five modules, including an original MDP module, an symmetric data generator, an mixed AIRLs module, an environment reconstruction module and an symmetric MDP module. The data processing flow is as follows:

1. The original MDP module receives language instructions $L$ and performs the meta-training task MDP to generate success trajectories $\tau$ in trial phases.
2. The symmetric data generator receives the $L$ and $\tau$ of the meta-training task and generates the symmetric task’s language instructions $\tilde{L}$ and trajectories $\tilde{\tau}$.
3. The mixed AIRLs module processes the $\tilde{\tau}$ to recover the symmetric task’s reward function $\tilde{R}$.

Fig. 1. The symmetric task set $D_{\text{sym}}^T$ is augmented by $D_{\text{train}}^T$. The tasks of $D_{\text{sym}}^T$ resemble that of $D_{\text{test}}^T$. 

Fig. 2. The mixed AIRLs module processes the $\tau$ to recover the symmetric task’s reward function $\tilde{R}$. 

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Fig. 2. The mixed AIRLs module processes the $\tau$ to recover the symmetric task’s reward function $\tilde{R}$.
The environment reconstruction module builds the symmetric task environment $SEnv$ by reconstructing the meta-training task environment $Env$. The symmetric MDP receives the $\tilde{L}$ and performs the symmetric task MDP with the $\tilde{R}$ and $SEnv$, wherein the agent tries to learn the symmetric task of $D_{sym}^T$. Finally, the agent quickly adapts to the meta-test task in the meta-test phase.

The algorithm of our method is shown in **Algorithm 1**. In this section, we first define what are the symmetric tasks and introduce several symmetric tasks, and then describe each module in detail.

### A. Symmetric Tasks

**Definition 1**: Assume that there are two tasks sampled from the same task family. The agent solves these two tasks in individual MDPs, resulting in two trajectories $\tau_1$ and $\tau_2$, respectively. As illustrated in Figure 3 if the start point and end point of $\tau_1$ coincide with those of $\tau_2$ after the symmetry or exchange operation, then $\tau_1$ and $\tau_2$ are symmetrical to each other, and these two tasks are symmetric tasks.

Figure 3 visualizes six symmetric task families in the Mujoco simulation environment [25]. The yellow line with arrow represents part of the trajectory of the agent solving the task, and the red point represents the object key point $P_{key}$ that the agent manipulates when solving the task, and the green point indicates the task goal $P_{goal}$ to be achieved. $P_{key}$ and $P_{goal}$ are the start point and the end point of Definition 1, respectively. The whole trajectory $\tau$ can be divided into two parts: reaching trajectory $\tau_e$, and controlling trajectory $\tau_c$, where $\tau_e$ represents the trajectory of the agent from its initial state to reach the object key point $P_{key}$, and $\tau_c$ indicates the trajectory generated by the agent that controls the object key point $P_{key}$ to achieve the task goal $P_{goal}$.

### Algorithm 1 A dual-MDP Meta-RL

**Input**: $Ag$: an untrained agent; $L$: language instructions; $T$: the meta-training task; $\tilde{T}$: the meta-testing task.

**Output**: A trained agent

1. reward function $R \in T$ and environment $Env \in T$;
2. repeat
3. do MDPs of task $T$: $\text{OMDP}(Ag, Env, R, L)$;
4. until the agent $Ag$ solves the task $T$
5. collect success trajectory of $T$: $\tau \leftarrow \text{OMDP}$;
6. generate the trajectory and language instructions of the symmetric task $\tilde{T}$: $\tilde{\tau} \leftarrow \tilde{\text{OMDP}}(\tau)$ and $\tilde{L} \leftarrow \tilde{\text{OMDP}}(L)$;
7. recover a reward function for $\tilde{T}$: $\tilde{R} \leftarrow \text{AIRL}(\tilde{\tau})$;
8. $SEnv \in \tilde{T}$ is reconstructed by $Env$;
9. do MDPs of $\tilde{T}$: $\text{SMDP}(Ag, SEnv, \tilde{R}, \tilde{L})$;
10. adapt to the meta-test task in the meta-test phase.

Specifically,

\[
\tau = \tau_e + \tau_c
\]

\[
\tau_e = (s_0, a_0, s_1, a_1, ..., s_e, a_e)
\]

\[
\tau_c = (s_{e+1}, a_{e+1}, s_{e+2}, a_{e+2}, ..., s_N)
\]

\[
a = [\Delta x, \Delta y, \Delta z, f]
\]

\[
s = S_{obj} + S_{claw} = [\text{claw}_x, \text{claw}_y, \text{claw}_z, \text{obj}_x, \text{obj}_y, \text{obj}_z]
\]

where action $a$ represents the displacement and the force of the claw during a time step, state $s$ records the position of the claw and the object at the current time step, $e$ is the time step at which the agent reaches the key point $P_{key}$, and $s_N$ is the terminal state that achieves the MDP’s horizon.

### B. Original MDP and Symmetric MDP

The agent learns different tasks by interacting with different MDP environments, and each MDP can only contain the information of one task, otherwise the agent will be confused and unable to learn different tasks accurately. Thus the symmetric task MDP should be separated from the meta-training task MDP. In this work, the original MDP module performs the meta-training tasks’ MDPs, and the symmetric MDP (SMDP) module setups the symmetric tasks’ MDPs.
C. Environment Reconstruction

In each MDP set up by the SMDP module, the agent interacts with the environment $SEnv$ of the symmetric task $T$, which is slightly different from the environment $Env$ of the meta-training task $\hat{T}$. Thus the agent cannot learn $T$ and $\hat{T}$ in the same environment. Therefore, $SEnv$ needs to be built by reconstructing $\hat{Env}$. To take the drawer task family as an example, the initial state of the object (drawer) $S_{obj,0}$ in the original task (drawer closing) is “open”, while $\hat{S}_{obj,0}$ in the symmetric task (drawer opening) is “close”, and the object key point $P_{key}$ and the task goal $P_{goal}$ of the two tasks are also different. The meta-training task $T$ and its symmetric task $\hat{T}$ share the dynamics transition $P(s_{t+1}|s_t, a_t)$ and the object. Thus, building $SEnv$ requires obtaining $\hat{P}_{key}$, $\hat{P}_{goal}$ and $\hat{S}_{obj,0}$ by reconstructing $P_{key}$, $P_{goal}$ and $S_{obj,0}$ of $\hat{Env}$.

According to Definition 1, $\hat{P}_{key}$ and $\hat{P}_{goal}$ can be obtained by applying an exchange or symmetry operation to $P_{key}$ and $P_{goal}$ of the meta-training task $T$. For the task family in which the agent solves the task $T$, the object’s end state $\hat{S}_{obj,N}$ in the task $T$ shows no difference from the object’s initial state of the task $\hat{T}$, thus $\hat{S}_{obj,0} = S_{obj,N}$. Meanwhile, $\hat{P}_{key}$ and $\hat{P}_{goal}$ are obtained by exchanging $P_{key}$ and $P_{goal}$ of the task $T$. This is the case for the drawer, door and window task family in this work. For the task family in which the object’s initial state in the task $T$ is the same as that in the task $\hat{T}$, $\hat{S}_{obj,0} = S_{obj,0}$, such as the reach, push and faucet task family shown in Figure 4. Besides, there is a line parallel to the x or y axis and crossing through the midpoint of the object, and the $P_{goal}$ of the task $T$ are symmetrical about the line to generate the $\hat{P}_{key}$ and $\hat{P}_{goal}$ respectively, such as the blue dotted line in the push and faucet task family shown in Figure 4.

D. Symmetric Data Generator

The symmetric data generator module consists of two submodules: symmetric trajectory generator and symmetric language instructions generator.

1) Symmetric trajectory generator: The symmetric trajectory generator converts the meta-training task trajectory $\tau$ collected in a success trial in the original MDP module to the symmetric task trajectory $\hat{\tau}$. Specifically, the converting process includes converting the reaching trajectory $\tau_c$ to $\hat{\tau}_c$ and converting the controlling trajectory $\tau_e$ to $\hat{\tau}_e$ according to (2).

Converting $\tau_c$ to $\hat{\tau}_c$ must take into account the initial state $s_0$ and the reaching state $s_e$ when the agent reaches the key point $P_{key}$ in the meta-training task and the symmetric task. In the reach, push and faucet task family, the initial state of $\hat{\tau}_c$ is the same as that of $\tau_c$, and so is the reaching state. Therefore, the reaching trajectories of the two tasks in these task families are the same, i.e., $\hat{\tau}_c = \tau_c$. For other task families, not only is the initial state of $\hat{\tau}_c$ different from that of $\tau_c$, but also the reaching state is different, thus $\hat{\tau}_c \neq \tau_c$. To obtain $\hat{\tau}_c$, we design an action generator $G_a$, which generates actions for the agent to transition from the initial state to the reaching state. Consequently, $\hat{\tau}_c = \{s_0, G_a(s_0), ..., s_e, G_a(s_e)\}$, where $s_0$ is the initial state of the symmetric task environment.

\[
G_a(s) = clip(-1, 1, [obj_x - claw_x, obj_y - claw_y, obj_z - claw_z, f]) \tag{2}
\]

Converting $\tau_c$ to $\hat{\tau}_c$ must consider action construction rules. The actions of the trajectory $\tau_c$ are selected from the meta-training task’s policy $\pi(a|s)$, which cannot generate the actions of $\hat{\tau}_c$. However, the actions of $\hat{\tau}_c$ can be constructed by the actions of $\tau_c$ with specific construction rules, thus we define the following three action constructors:

\[
\begin{align*}
  a^1 &= [-a_{\Delta x}, a_{\Delta y}, a_{\Delta z}, a_f] \\
  a^2 &= [a_{\Delta x}, -a_{\Delta y}, a_{\Delta z}, a_f] \\
  a^3 &= [-a_{\Delta x}, -a_{\Delta y}, a_{\Delta z}, a_f]
\end{align*} \tag{3}
\]

where $-a_{\Delta x}$ represents the opposite number of $\Delta x$ in $a$.

The action constructor $a^1$ is applicable to the reach, push, faucet and window task shown in Figure 4 because the controlling trajectory $\tau_c$ of these tasks is symmetric with the controlling trajectory $\hat{\tau}_c$ of their symmetric task about the y axis (or the yz plane). Similarly, $a^2$ is applicable to the drawer task, and $a^3$ is applicable to the door task. Significantly, in the drawer, door and window task family, $\hat{P}_{key}$ and $\hat{P}_{goal}$ of the symmetric task are obtained by exchanging $P_{key}$ and $P_{goal}$ of the original task. Thus the action sequence of $\tau_c$ in these tasks is reverse to that of $\tau_c$ in their symmetric tasks. Therefore, the action sequence in $\hat{\tau}_c$ can be defined as $[\tau_c]$. For the reach, push and faucet
task family, the action sequence of the symmetric task can be defined as (5):

\[
a^m_{e+i} = a_{N-i+1}
\]

(4)

\[
a^m_{c+i} = a_{e+i}
\]

(5)

\[
\hat{s}_{e+i} = \hat{s}_{e+i-1} \oplus a^m_{e+i-1}
\]

(6)

\[
\hat{r}_c = \{\hat{s}_{e+1}, a^m_{e+1}, \hat{s}_{e+2}, a^m_{e+2}, \ldots, \hat{s}_N, a^m_N\}
\]

(7)

where \(a^m\) is the action constructor in \(\tilde{\mathcal{A}}\), \(m \in \{1, 2, 3\}\), according to what the task is, \(a\) is the action of \(\tau_c\), \(i \in \{1, 2, \ldots, N - \tilde{\tau}\}\). (6) is another expression of the symmetric task’s dynamics function \(P(\tilde{s}_{t+1}|\tilde{s}_t, \tilde{a}_t)\), and \(\hat{s}\) represents the state of \(\hat{r}_c\). Finally, the symmetric task’s controlling trajectory \(\hat{r}_c\) can be written as (7).

2) Symmetric language instructions generator: The language instructions generator interprets the language instructions \(L\) of the meta-training task \(\tilde{T}\) to generate the symmetric language instructions \(\hat{L}\) which has the opposite meaning to the \(L\) for the symmetric task.

Taking the drawer task as an example, \(L = \{\text{“close drawer”, “push forward the drawer handle”}\}\), while the corresponding symmetric instruction is \(\hat{L} = \{\text{“open drawer”, “pull backward the drawer handle”}\}\). Actually, this process has two steps: extracting the verb phrase of each language instruction and replacing it with an antonym verb phrase. Here a constituency parser [26] is considered, which extracts a constituency-based parse tree from a sentence that represents its syntactic structure. The extracting result of the language instruction “push forward the drawer handle” is shown in Figure 5 where the phrase “push forward” is verb phrase (VP). Then, the antonym phrase of the verb phrase is generated by WordNet [27], where WordNet is a lexical database in English and it links words into semantic relations including synonyms and antonyms. For each word in the verb phrase “push forward”, WordNet lists several antonyms in descending order of probability. As a result, the antonym verb phrase “pull backward” can be formed by selecting the highest probability antonym of each word. Finally the symmetric task’s language instructions \(\hat{L}\) can be obtained by replacing the verb phrase in \(L\) with the antonym verb phrase. Language instructions for all tasks are listed on our website.

E. Mixed AIRLs Module

The symmetric trajectory \(\hat{\tau}\) generated by the symmetric data generator is used for two purposes. One is to train an AIRL network to recover a stable and state-only reward function for the symmetric task \(\tilde{T}\), and the other is to serve as expert demonstrations that demonstrating to the agent to effectively solve \(\tilde{T}\) in the symmetric MDP module [28].

The mixed AIRLs module consists of several different AIRL networks, each of which is trained with the trajectories of the symmetric task of different task families. However, it is time-consuming and inefficient to train the agent algorithm and multiple AIRLs simultaneously. Therefore, first the agent algorithm is trained with the meta-training tasks, until the algorithm converges to a high success rate, resulting in an optimal policy \(\pi^*\). Then \(\pi^*\) is applied to generate huge amount of \(\tau\) for the symmetric data generator to generate symmetric task’s trajectories \(\hat{\tau}\). Next the AIRL network is trained off-line with \(\hat{\tau}\) to recover the symmetric task’s reward function \(\tilde{R}\) that is used in the symmetric MDP. Finally, we train our whole algorithm without training AIRLs.

When the training of \(\text{AIRL}_{\tilde{T}}\) finishes, we obtain an optimal AIRL policy and a state-only reward function \(\tilde{R}\) recovered by the discriminator for the symmetric task \(\tilde{T}\). Similarly, the mixed AIRLs module recovers reward functions for the symmetric task set \(D^\text{sym}\) of each task family. The maximum reward of the recovered reward function \(\tilde{R}\) is two orders of magnitude smaller than that of the ground-truth reward function provided by Meta-World [4]. To alleviate the impact of the small numerical scale of \(\tilde{R}\) in training the agent, the rewards of \(\tilde{R}\) are rescaled to (0, 2000).

V. Experiments

Figure 6 shows the performance of the recovered reward function \(\tilde{R}\) and the corresponding ground-truth reward function of the symmetric task. We can see: (1) the agent can solve the task through the optimal policy \(\pi^*\) of the task \(\text{AIRL}\), showing that the \(\text{AIRL}\) policy trained with the generated symmetric trajectories \(\hat{\tau}\) can solve the corresponding symmetric task; (2) \(\tilde{R}\) shows asymptotic performance with the corresponding ground-truth reward function, indicating that the reward function recovered by \(\text{AIRL}\) performs as well as the ground-truth reward function.

We first evaluate our method and the baseline method, namely MILLION [6], shown as Figure 7. Firstly, our method can successfully solve the meta-training and the meta-test task in each task family, while MILLION performs poorly in

![Fig. 6. The performance comparison between the symmetric task’s recovered reward function and the ground-truth reward function provided by Meta-World [4]. The results of each task are generated from the agent by following the optimal AIRL policy in 200 episodes, each of which has 300 time steps. The red dashed dotted line indicates the average time step which the agent successfully solves the task. Other comparison results can be found on our website.](https://tumi6robot.wixsite.com/symmetry/)
In this paper, we propose a dual-MDP meta-RL method combining the symmetry and language instructions to improve the algorithm’s generalization and learning efficiency. In our method, the agent learns the meta-training task and the symmetric task in the meta-training stage at the same time, where the symmetric task is generated by the original task with symmetry and is similar to the meta-test task. Thus the agent can adapt quickly to the meta-test task in the meta-test stage. Learning from symmetry and language is one of the task setting with all task families, shown as Figure 8. Our method shows asymptotic performance with MILLION in the meta-training tasks, while the average success rate of our method and MILLION in the meta-test tasks are 0.843 and 0.458, respectively, which shows that our method still has stable performance in the multi-tasks scenario. Furthermore, we conduct a comparative experiment with the state-of-the-art method of the Meta-World benchmark [4], namely RL²-PPO, shown in Table I. Although our method performs slightly worse than MILLION on the meta-training set, the performance of our method is far better than that of the other two methods on the meta-test set.

Finally, real robot experiments in the reach task family with multiple task goals are carried out, shown as Figure 9. We transfer the policy learned from the Mujoco simulation to the real world and set different task goals to verify the generalization of the policy. The result shows that the policy has good generalization in solving the reach family tasks. What’s more, it is interesting to note that the trajectories of the reach-left and reach-right tasks are nearly symmetrical.

VI. CONCLUSIONS AND OUTLOOK

In this paper, we propose a dual-MDP meta-RL method combining the symmetry and language instructions to improve the algorithm’s generalization and learning efficiency. In our method, the agent learns the meta-training task and the symmetric task in the meta-training stage at the same time, where the symmetric task is generated by the original task with symmetry and is similar to the meta-test task. Thus the agent can adapt quickly to the meta-test task in the meta-test stage. Learning from symmetry and language is one of the

In addition, we also evaluate the two methods in a multi-stage. Learning from symmetry and language is one of the
most important forms of human learning, which might bring more inspiration to improve meta-RL.

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