Learning Hierarchical Teaching in Cooperative Multiagent Reinforcement Learning

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Abstract

Heterogeneous knowledge naturally arises among different agents in cooperative multiagent reinforcement learning. As such, learning can be greatly improved if agents can effectively pass their knowledge on to other agents. Existing work has demonstrated that peer-to-peer knowledge transfer, a process referred to as action advising, improves team-wide learning. In contrast to previous frameworks that advise at the level of primitive actions, we aim to learn high-level teaching policies that decide when and what high-level action (e.g., sub-goal) to advise a teammate. We introduce a new learning to teach framework, called hierarchical multiagent teaching (HMAT). The proposed framework solves difficulties faced by prior work on multiagent teaching when operating in domains with long horizons, delayed rewards, and continuous states/actions by leveraging temporal abstraction and deep function approximation. Our empirical evaluations show that HMAT accelerates team-wide learning progress in difficult environments that are more complex than those explored in previous work. HMAT also learns teaching policies that can be transferred to different teammates/tasks and can even teach teammates with heterogeneous action spaces.

1. Introduction

In cooperative multiagent reinforcement learning (MARL), agents commonly develop their own knowledge of a domain. In analogy to human social groups, the collective intelligence of MARL agents may be greatly boosted if agents share their individual learning. The fundamental problem that we address in this paper is to develop a method to enable agents to effectively pass on their knowledge and/or learn from their peers.

Several recent frameworks allow a wide variety of transferring different types of knowledge (e.g., policy transfer, value function transfer) (Taylor & Stone, 2009). In this paper we focus on transfer based on action advising, where an experienced “teacher” agent helps a less experienced “student” agent, by suggesting which action to take next. Compared to sharing other types of knowledge, action advising allows a student to directly execute suggested actions without incurring much computation overhead. Works on action advising includes the recent Learning to Coordinate and Teach Reinforcement (LeCTR) framework of Omidshafiei et al. (2018), in which the agents learn when and what actions to advise. While LeCTR significantly improves learning performance compared to prior teaching methods that advise based on various heuristics (Clouse, 1996; Torrey & Taylor, 2013; Amir et al., 2016; da Silva et al., 2017), it faces limitations in scaling to more complicated tasks with high-dimension state-action spaces and longer time horizons. The key issue in LeCTR is teacher credit assignment: learning teacher policies requires estimates of the impact of each piece of advice on the student agent’s learning progress, but these estimates are difficult to obtain. As such, the approach is limited to simple function approximations (e.g., tile coding) and uses an online policy update that stabilizes learning of teaching policies.

This paper proposes a new learning to teach framework, hierarchical multiagent teaching (HMAT), which extends the approach of Omidshafiei et al. (2018) to address these limitations. Scalability is improved by representing agent policies with hierarchical reinforcement learning (HRL) (Sutton et al., 1999; Kulkarni et al., 2016; Nachum et al., 2018) and nonlinear function approximations (e.g., deep neural networks (DNNs)), which avoids advising only at the level of basic (primitive) actions and eliminates the use of tile coding. However, there are numerous technical challenges to overcome first. For example, the aforementioned teacher credit assignment issue becomes more significant due to deep function approximations. DNNs use mini-batches for stable learning (Goodfellow et al., 2016), and these mini-batches can be randomly selected from a replay memory (Mnih et al.,
As a result, a student’s progress is affected by a batch of advice suggested at varying times, and identifying the amount that each piece of advice contributed to the student’s learning becomes very difficult. Similarly, choosing advice is challenging since teachers must not only convey their best action choices, but also guide students to explore when necessary. Partial observability, delayed rewards, and large state spaces provide additional challenges.

HMAT addresses these challenges with an improved algorithm, resolves the teacher credit assignment issue, and learns high-level teacher policies that advise one another to take high-level actions (e.g., sub-goal). As our empirical evaluations demonstrate, HMAT offers multiple advantages. For example, HMAT can accelerate team-wide learning progress for complex tasks. Challenges, such as long horizons, delayed rewards, and high-dimensional states, are addressed via temporal abstractions of HRL and deep function approximations. Agents can also learn teaching policies that are transferable to different types of agents and/or tasks. Finally, agents can have different dynamics/action spaces because the high-level teaching enables knowledge transfer that is agnostic to these details.

2. Background

We consider a cooperative MARL setting in which \( n \) agents jointly interact in the environment, then receive feedback via local observations and a shared team reward. This setting can be formalized as a decentralized POMDP (Dec-POMDP), defined as a tuple \((\mathcal{I}, \mathcal{S}, \mathcal{A}, \mathcal{T}, \Omega, \mathcal{O}, \mathcal{R}, \gamma)\) (Oliehoek & Amato, 2016); \( \mathcal{I} = \{1, \ldots, n\} \) is the set of agents, \( \mathcal{S} \) is the set of states, \( \mathcal{A} = \times_{i \in \mathcal{I}} \mathcal{A}^i \) is the set of joint actions, \( \mathcal{T} \) is the transition probability function, \( \Omega = \times_{i \in \mathcal{I}} \Omega^i \) is the set of joint observations, \( \mathcal{O} \) is the observation probability function, \( \mathcal{R} \) is the reward function, and \( \gamma \in [0, 1) \) is the discount factor. At each timestep \( t \), each agent \( i \) executes an action according to its policy \( a_t^i \sim \pi^i(h_t^i; \theta^i) \) parameterized by \( \theta^i \), where \( h_t^i = (o_t^0, \ldots, o_t^n) \) is the observation history. Joint action \( a_t = \{a_t^1, \ldots, a_t^n\} \) yields a transition from current state \( s_t \in \mathcal{S} \) to next state \( s_{t+1} \in \mathcal{S} \) with probability \( \mathcal{T}(s_{t+1}|s_t, a_t) \). Then, a joint observation \( o_{t+1} = \{o_{t+1}^1, \ldots, o_{t+1}^n\} \) is obtained and the team receives a shared reward \( r_t = \mathcal{R}(s_t, a_t) \). The agents’ objective is to maximize the expected cumulative reward \( \mathbb{E}[\sum_t \gamma^t r_t] \). To simplify notation, the observation history and the policy parameter will often be omitted, but we use the most recent observation when discussing an action according to a policy or computing a Q-value (e.g., \( \pi^i(h_t^i; \theta^i) \equiv \pi^i(o_t^i) \)).

2.1. Learning to Teach in Cooperative MARL

We review key concepts and notations in the learning to teach framework (LeCTR) (Omidshafiei et al., 2018) that are related to developing our new method.

Task-Level Learning Problem LeCTR considers a cooperative MARL setting with two agents \( i \) and \( j \) in a shared environment. At each learning iteration, agents interact in the environment, collect experiences, and update their policies, \( \pi^i \) and \( \pi^j \), with learning algorithms, \( \mathcal{L}^i \) and \( \mathcal{L}^j \). The resulting policies aim to coordinate and optimize final task performance. This problem of learning task-related policies is referred to as the task-level learning problem \( \mathcal{P}_{\text{Task}} \).

Advice-Level Learning Problem Throughout task-level learning, without assuming any agents to be experts, each agent may still learn skills and local knowledge from its unique experiences. Hence it is potentially beneficial for agents to advise one another using their local knowledge, in order to improve final performance and accelerate team-wide learning. The problem of learning teacher policies that decide when and what to advise is referred to as the advice-level learning problem, \( \mathcal{P}_{\text{Advise}} \).

Learning task-level policies and advice-level policies are both reinforcement learning problems, interleaved in the learn to teach framework. However, there are important differences between \( \mathcal{P}_{\text{Task}} \) and \( \mathcal{P}_{\text{Advise}} \). One difference lies in the definition of learning episodes. For \( \mathcal{P}_{\text{Task}} \), an episode terminates either when agents arrive at terminal states or a timestep \( t \) exceeds a prespecified value \( T \). By contrast, for \( \mathcal{P}_{\text{Advise}} \), an episode ends when task-level policies have converged, forming one “episode” for learning teaching policies. Upon completion of the advising-level episode, task-level policies are re-initialized and training proceeds for another advising-level episode. To avoid confusion, we refer to an episode as one task-level problem episode and a session as one advice-level problem episode (see Figure 1). Moreover, \( \mathcal{P}_{\text{Task}} \) and \( \mathcal{P}_{\text{Advise}} \) have different learning objectives. The task-level learning aims to coordinate and maximize the cumulative environment reward in an episode, whereas the advice-level learning aims to maximize the cumulative teacher reward in a session, which corresponds to accelerating team-wide learning progress (i.e., a maximum area under the learning curve in one session). Lastly, task-level policies are inherently off-policy while teacher policies are not necessarily off-policy. This is because task-level policies are updated with experiences affected by teacher policies, instead of experiences generated by task-level policies alone.

2.2. Hierarchical Reinforcement Learning

Hierarchical reinforcement learning (HRL) is a structured framework with multi-level reasoning and extended temporal abstraction (Parr & Russell, 1998; Sutton et al., 1999; Dietterich, 2000; Kulkarni et al., 2016; Bacon et al., 2017; Vezhnevets et al., 2017; Riemer et al., 2018). HRL eff-
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3. Overview of HMAT

HMAT addresses the aforementioned limitations of LeCTR (e.g., scalability) by using HRL and deep function approximations. Specifically, we learn high-level function policies that learn when and what high-level actions (e.g., sub-goal) to advise fellow agents. We first provide an overview of our approach, and then discuss our algorithm in detail.

3.1. Deep hierarchical Task-Level Policy

To extend task-level policies with hierarchical representations and DNNs, we replace \( \pi^i \) and \( \pi^j \) with deep hierarchical policies consisting of manager policies, \( \pi^i_M \) and \( \pi^j_M \), and worker policies, \( \pi^i_W \) and \( \pi^j_W \) (see Figure 2). Manager and worker policies have different objectives. Manager policies learn to accomplish a task together (i.e., solving \( P_{\text{task}} \)) by optimizing the cumulative environment reward. By contrast, worker policies are trained to successfully reach sub-goals suggested by managers.

3.2. Advice-Level Learning in Hierarchical Settings

For a hierarchical setting, we consider sharing heterogeneous knowledge between manager policies via teacher policies, \( \tilde{\pi}^i \) and \( \tilde{\pi}^j \), which learn when and what sub-goal actions to advise. Consider Figure 2, where agents are learning to coordinate with hierarchical task-level policies (i.e., solving \( P_{\text{task}} \)) while advising one another via teacher policies (i.e., solving \( P_{\text{Advice}} \)). There are two roles in Figure 2: that of a student agent \( j \) (i.e., an agent whose manager policy receives advice) and that of a teacher agent \( i \) (i.e., an agent whose teacher policy gives advice). Note that agents \( i \) and \( j \) can simultaneously teach each other, but, for clarity, Figure 2 only shows a one-way interaction. Here, student \( j \) has decided that it is appropriate to strive for sub-goal \( g^j \) by querying its manager policy. Before \( j \) passes the sub-goal \( g^j \) to its worker, \( i \)'s teaching policy checks \( j \)'s intended sub-goal; considers \( i \) and \( j \)'s heterogeneous knowledge at the task-level; and decides whether to advise or not. Having decided to advise, \( i \) transforms its local task-level knowledge into desirable sub-goal advice via its teacher policy and suggests it to \( j \). After student \( j \) accepts the advice from the teacher, the updated sub-goal \( g^j \) is passed to \( j \)'s worker policy, which then generates a primitive action \( a^j \).
4. Details of HMAT

This section explains in detail how challenges in HMAT (e.g., teacher credit assignment issue) are addressed, and remaining components about the algorithm are clarified.

4.1. Algorithm of Hierarchical Multiagent Teaching

HMAT iterates over the following three phases to simultaneously learn how to coordinate with deep hierarchical task-level policies (i.e., solving $P_{\text{Task}}$) and how to advise one another via teacher policies (i.e., solving $P_{\text{Advise}}$).

**Phase I (Advising Phase)** Agents advise one another via teacher policies according to the advising protocol (see section 3.2) during one episode. This process generates a batch of task-level experiences influenced by teachers.

**Phase II (Advice Evaluation Phase)** This phase evaluates and estimates the amount of advice impact on improving team-wide learning progress. This process yields the teacher reward for the advice given in the advising phase.

**Phase III (Policy Update Phase)** Task-level policies are updated to solve $P_{\text{Task}}$ by using their learning algorithms, $L^t$ and $L^j$. Similarly, advice-level policies are updated to solve $P_{\text{Advise}}$ by using their learning algorithms, $L^t$ and $L^j$.

4.1.1. Teacher Credit Assignment

The above phases are designed to address a teacher credit assignment issue, especially when task-level policies are represented by DNNs, and a replay memory is used. In such setting, identifying which portions of advice led to successful student learning is difficult. For instance, given teacher advice $\tilde{g}_i^j$, teacher $i$ requires feedback that reflects the impact of the advice on agents $j$’s learning progress at timestep $t$. If agent $j$ updates its task policy with a mini-batch of experiences with random samples, then it is unclear how much the advice $\tilde{g}_i^j$ contributed to its learning improvement at timestep $t$. As a result, an accurate estimate of the teacher reward is a major issue in our settings.

We address the teacher credit assignment issue by adopting ideas developed for learning an exploration policy for a single agent (Xu et al., 2018): an enlarged MDP view and the use of the temporary policy for measuring a reward for the exploration policy. These two ideas are extended from a single-agent learning to exploration setting into our multiagent learning to teach setting.

4.1.2. Details of Each Phase

**Phase I (Advising Phase)** We enlarge a view of teacher policies by providing multiple sub-goal advice, $g_{0:T} = \{\tilde{g}_0^0, \tilde{g}_0^1\}$, instead of providing one advice $g_t = \{\tilde{g}_t^0, \tilde{g}_t^1\}$, before updating task-level policies. This contrasts to previous teaching approaches, where task-level policies are updated based on a single advice (Torrey & Taylor, 2013; Amir et al., 2016; Omidshafiei et al., 2018). One teacher action in this enlarged view corresponds to providing multiple advice during one episode. Following advice $\tilde{g}_{0:T}$ in an episode, a batch of task-level experiences for agent $i$ and $j$, $E_{\text{Advice}}^{g_{0:T}} = \{(o_{0:t}^i, \tilde{g}_{0:t}^i, r_{0:t}^i, o_{0:t}^j), (o_{0:t}^j, \tilde{g}_{0:t}^j, r_{0:t}^j, o_{0:t}^i)\}$, are generated to enable stable mini-batch update of DNN policies.

**Phase II (Advice Evaluation Phase)** Learning teacher policies requires the teacher reward as a result of providing advice at the advising phase. As in Xu et al. (2018), we utilize temporary task-level policies to estimate the teacher reward for $g_{0:T}$. Specifically, agents copy their current task-level policies to temporary task-level policies (i.e., $\pi_{\text{temp}} \leftarrow \pi$). To measure the teacher reward for $g_{0:T}$, $\pi_{\text{temp}}$ are updated a small number of iterations by only using $E_{\text{Advice}}^{g_{0:T}}$ (i.e., $\pi_{\text{temp}} \leftarrow L(\pi_{\text{temp}}, E_{\text{Advice}}^{g_{0:T}})$). Then, the updated temporary policies generate a batch of self-practice experiences $E_{\text{Self-prac}}$ by rolling out a total of $T$ timesteps without involving teacher policies. The self-practice experiences, which are based on $\pi_{\text{temp}}$, are important: they reflect how agents by themselves would perform after one advising phase and can be used to estimate the impact of $g_{0:T}$ on the team-wide learning. Thus, a teacher reward function $R$ (section 4.2) uses the self-practice experiences and returns the teacher reward for $g_{0:T}$ (i.e., $\bar{r} = R(E_{\text{Self-prac}}^{g_{0:T}})$).

**Phase III (Policy Update Phase)** Note that the temporary policies $\pi_{\text{temp}}$ used to measure $\bar{r}$ in Phase II are updated only based on $E_{\text{Advice}}^{g_{0:T}}$, so experiences from the past iterations are not utilized. Task-level policies, $\pi^t$ and $\pi^j$, are updated for the next iteration by randomly sampling experiences from the task-level experience memories, $D^t$ and $D^j$, and efficiently learn from experiences from the past iterations. As in (Xu et al., 2018), both $E_{\text{Advice}}^{g_{0:T}}$ and $E_{\text{Self-prac}}^{g_{0:T}}$ are added to the task-level memories. Similarly, teacher policies add the teacher experience collected from the advising (Phase I) and advice evaluation phases (Phase II) to the team-level experience memories, $D^t$ and $D^j$. Teacher policies are also updated by randomly selecting samples from the replay memories, but at a slower update frequency than those of task-level policies.

4.2. Details of Teacher Policy

**Teacher Observation and Action** The teacher policy decides when and what to advise, considering heterogeneous knowledge between the teacher and student agent. Teacher-level observations $\tilde{g}_t = \{\tilde{g}_t^0, \tilde{g}_t^1\}$ compactly provide information about heterogeneous knowledge between the two.

$g_{0:T} = (g_0^0, g_1^0, g_2^0, \ldots, g_T^0)$ denotes multiple sub-goals in one episode.
While agents can simultaneously advise one another, for clarity, we detail the teacher observation when agents $i$ and $j$ are the teacher and student agent, respectively (Figure 2). For agent $i$’s teacher policy, its observation $\tilde{o}_i$ consists of:

$$\tilde{o}_i = \{o_i, g_i, g_i^j, Q_i(\tilde{o}_i, g_i, g_i^j), Q^j(\tilde{o}_i, g_i, g_i^j), t_{\text{remain}}\}_{\text{Teacher Knowledge}}$$

where $o_i = \{o_i^j, o_i^s\}; g_i^j \sim \pi^j(o_i^j); g_i \sim \pi^i(o_i^s); g_i^j \sim \pi^j(o_i^s); Q^i, Q^j$ are the centralized critics for agent $i$ and $j$, respectively; and $t_{\text{remain}}$ is the remaining time in current session.

Given a teacher observation $\tilde{o}_i$, teacher $i$ decides what to advise: one action for deciding whether to or not to advise; the other action for the sub-goal advice. If no advice, student $j$ executes its originally intended sub-goal.

**Teacher Reward Function** The objective of teacher policies is to maximize the cumulative teacher reward in a session that should result in accelerating team-wide learning progress. Recall in Phase II that the batch of self-practice experiences reflects how agents by themselves perform after one advising phase. The open question is to identify an appropriate teacher reward function $R_T$ that can transform the self-practice experiences into the learning performance. Intuitively, maximizing the reward returned by a teacher reward function $\tilde{r} = R_T(E_{\text{self-prac}})$ means that teachers should advise such that the learning performance is maximized after one advising phase. We evaluate many choices of teacher reward functions, including the ones in Omidshafehi et al. (2018) and Xu et al. (2018), as described in Table 1. To induce cooperative behavior between the two teacher policies, a reward function returns a joint teacher reward: $\tilde{r} = \tilde{r}^i + \tilde{r}^j$.

**Teacher Experience** We summarize what consists of a teacher experience in the *enlarged* teacher perspective. We again focus on teacher $i$ for clarity. One teacher experience corresponds to $E_{0:T}^i = (\tilde{o}_{0:T}^i, g_{0:T}^i, \tilde{r}, \tilde{o}_{0:T}^j)$ is a teacher observation; $\tilde{o}_{0:T}^i = (\tilde{o}_{0:T}^i, \tilde{o}_{0:T}^j, \tilde{o}_{0:T}^j, \tilde{o}_{0:T}^j)$ is a teacher action; $\tilde{r}$ is an estimated teacher reward with $\tilde{R}$; and $\tilde{o}_{0:T}^j = (\tilde{o}_{0:T}^j, \tilde{o}_{0:T}^j, \tilde{o}_{0:T}^j, \tilde{o}_{0:T}^j)$ is a next teacher observation, obtained by updating $\tilde{o}_{0:T}^j$ with the updated temporary policy $\pi_{\text{temp}}^j$ (i.e., representing the change in student $j$’s knowledge due to advice $g_{0:T}^j$). Experience $E_{0:T}^i$ can be stored in a teacher replay memory $D^i$ and sampled to update teacher policies.

### 4.3. Training Protocol

**Task-Level Training** To accommodate the fact that task-level policies in the learning to teach framework are inherently off-policy (section 2.1), we utilize an off-policy learning algorithm, the twin delayed deep deterministic policy gradients (TD3) (Fujimoto et al., 2018) to train the worker and manager policies. TD3 is an actor-critic algorithm which introduces two critics, $Q_1$ and $Q_2$, to reduce overestimation of Q-value estimate in deep deterministic policy gradient algorithm (DDPG) (Lillicrap et al., 2015) and yields more robust learning performance. Originally, TD3 is a single-agent deep RL algorithm accommodating continuous spaces/actions. Here, we extend TD3 to multi-agent settings with a resulting algorithm termed MATD3, and the non-stationarities in MARL is addressed by applying centralized critics/decentralized actors (Lowe et al., 2017; Foerster et al., 2017). In MATD3, an agent $i$’s task policy critics, $Q_1^i$ and $Q_2^i$, minimize the following critic loss:

$$L = \sum_{\alpha=1}^{2} \mathbb{E}_{o, g, r, o', r' \sim D^i} \left[ y - Q_\alpha(o, g) \right]^2,$$

s.t. $y = r + \gamma \min_{\beta=1,2} Q_\beta^{\text{target}}(o', \pi^{\text{target}}(o') + \epsilon)$,

where $o = \{o^i, o^j\}; g = \{g^i, g^j\}; o' = \{o'^i, o'^j\}; \pi^{\text{target}} = \{\pi^{\text{target}}_i, \pi^{\text{target}}_j\};$ the subscript “target” denotes the target network; and $\epsilon \sim N(0, \sigma)$. The agent $i$’s actor policy $\pi^i$ with parameter $\theta^i$ is updated by:

$$\nabla_{\theta^i} J(\theta^i) = \mathbb{E}_{o, g \sim D^i} \left[ \nabla_{\theta^i} \pi^i(g|o') \nabla_{r} Q_2(o, g) \right],$$

where $o = \{o^i, o^j\}; g = \{g^i, g^j\}; o' = \{o'^i, o'^j\}; \pi^{\text{target}} = \{\pi^{\text{target}}_i, \pi^{\text{target}}_j\}$. The agent $i$’s actor policy $\pi^i$ with parameter $\theta^i$ is updated by:

$$\nabla_{\theta^i} J(\theta^i) = \mathbb{E}_{o, g \sim D^i} \left[ \nabla_{\theta^i} \pi^i(g|o') \nabla_{r} Q_2(o, g) \right],$$

where $z = \nabla_{\theta^i} \pi^i(g|o') \nabla_{r} Q_2(o, g) |_{g = \pi(o)}$. Pseudocode of HMAT is presented in Algorithm 1.

### 5. Related Work

Action advising is not only the possible approach to transfer knowledge. Works on imitation learning study how to learn a policy from expert demonstrations (Ross et al., 2011; Ross & Bagnell, 2014; Daswani et al., 2015). Recent work applied imitation learning for multiagent coordination (Le et al., 2017). The same authors also explored effective ways to combine imitation learning and reinforcement learning (Le et al., 2018) in hierarchical settings. The field of curriculum learning (Bengio et al., 2009; Tsvetkov et al., 2016;...
Copy temporary task-level policies: \( \tilde{E}(E_{0:T}^{\text{self-prac.}}) \)

Table 1. Summary of teacher reward functions \( \tilde{R} \). Rollout reward \( \tilde{R} \) denotes the sum of rewards in the self-practice experiences \( \tilde{E}(E_{0:T}^{\text{self-prac.}}) \) (see the supplementary material for more detail).

| Teacher Reward Name | Description | Teacher Reward \( \tilde{R} \) |
|---------------------|-------------|-----------------------------|
| VEG: Value Estimation Gain | Student’s Q-value above threshold \( \tau \) (Omidshafiei et al., 2018) | \( I(Q_{\text{student}} > \tau) \) |
| DR: Difference Rollout | Difference in rollout reward before/after advising (Xu et al., 2018) | \( \tilde{R} - \tilde{R}_{\text{before}} \) |
| CR: Current Rollout | Rollout reward after advising phase | \( \tilde{R} \) |

Algorithm 1 HMAT Pseudocode

Require: Maximum number of episodes in session \( S \)

Require: Teacher update frequency \( f_{\text{teacher}} \)

1: Initialize advice-level policies \( \pi \) and memories \( \tilde{D} \)

2: for teaching session \( S \) do

3: Re-initialize task-level policy parameters \( \pi \)

4: Re-initialize task-level memories \( D \)

5: Re-initialize train episode count: \( e = 0 \)

6: while \( e \leq S \) do

7: Phase I

8: Update episode count: \( e \leftarrow e + 1 \)

9: Re-initialize task-level policies: \( \pi_{\text{temp}} \leftarrow \pi \)

10: Update to \( \pi_{\text{temp}} \) using Eqn (1)–(2) with \( E_{0:T}^{\text{advise}} \)

11: Phase II

12: Update episode count: \( e \leftarrow e + 1 \)

13: \( \tilde{R} \leftarrow \) Get teacher reward with \( \tilde{R} \)

14: Add \( E_{0:T}^{\text{advise}} \) and \( E_{0:T}^{\text{self-prac.}} \) to \( D \)

15: Add a teacher experience \( E_{0:T} \) to \( \tilde{D} \)

16: Phase III

17: if \( e \mod f_{\text{teacher}} == 0 \) then

18: Update \( \pi \) using Eqn (3)–(4) with \( \tilde{D} \)

19: end if

20: end while

21: end for

Graves et al., 2017) is also relevant. Works on curriculum learning measure or learn the hardiness of tasks, and design a curriculum for a learning agent to follow. Curriculum learning has many applications, including recent works that learn a training data curriculum for an image classifier (Fan et al., 2018; Jiang et al., 2018). While these works study diffusion of knowledge for solving single agent problems, we study peer-to-peer knowledge transfer in MARL.

Related work by Xu et al. (2018) learns an exploration policy (i.e., mean and standard deviation of a Gaussian noise) for a single agent policy, but there are several key differences between this work and Xu et al. (2018). First, Xu et al. (2018) learns an exploration policy in a single-agent/primitive RL setting, but our approach learns teacher policies that transfer heterogeneous knowledge by sub-goal advising in a multiagent/hierarchical RL setting. Second, the exploration policy of Xu et al. (2018) is updated based on a variant of REIN-
other agent, the box will follow a curved path taking a longer time to reach the target. The domain returns a team reward \( r_t = -||\text{loc}(\text{target}) - \text{loc}(\text{box})||^2 \), but this is a delayed reward because there is no change in reward until the box is moved by the two agents.

Cooperative Two Box Push Domain This domain is similar to the one box domain but with increased complexity. There are two round boxes in the domain (Figure 4). The objective is to move box 1 to the left target (target 1) and box 2 to the right target (target 2). In addition, the boxes have different mass – box 1 is three times heavier than box 2. The domain returns a team reward \( r_t = -\{||\text{loc}(\text{target}1) - \text{loc}(\text{box}1)||^2 + ||\text{loc}(\text{target}2) - \text{loc}(\text{box}2)||^2\} \).

6.1.1. Tasks with Heterogeneous Knowledge

For each domain, we provide each agent with different prior knowledge to ensure heterogeneous knowledge between the agents and motivate interesting teaching scenarios.

Cooperative One Box Push Domain (Figure 3) Agent \( i \) and \( j \) have prior knowledge about how to move the box to the target. Then, agents \( i \) and \( k \) are teamed up, and agent \( k \) has no knowledge about the domain. Agent \( i \), which understands how to move the box, should teach agent \( k \), and by giving good advice, it will improve \( k \)’s learning progress.

Cooperative Two Box Push Domain (Figure 4) Agents \( i \) and \( j \) have prior knowledge about how to move box 1 to target 1, and agents \( k \) and \( l \) understand how to move box 2 to target 2. However, these two teams have different skills as the tasks involve moving boxes with different weights (light vs heavy) and also in different directions (left vs right). Then agents \( i \) and \( k \) are teamed up, and in this scenario, agent \( i \) should transfer its knowledge about moving box 1 to agent \( k \). Simultaneously agent \( k \) should teach agent \( i \) how to move box 2, so there is a two-way transfer of knowledge.

6.2. Baselines

Several baselines (see supplementary material for details) are compared to HMAT. All methods employ centralized critics/decentralized actors (Lowe et al., 2017; Foerster et al., 2017) to mitigate the non-stationarities in MARL. Also, all HRL-based approaches use pre-trained worker policies that follow sub-goals suggested by manager policies.

Multiagent TD3 (MATD3) TD3 is extended to a cooperative MARL setting. This baseline is for a primitive MARL without teaching.

Hierarchical Multiagent TD3 (HMATD3) The MATD3 baseline is extended with HRL. This baseline is for a hierarchical MARL without teaching.

Importance Advising The MATD3 baseline is extended with importance advising (Torrey & Taylor, 2013), which is a heuristic-based teaching algorithm. Each teacher advises with its best action when the importance of a state \( I_{\text{teacher}} \) is larger than threshold \( \tau \): \( I_{\text{teacher}} = \max_a Q_{\text{teacher}}(o, a) - \min_a Q_{\text{teacher}}(o, a) > \tau \). This baseline is for a hierarchical MARL with a teacher-initiative heuristic teaching.

Ask Uncertain The HMATD3 baseline is extended with ask uncertain (Clouse, 1996), which is another heuristic-based teaching algorithm. Each student asks for advice when the importance of a state \( I_{\text{student}} \) is smaller than threshold \( \tau \): \( I_{\text{student}} = \max_a Q_{\text{student}}(o, a) - \min_a Q_{\text{student}}(o, a) < \tau \). When asked, a teacher agent advises with its best action at a given student state. This baseline is for a hierarchical MARL with a student-initiative heuristic teaching.

HMAT Variants We consider different variants of HMAT using different teacher reward function \( R \) in Table 1.

6.3. Results on One Box and Two Box Push

Table 2 compares the no-teaching, heuristics-based teaching, and HMAT (with varying teacher reward functions) approaches. The results show both final task-level performance (\( \bar{V} \)) and area under the task-level learning curve (AUC) – higher values are better for both metrics.

Comparisons between HMAT and no-teaching baselines (MATD3, HMATD3) demonstrate improved task-level learning performance with HMAT. Figures 5a and 5b illustrate that agents learning with HMAT show higher final performance (\( \bar{V} \)) and larger rate of learning (AUC). HMAT also attains the best performance in terms of \( \bar{V} \) and AUC, compared to heuristics-based baselines (importance advising, ask uncertain). Consistent with Amir et al. (2016), an interesting observation regarding the baselines is that the teacher-initiative heuristic (importance advising) outperforms the student-initiative heuristic (ask uncertain). This is likely a result of the fact that teachers have better knowledge than students and thus are better at determining when to give advice than students are at determining when to ask for it. Additionally, a poor choice of the heuristic can result in a worse result than no-teaching. For instance, with the ask uncertain heuristic in the one-box push domain, the student agent \( k \) asks for advice early-on as it does not understand the task well. Therefore, the teacher agent \( i \) advises with its best action (i.e., exploitation action), which results in relatively no exploration of the student \( k \) and worse performance than HMATD3. Finally, our empirical experiments show HMAT with CR performs the best. Consistent with this observation, the learning progress estimated with CR has a very high correlation with the true learning progress (see supplementary material). These combined results demonstrate the key advantage of our framework in that HMAT can accelerate team-wide learning progress for complex tasks with long horizons, delayed rewards, and continuous states/actions.
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Table 2. V̄ and Area under the Curve (AUC) for different algorithms. Best results in bold (computed via a t-test with p < 0.05). Results show a mean and a standard deviation computed for 10 sessions. † denotes final version of HMAT using the CR reward function.

| Algorithm      | Hierarchical? | Teaching? | One Box Push | Two Box Push |
|----------------|---------------|-----------|--------------|--------------|
|                |               |           | V̄           | AUC          | V̄           | AUC          |
| MATD3          | x             | x         | −11.43 ± 0.54| 164 ± 35     | −47.09 ± 4.08| 254 ± 55     |
| HMATD3         | ✓             | x         | −10.36 ± 0.19| 418 ± 09     | −31.55 ± 3.51| 776 ± 67     |
| Import. Advising | ✓             | ✓         | −10.40 ± 0.15| 416 ± 12     | −30.31 ± 4.01| 853 ± 74     |
| Ask Uncertain  | ✓             | ✓         | −10.41 ± 0.20| 399 ± 27     | −29.73 ± 3.05| 831 ± 27     |
| HMAT (with VEG)| ✓             | ✓         | −10.38 ± 0.25| 424 ± 28     | −29.73 ± 2.89| 857 ± 73     |
| HMAT (with DR) | ✓             | ✓         | −10.36 ± 0.32| 416 ± 30     | −28.12 ± 1.58| 870 ± 57     |
| HMAT†          | ✓             | ✓         | −10.13 ± 0.15| 448 ± 10     | −27.49 ± 0.96| 925 ± 37     |

Figure 5. (a) Task-level learning progress in the one box push domain. (b) Task-level learning progress in the two box push domain. The oracle in (a) and (b) refers to performance of converged HMATD3. For fair comparisons, HMAT includes both the number of episodes used in the Phase I and II when counting the number of train episodes. (c) Heterogeneous action AUC with mean and standard deviation.

6.4. Transferability and Heterogeneous Action

HMAT can learn high-level teaching strategies transferable to different types of agents and/or tasks. We evaluate the transferability in the following two perspectives.

Transfer between Different Student Type We first create a small population of students in which each member has different knowledge. Specifically, we create 7 students that can push one box to distinct areas in the one-box push domain: top-left, top, top-right, right, bottom-right, bottom, and bottom-left. This population is divided into train, validation, and test groups.

We train a teacher that learns to teach students in the training group about how to move the box to left. After the teacher policy has converged, we fix the policy and transfer it to a different setting in which the teacher advises a student in the test group. Although the teacher has never interacted with the student in the test group before, it achieves an AUC of 400 ± 10, compared to no-teaching baseline (HMATD3) AUC of 368 ± 27.

Transfer between Different Task We first train the teacher in the one box push domain that learns to transfer knowledge to agent k about how to move the box to left. Then we fix the converged teacher policy and evaluate on a different task of moving the box to right. While task-level learning without teaching achieves AUC of 362 ± 43, task-level learning with teaching achieves AUC of 413 ± 11. Thus, learning is accelerated even when using teacher policies that are pre-trained from different tasks.

Results on heterogeneous action We consider heterogeneous action space variants in the one-box push domain, where agent k has flipped primitive action space (i.e., 180°) compared to its teammate i. The original algorithms of importance advising and ask uncertain advise at primitive actions and thus assume the action space homogeneity. As Figure 5c shows, both heuristics with primitive action advising fail to advise when the action space is flipped. Advising with HRL helps advising a teammate with a heterogeneous action space, and HMAT achieves the best performance regardless of action rotation.

7. Conclusion

We introduce HMAT, utilizing HRL and deep function approximations, to transfer heterogeneous knowledge in cooperative MARL. We show agents in HMAT accelerate learning progress in challenging domains. We also demonstrate that HMAT can learn high-level teaching policies transferable to different teammates/tasks and can teach teammates with different action spaces. Future works include expanding the framework when more than two agents are involved.
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A. Teacher Reward Details

Recall in the advice evaluation phase of HMAT that the batch of self-practice experiences \( E_{0:T}^{\text{self-prac.}} \) reflects how agents by themselves perform after one advising phase. Then, the next important question is to identify an appropriate teacher reward function \( \tilde{R} \) that can transform the self-practice experiences into the learning performance. In this section, we detail our choices of teacher reward functions, including the ones in Omidshafiei et al. (2018) and Xu et al. (2018).

Value Estimation Gain (VEG): The value estimation gain (VEG) teacher reward function is introduced and performed the best in the Learning to Coordinate and Teach Reinforcement (LeCTR) framework of Omidshafiei et al. (2018). VEG rewards a teacher when its student’s Q-value exceeds a threshold \( \tau \): \( \mathbf{1}(Q_{\text{student}}^* > \tau) \). The motivation of VEG is that the student’s Q-value is correlated to its estimated learning progress (Omidshafiei et al., 2018). Algorithm 2 describes how teachers receive the VEG teacher reward. Note that the Q-functions in the algorithm correspond to the ones of the updated temporary task-level policies \( \pi_{\text{emp}}^t \). The threshold values of \(-6.0\) and \(-20.0\) are used for the one-box and two-box push domain, respectively.

Algorithm 2 VEG Reward Pseudocode

Require: Self-practice experiences \( E_{0:T}^{\text{self-prac.}} \)
Require: Threshold \( \tau \)
1: Initialize agent \( i \)’s teacher reward \( \tilde{r}_i^j = 0 \)
2: Initialize agent \( j \)’s teacher reward \( \tilde{r}_j^j = 0 \)
3: for \( (o, g, r, o') \in E_{0:T}^{\text{self-prac.}} \) do
4: \( Q^i(o, g) > \tau \) then
5: \( \tilde{r}_i^j \leftarrow \tilde{r}_i^j + 1 \)
6: end if
7: \( Q^j(o, g) > \tau \) then
8: \( \tilde{r}_j^j \leftarrow \tilde{r}_j^j + 1 \)
9: end if
10: end for
11: \( \tilde{r} = \tilde{r}_i^j + \tilde{r}_j^j \)

Difference Rollout (DR): The difference rollout (DR) teacher reward function is used in the work of Xu et al. (2018) for learning an exploration policy for a single agent. DR requires another self-practice experiences collected before the advising phase \( E_{0:T}^{\text{self-prac. before}} \). Then, the teacher reward is calculated by the difference between the sum of rewards in \( E_{0:T}^{\text{self-prac.}} \) (denoted by \( \tilde{R} \)) and the sum of rewards in \( E_{0:T}^{\text{self-prac. before}} \) (denoted by \( \tilde{R}_{\text{before}} \)).

Current Rollout (CR): The current rollout (CR) is a simpler reward function than DR. CR returns the sum of rewards in the self-practice experiences \( E_{0:T}^{\text{self-prac.}} \) (denoted by \( \tilde{R} \)).

B. Additional Experimental/Domain Details

B.1. Implementation and Algorithm Details

Each policy’s actor and critic are two-layer feed-forward neural networks, consisting of rectified linear unit (ReLU) activations and 400 nodes per layer. A final layer of tanh activation (i.e., outputs between \(-1\) and \(1\)) is used at the output of each actor policy. The policy actor for the worker and manager outputs two actions that correspond to \(x\)-\(y\) forces to move in the environment and sub-goals (i.e., \(x\)-\(y\) coordinate), respectively. The policy actor for the teacher outputs three actions, where the first two outputs correspond to the sub-goal advice (what to advise) and the last output corresponds to when to advise.\(^6\) Since we focus on teaching at the manager level, not at the worker level, we pre-train and fix the worker policies by giving randomly generated sub-goals. The intrinsic reward function to pre-train the worker policy is the negative distance between the current observation and the sub-goal: \( r_t^{\text{intrinsic}} = -||o_t - g_t||^2_2 \), where \( o_t \) and \( g_t \) correspond to \((x, y)\) position in the domain. Lastly, it might be desirable to consider a recurrent neural network to compress the observation history. However, we didn’t find the observation history necessary in our experiments.

B.2. Cooperative One-Box Push Domain Details

- Each agent observes its position/speed, the position of the box, the position of the target, and the other agent’s position.
- Every episode, the box and target initialize at \((-25, 0.00)\) and \((-85, 0.00)\), respectively. Agents initialize at random locations.
- The box and the agents have a radius of 0.25 and 0.10, respectively.
- The width and height of the domain are from \(-1\) to 1.
- Maximum timestep per episode \( T = 50 \).
- Self-practice rollout timestep \( T = 100 \) (two episodes).
- A maximum number of episodes in a session \( S = 600 \) episodes.
- Teacher update frequency \( f_{\text{teacher}} = 15 \) episodes.
- Discount factor \( \gamma = 0.99 \) for all methods.
- Adam optimizer; actor learning rate of 0.0001 and critic learning rate of 0.001.
- Exploration with a Gaussian noise; mean of 0 and a standard deviation of 0.10.
- Task-level batch size 50; Teacher-level batch size 16.

B.3. Cooperative Two-Box Push Domain Details

- Each agent can observe its position/speed, the positions of the boxes, the positions of the targets, and the other agent’s position.
- Every episode, the two boxes initialize at \((-30.0, 0.00)\) and \((30.0, 0.00)\), respectively. The two targets initialize...
at (−0.80, 0.00) and (0.80, 0.00), respectively. Agents reset at random locations.

- The boxes have a radius of 0.25. The agents have a radius of 0.10.
- The width and height of the domain are from −1 to 1.
- Maximum timestep per episode \( T = 100 \).
- Self-practice rollout timestep \( T^\prime = 200 \) (two episodes).
- A maximum number of episodes in a session \( S = 1800 \) episodes.
- Teacher update frequency \( f_{\text{teacher}} = 15 \) episodes.
- Discount factor \( \gamma = 0.99 \) for all methods.
- Adam optimizer; actor learning rate of 0.0001 and critic learning rate of 0.001.
- Exploration with a Gaussian noise; mean of 0 and a standard deviation of 0.10.
- Task-level batch size 50; Teacher-level batch size 16.

### B.4. Heuristic-Based Teaching Details

Heuristic-based teaching methods (Clouse, 1996; Torrey & Taylor, 2013; Amir et al., 2016; da Silva et al., 2017) use various heuristics to decide when to advise. When decided to advise, a teacher advises with its best action at a student state/observation. Heuristic-based teaching methods can largely broadly fall into either teacher-initiative or student-initiative teaching. We compare the importance advising heuristic (Torrey & Taylor, 2013) for the teacher-initiative method and the ask uncertain heuristic (Clouse, 1996) for the student-initiative method in our experiments. As heuristic-based teaching approaches are based on tile-coding/discrete action space, we apply minor modifications to these approaches to combine with HMATD3, which is the continuous action MARL with centralized critics. In this section, we detail our modifications to the importance advising and ask uncertain heuristic.

**Importance Advising** Importance advising (Torrey & Taylor, 2013) is a heuristic-based teacher-initiative advising. Each teacher decides to advise with its best action when the importance of a state \( I_{\text{teacher}} \) is larger than a threshold \( \tau \): \( I_{\text{teacher}} = \max_a Q_{\text{teacher}}(o, a) - \min_a Q_{\text{teacher}}(o, a) > \tau \). \( I_{\text{teacher}} \) represents an important state when advising the best action can yield a significantly better performance, as determined by the teacher agent’s Q-function. We make the following modifications to measure \( I_{\text{teacher}} \) with HMATD3. First, we uniformly sample 50 actions to effectively represent all possible actions. Second, \( I_{\text{teacher}} \) is modified to include the centralized critics. Specifically, considering the teacher agent \( i \) and the student agent \( j \) for clarity, the teacher \( i \) decides to advise when: \( I_{\text{teacher}} = \max_{a \in A} Q_i(o^i, o^j, a^i, a) - \min_{a \in A} Q_i(o^i, o^j, a^i, a) > \tau \); where \( A \) denotes the set of sampled 50 actions; and \( a^i \sim \pi_i(o^i) \). \( \tau \) values of 5.0 and 7.0 are used for the one box and two box push domain, respectively.

**Ask Uncertain** Ask uncertain (Clouse, 1996) is a heuristic-based student-initiative advising. Each student asks for an advice when the importance of a state \( I_{\text{student}} \) is less than threshold \( \tau \): \( I_{\text{student}} = \max_a Q_{\text{student}}(o, a) - \min_a Q_{\text{student}}(o, a) < \tau \). \( I_{\text{student}} \) represents when the student agent is uncertain about which action to take in current state/observation. Similar to the above modifications, we also uniformly sample 50 actions and include the centralized critics in measuring \( I_{\text{student}} \). Considering the teacher agent \( i \) and the student agent \( j \) for clarity, the student asks for advice when: \( I_{\text{student}} = \max_{a \in A} Q_j(o^i, o^j, a^i, a) - \min_{a \in A} Q_j(o^i, o^j, a^i, a) < \tau \); where \( A \) represents the set of sampled 50 actions; and \( a^i \sim \pi_j(o^i) \). \( \tau \) value of 0.4 is used for experiments.
C. Analysis of Teacher Reward Function

Developing ground-truth learning progress of task-level policies often requires an expert policy or is computationally undesirable (Graves et al., 2017). Thus, our framework uses an estimation of the learning progress as a teacher reward. However, it is important to understand how close the estimation is to the true learning progress. The goal of teacher policies is to maximize the cumulative teacher reward, so a wrong teacher reward that doesn’t estimate closely would result in learning undesirable teachers. In this section, we aim to measure the differences between the true and estimated learning progress and analyze the CR teacher reward function, which performed the best.

In imitation learning, with an assumption of a given expert, one method to measure the true learning progress is by the distance between an action by a learning agent and an optimal action by an expert (Ross & Bagnell, 2014; Daswani et al., 2015). Similarly, we pre-train expert policies (HMATD3) and measure the true learning progress by the action differences. The comparison between the true and the estimated learning progress using the CR teacher reward function is shown in Figure 6. The Pearson correlation is 0.946, which empirically shows that the CR teacher reward function well estimates the true signal.

D. Asynchronous Hierarchical Multiagent Teaching

Similar to a deep RL algorithm requiring millions of episodes to learn an useful policy (Mnih et al., 2015), our teacher policies would require many sessions to learn. As one session consists of many episodes, much time might be needed until teacher policies converge. We address this potential issue with asynchronous policy update with multi-threading as in asynchronous advantage actor-critic (A3C) (Mnih et al., 2016). A3C demonstrated a reduction in training time that is roughly linear in the number of threads. We also show that our HMAT variant, asynchronous HMAT, achieves a roughly linear reduction in training time as a function of number of threads (see Figure 7).