Hierarchical Deep Multiagent Reinforcement Learning

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Abstract

Despite deep reinforcement learning has recently achieved great successes, however in multiagent environments, a number of challenges still remain. Multiagent reinforcement learning (MARL) is commonly considered to suffer from the problem of non-stationary environments and exponentially increasing policy space. It would be even more challenging to learn effective policies in circumstances where the rewards are sparse and delayed over long trajectories. In this paper, we study Hierarchical Deep Multiagent Reinforcement Learning (hierarchical deep MARL) in cooperative multiagent problems with sparse and delayed rewards, where efficient multiagent learning methods are desperately needed. We decompose the original MARL problem into hierarchies and investigate how effective policies can be learned hierarchically in synchronous/asynchronous hierarchical MARL frameworks. Several hierarchical deep MARL architectures, i.e., Ind-hDQN, hCom and hQmix, are introduced for different learning paradigms. Moreover, to alleviate the issues of sparse experiences in high-level learning and non-stationarity in multiagent settings, we propose a new experience replay mechanism, named as Augmented Concurrent Experience Replay (ACER). We empirically demonstrate the effects and efficiency of our approaches in several classic Multiagent Trash Collection tasks, as well as in an extremely challenging team sports game, i.e., Fever Basketball Defense.

1 Introduction

Deep Reinforcement Learning (DRL) has achieved a great number of successes in recent years (Mnih et al. 2015, Levine et al. 2016, Gu et al. 2017). However, many real-world tasks such as sensor networks (Zhang and Lesser 2013), traffic control (Van der Pol and Oliehoek 2016), are naturally modeled as multiagent systems (MASs), where multiple agents have cooperative or competitive interactions with others. In MASs, the problem complexity increases exponentially with the number of agents, thus making it infeasible to apply traditional RL approaches directly. Independent learning (Tan 1993, Foerster et al. 2017) relieves this complexity but suffers from the non-stationary environment due to decentralized policy updates.

To address such challenging tasks, a large amount of works have studied deep Multiagent Reinforcement Learning (MARL) approaches from a variety of perspectives. Palmer et al. (2018) apply leniency to Deep Q-Network (DQN) (Mnih et al. 2015) which helps decentralized agents achieve good performance in cooperative tasks with noisy observation and stochastic rewards. Peng et al. (2017) propose Multiagent Bidirectionally Coordinated Network (BiCNet) to learn effective collaborative strategies centrally in the challenging StarCraft Micromanagement. Following the centralized training with decentralized execution paradigm, Foerster et al. (2018) propose counterfactual multiagent policy gradients (COMA) to address the thorny multiagent Credit Assignment issue. Besides, CommNet (Sukhbaatar, Szlam, and Fergus 2016) is proposed to learn cooperative communication protocols among multiple agents.

The aforementioned previous works mainly focus on the design of agents’ policy networks to improve their coordinated policy updates. However, another important direction of reducing multiagent coordination complexity is temporal abstraction, which is still neglected in DRL literature. Temporal abstraction in multiagent settings allows agents to learn their policies at different temporal scales (Mehta and Tadepalli 2005; Ghavamzadeh and Mahadevan 2004). In hierarchical fashion, the difficulties of learning is reduced through decomposing the original problem into hierarchies with prior knowledge, where cooperative strategies can be efficiently learned at high level and lower level learning can be reduced into single-agent learning problems. In the traditional tabular RL settings, one representative hierarchical multiagent learning approach is (Makar, Mahadevan, and Ghavamzadeh 2001), in which the MAXQ framework (Dietterich 2000) is extended to multiagent settings. It shows that coordination can be learned faster over high-level goals in multiagent trash collection and AGV scheduling tasks, through sharing the same task decomposition among cooperative agents. However, the efficacy of temporal abstraction in complex multiagent domains need to be further verified.

In this paper, we firstly study hierarchical deep Multiagent Reinforcement Learning (hierarchical deep MARL) and show how hierarchical deep MARL approaches can facilitate multiagent negotiation problem. In contrast, we study multiagent hierarchical policies in the context of multiagent temporal abstraction.

¹Note that our paper differs from the Federated Control Framework (Kumar et al. 2017), which studies hierarchical control on pairwise communication between agents in multiagent constrained negotiation problem. In contrast, we study multiagent hierarchical policies in the context of multiagent temporal abstraction.
tate delay learning in cooperative multiagent problems with sparse delayed reward. We investigate multiagent hierarchical policy learning in both synchronous/asynchronous hierarchical MARL. We extend hierarchical Deep Q-Networks (hDQN) (Kulkarni et al. 2016) to hierarchical deep MARL, which induces Independent QDQN (Ind-hDQN), through decomposing the cooperative multiagent problem into independent goals and allowing agents to learn hierarchical policies independently. Low-level policies, i.e., skills and behaviors, can be easily learned by realizing the goals and cooperative strategies over abstracted actions (i.e., goals) can be learned efficiently at high level. To further facilitate the high-level learning among agents, we also propose two other hierarchical deep MARL frameworks, named as hierarchical Communication networks (hCom) and hierarchical Qmix (hQmix). For synchronous and asynchronous scenarios, hCom learns inter-layer communication protocols among cooperative agents in a centralized fashion to facilitate high-level coordinated policy learning among agents. hQmix utilizes the Qmix architecture (Rashid et al. 2018) at the high level for coordinated policy updates. Besides, a new experience replay mechanism named Augmented Experience Replay (ACER) is introduced for hierarchical deep MARL to alleviate the issues of sparse experiences and non-stationarity of the environments. In experiments, we demonstrate that our approaches can learn effective strategies in several classic Multiagent Trash Collection tasks and the challenging team sports game, Fever Basketball Defense.

The remainder of the paper is organized as follows. We briefly introduce the preliminaries in Section 2, followed by the hierarchical MARL framework in Section 3. In Section 4, we propose our approaches, consisting of several multiagent DRL architectures and a new experience replay mechanism. In Section 5, we empirically demonstrate the effects of our approaches in several Multiagent Trash Collection tasks and Fever Basketball Defense game. Conclusion and future work are in Section 6.

2 Preliminaries

Temporal Abstraction. Learning and operating over different levels of temporal abstraction are the key problems in solving long-period tasks. In the context of Hierarchical Reinforcement Learning (HRL) (Dayan and Hinton 1993; Parr and Russell 1997), the tasks are usually decomposed into multi-level hierarchies and the agent takes hierarchical control in a Call-and-Return fashion. For example, Sutton et al. introduce Options (Sutton, Precup, and Singh 1999) for HRL, in which the agent chooses discrete options occasionally and a sequence of primitive actions are made according to the current option chosen by the agent. As shown in

Figure 1, high-level flow represents the decisions made by high-level policies at relatively sparse time points and low-level flow consists of primitive actions at every timestep. Intuitively, high-level policies focus more on semantic behavior learning and long-run planning at large temporal scale. Meanwhile, low-level policies take related information as input and learn simple behavior or subpolicies over primitive actions.

Hierarchical Policy Learning with Deep RL. To learn over different levels of temporal abstraction, we consider that a high-level learner learns a policy over multi-step goals and a low-level learner learns policies over one-step primitive actions to realize high-level goals. This is commonly seen in recent hierarchical Deep RL approaches such as Option-Critic (Bacon, Harb, and Precup 2017), FeUDal Networks (FUNs) (Vezhnevets et al. 2017) and Hierarchical Actor-Critic (HAC) (Levy, Jr., and Saenko 2017). One example is hDQN, in which Meta-Controller learns a policy over goals and Controller learns a subpolicy over primitive actions to achieve the goals. For high-level policy learning, it extends a traditional MDP to a semi-Markov decision process (SMDP) as the goal may last for multiple timesteps. The transition function in SMDP can be defined as $P(s_{t+1} | s_t, g_t)$, which describes the probability for taking goal $g_t$ at state $s_t$ and reaching a given state $s_{t+\tau}$ after $\tau$ timesteps. An accumulated reward $r_t$ is obtained when reaching state $s_{t+\tau}$, i.e., $r_t = R(s_{t+\tau} | s_t, g_t) = r_t + \cdots + r_{t+\tau}$, where $r$ is the reward given by the environment. With Deep Q-Learning (Mnih et al. 2015), a high-level policy $\pi(g_t | s_t)$ can be learned by minimizing the loss with parameters $\theta$,

$$L(\theta) = \mathbb{E}_{s_t, g_t, r_t, t, t+\tau, t+\tau+\tau} \left[ (y - Q^\theta(s_t, g_t))^2 \right],$$

where $y = r_t + \gamma^\tau \max_{g_{t+\tau}} Q^\theta(s_{t+\tau}, g_{t+\tau})$ and $Q^\theta$ is the target Q function. As to low-level policy learning, it can be regarded as the vanilla RL problem. To realize high-level goals, the agent takes goal-related state, i.e., $s_t = \phi(s_t, g_t)$, as input and outputs primitive action $a_t$. A low-level policy $\pi(a_t | s_t)$ is learned through maximizing accumulated intrinsic reward $\hat{r}$ given by a goal-dependent reward function $R(s_{t+1} | s_t, g_t, a_t)$. In the following paper, we use variables with a hat mark to denote low-level learning variables.

MARL in Markov Games. A Markov game (MG) (Littman 1994) for $N$ agents is defined by a set of states $S$, $N$ sets of actions $\{A_i\}_{i=0}^N$ and $N$ sets of observations $\{O_i\}_{i=0}^N$. The transition probabilities between states are described by a function $P(s_{t+1} | s_t, a_0^t, \cdots, a_N^t)$ where $s_t \in S$ and $a_i^t \in A_i$. Each agent $i$ obtains scalar rewards given by function $r_i^t = R(s_t, a_0^t, \cdots, a_N^t)$, and receives a private observation correlated with the state $O_i^t = O_i(s_t)$. The initial states are determined by a distribution $\rho: S \rightarrow [0, 1]$. Each agent $i$ aims to maximize its own total expected return $R_i = \sum_{t=0}^T \gamma^t r_i^t$, where $\gamma$ is a discount factor and $T$ is the time horizon, by selecting actions through a stochastic policy $\pi_i : S \times A_i \rightarrow [0, 1]$. The joint policy is defined as $\pi(a|s) = \prod_{i=1}^N \pi_i(a_i|s)$, where $a$ is the joint action. In
However, synchronous hierarchical MARL causes the loss of control among multiple agents. In synchronous cases, it is always holds. This situation can be seen in many practical scenarios and is illustrated in the bottom of Figure 2. This can be more general in hierarchical control since there is no restriction on when a high-level transition starts and terminates. It is much flexible as each agent can make high-level decisions at any time and no extra synchronization mechanism is necessary. However, achieving cooperation and coordination with asynchronous high-level decisions can be challenging in such situations.

**Multiagent Hierarchical Policy Learning** Similar to single-agent hierarchical policy learning, multiagent hierarchical policies can also be learned from high-level and low-level perspectives with temporal abstraction [Makar, Mahadevan, and Ghavamzadeh 2001] [Mehta and Tadepalli 2005] [Ghavamzadeh and Mahadevan 2004]. Following previous works, we consider low-level learning as a standard single-agent learning problem because it is relatively simple and independent. For example, to play a football match, an agent may need to run to ball and this skill is almost independent with the teammates. We view low-level policies as behaviors or skills that can be shared or transferred among homogeneous agents and similar tasks. To some extent, this reduces the difficulties of policy learning through extracting independent parts from the original multiagent learning problem. There also exists certain special skills such as pass-and-head or pass-and-shoot requiring explicit cooperation among agents, which are not considered in our setting. We are mainly interested in high-level learning where cooperative or coordination strategies should be derived from low-level policies, i.e., skills and behaviors. Compared with the whole task, high-level learning can be seen as a reduced Markov Game through temporal abstraction over primitive actions. Therefore, multiagent learning (exploration and exploitation) can be efficiently carried out at high level due to the reduction of action space and trajectory length.

For synchronous MARL, high-level policies can be learned in both independent and joint-action learning paradigms as standard MARL approaches. The only difference is that high-level decisions are made on relatively sparse timesteps, which results in multi-step state transitions and rewards. For asynchronous MARL, independent learning is suitable while joint-action learning is not applicable, because there is no guarantee to terminate when high-level decisions are made. Asynchronous communication protocols and centralized learning can also be applied in this case. We will introduce more learning details in the next section.

**3 Hierarchical Multiagent RL**

In this section, we introduce hierarchical MARL with temporal abstraction. To see the difference between MARL and hierarchical MARL, we illustrate an example of state trajectories in Figure 2. For MARL case shown in the top of Figure 2, agent 1 and agent 2 select primitive actions $a_1^t$ and $a_2^t$ under any state $s_t$, then the state transits to $s_{t+1}$. In contrast, with temporal abstraction, agents make decisions at different temporal scales according to hierarchical policies. This means that each agent makes multi-step goals at high-level and primitive actions are made by low-level policies per timestep accordingly. Assume that goals $g_1^t$ and $g_2^t$ are selected by agent 1 and agent 2 under state $s_t$ and are reached after $\tau_1$ and $\tau_2$ timesteps respectively. Thereafter, the high-level transitions are $\langle s_t, g_1^t, r_1^t, \tau_1, s_{t+\tau_1} \rangle$ and $\langle s_t, g_2^t, r_2^t, \tau_2, s_{t+\tau_2} \rangle$, where $r_i^t = \sum_{t_i}^n r_i^{t_i}$. Between the high-level decisions, a sequence of primitive actions are executed by low-level policies through following the current goal, which generates low-level transitions $\langle \langle s_{t+i}, g_1^t, a_1^{t+i}, r_1^{t+i}, s_{t+i+1} \rangle \rangle_{i=0}^{\tau_1-1}$ and $\langle \langle s_{t+i}, g_2^t, a_2^{t+i}, r_2^{t+i}, s_{t+i+1} \rangle \rangle_{i=0}^{\tau_2-1}$ for agent 1 and agent 2.

**Synchronous/Asynchronous Hierarchical MARL** We consider two cases of hierarchical MARL, i.e., synchronous hierarchical MARL and asynchronous hierarchical MARL. In synchronous hierarchical MARL, agents always make high-level decisions synchronously. As shown in the middle of Figure 2, high-level transitions of agent 1 and agent 2 start and terminate at the same time points, e.g., $\tau_1 = \tau_2$ always holds. This situation can be seen in many practical scenarios which have synchronization mechanism or joint control among multiple agents. In synchronous cases, it is convenient to build communication protocols if possible. However, synchronous hierarchical MARL causes the loss in flexibility as agents may not be able to make high-level decisions arbitrarily, which can be even severe especially when the number of agents is large. Another more flexible framework is asynchronous hierarchical MARL, as shown in the bottom of Figure 2. This can be more general in hierarchical control since there is no restriction on when a high-level transition starts and terminates. It is much flexible as each agent can make high-level decisions at any time and no extra synchronization mechanism is necessary. However, achieving cooperation and coordination with asynchronous high-level decisions can be challenging in such situations.

**4 Approaches**

**4.1 Hierarchical Multiagent DRL Architectures**

**Independent hDQN.** The simplest way to learn multiagent hierarchical policies is to let each agent learn their policies independently. Therefore, we extend hDQN to an independent multiagent learning version straightforwardly, named as Ind-hDQN, and use it as our baseline architecture for hierarchical MARL. As shown in Figure 3(a), each agent learns hierarchical policies independently. Agent $i$ takes its...
own observation $o_i^t$ as high-level input and decides which goal $g_i^t$ to execute. Thereafter, a sequence of primitive actions are taken by following a low-level policy to realize current goal $g_i^t$ with regarding to the goal-related observation $o_i^t = \phi(o_i^t, g_i^t)$. In hierarchical learning paradigm, agent $i$ updates its high-level policy $\pi_i(g_i^t | o_i^t)$ and low-level policy $\pi_i(a_i^t | o_i^t)$ regarding to the environment rewards $r_i^t$ and goal-related intrinsic rewards $r_i^t$ respectively. Note that each agent can learn multiple low-level policy networks and we use only one here for simplicity. Since each agent updates its own hDQN independently, Ind-hDQN is suitable for both synchronous and asynchronous hierarchical MARL settings.

Hierarchical Communication Networks. In many scenarios, agents’ policies can be trained and executed centrally. For example, multiple agents play a basketball match within the same environment simulator. Thus, we can utilize the centralized learning and execution environments to allow agents to communicate their information for the purpose of facilitating the learning process. Inspired by commNet (Sukhbaatar, Szlam, and Fergus 2016), we introduce hierarchical communication networks (hCom). commNet was originally proposed to learn multiagent communication along consecutive timesteps horizontally, here we realize the vertical intra-layers communication among agents at high level for either synchronous or asynchronous cases. As illustrated in Figure 3(b), agent $i$ takes the communication as additional inputs at high-level. One way to define the communication $c_i$ is

$$c_i = \frac{1}{N-1} \sum_{k \neq i} h_k,$$  \hspace{1cm} (2)

where $N$ is the number of agents and $h_k$ is agent $k$’s hidden state of the layer before communication. Intuitively, this allows agent $i$ to reason about the hidden information of other agents when making a high-level decision instead of simply viewing other agents as parts of the environment. This naturally requires agents to learn and execute high-level policies in a centralized paradigm. However, it is not necessary for agents to select actions in synchronization and thus hCom can be applied in asynchronous hierarchical MARL settings.

Hierarchical Qmix Networks. For efficient learning in the circumstances where agents have different observations and share a joint reward function (e.g., team sports games), we propose another variant called hierarchical Qmix networks (hQmix), i.e., a combination of Ind-hDQN and Qmix architecture (Rashid et al. 2018). Qmix assumes the joint action-value function is an implicit monotonic function with respect to agents’ individual action-value functions,

$$Q_{tot}(o^i, g^i) = M(Q_1(o_1^i, g_1^i), \ldots, Q_n(o_n^i, g_n^i)),$$

$$\frac{\partial Q_{tot}}{\partial Q_i} \geq 0, \forall i \in N,$$  \hspace{1cm} (3)

which ensures that a global $\text{arg max}$ performed on $Q_{tot}$ yields the same result as a set of individual $\text{arg max}$ operations performed on each individual $Q_i$. We utilize the Qmix architecture at the high level of hDQN and the monotonicity property enables agents to learn decentralized execution policies through updating $Q_{tot}$ in a centralized training fashion. The structure of hQmix is shown in Figure 3(c). A feed-forward mixing network (green) takes the agent network outputs $Q_i$ as input and mixes them monotonically, producing the values of $Q_{tot}$. The weights of mixing network are produced by separate hypernetworks (red). Each hypernetwork takes state $s_t$ as input and generates the weights of one layer of the mixing network. The weights are restricted to be non-negative with an absolute activation function to enforce the monotonicity constraint in Equation (3). The biases are produced similarly but are not necessary to be non-negative. The final bias is produced by a 2-layer hypernetwork with a ReLU non-linearity, the same as that in Qmix. Another
thing is that hQmix requires agents to act synchronously since \( Q_{\text{tot}} \) is estimated over joint high-level actions, Thus it is inapplicable for asynchronous settings.

**Low-level Parameter Sharing.** One advantage of hierarchical structure is that, low-level learning problems are relatively independent and learned policies can be transferred and reused among agents. To further take the advantage of the opportunity for centralized learning, we utilize parameter sharing in two aspects. On the one hand, we share network parameters across multiple low-level policies that have similar input and output spaces, such as shooting skill and passing skill. On the other hand, low-level policy parameters are shared among the agents. For specialization, low-level policy takes extra goal index and agent identifier as input. This allows us to learn only one low-level network, which can be used by all goals and agents. However, actions can still be executed differently due to different inputs and thus different hidden states evolved. Parameter sharing can facilitate the learning of a common policy while also allowing for specialization, and speed up learning by reducing the number of parameters that must be learned.

### 4.2 Augmented Concurrent Experience Replay

Experience replay is crucial for stable deep Q-learning since it enables rapid Q-value propagation and breaks temporal correlations of samples meanwhile. However, in hierarchical MARL, experience replay can be flawed in two aspects. First, agents learn high-level policies from transitions that start and terminate at sparse time points due to temporal abstraction. It causes inefficient updates of sparse states for high-level learning as the intermediate experiences (sub-transitions) are not utilized. Second, experiences can be obsolete and misleading due to the non-stationarity that occurs when multiple agents learn concurrently. Thus, existing experience replay mechanism in single-agent DRL cannot be applied directly.

To this end, we propose Augmented Concurrent Experience Replay (ACER) mechanism for hierarchical MARL. As illustrated in Figure 4(a), the goal \( g^{\tau}_{i} \) is chosen by agent \( i \) at timestep \( t \) and terminates after \( \tau \) timesteps, producing a transition tuple \( \langle o^{t+k}_{i}, g^{t+k}_{i}, \tilde{r}^{t+k}_{i}, \tau, o^{t+k+\tau}_{i} \rangle \). For better utilization of experiences, ACER stores an augmented experience consisting a stack of sub-transitions, i.e., \( AE_{i}(t, \tau) = \{ \langle o^{t+k}_{i}, g^{t+k}_{i}, \tilde{r}^{t+k}_{i}, \tau - k, o^{t+k+\tau}_{i} \rangle \}_{k=0}^{\tau-1} \), instead of the original transition. The loss of an augmented experience is calculated as the sum of those of sub-transitions in it,

\[
L(t, \tau) = \sum_{k=0}^{\tau-1} (y_i - Q^{\theta_i}(o^t_i, g^t_i))^2 ,
\]

where \( y_i = \tilde{r}^t_i + \gamma^\tau \max_{a} Q^{\theta_{i+\tau}}(o^{t+\tau}_{i+\tau}, g^{t+\tau}_{i+\tau}) \). It allows agents to learn high-level policies more efficiently from denser experiences by updating each state encountered along the trajectory with regard to the corresponding accumulated reward. In practice, due to the limitation of replay buffer size, sub-transitions in \( AE_{i}(t, \tau) \) can be selectively stored in the replay buffer to alleviate the additional storage and computational cost during training. Besides, we adopt the similar idea of Concurrent Experience Replay Trajectories (CERTs) in ACER for concurrent sampling of experiences across a team of agents. As demonstrated in Figure 4(b), in each episode, augmented experiences of agents (illustrated as squares of different colors) are stored in a sequence along the timestep axis, which ensures concurrent experiences are stored at the same position in memory. Instead of sampling experiences independently for each agent, ACER samples piles of concurrent experiences for all agents. In this way, agents’ policy updates are concurrent and thus it facilitates learning towards coordinated policies and stabilize training as well.

### 5 Experiments

In this section, we first illustrate the effects of temporal abstraction in several Multiagent Trash Collection tasks, and then we evaluate our approaches in the challenging team sports game, i.e., Fever Basketball Defense.

#### 5.1 Multiagent Trash Collection

We devise a range of two-player grid-world domains, i.e., Multiagent Trash Collection (MATC) tasks, by extending the classic game in (Makar, Mahadevan, and Ghavamzadeh 2001). In all three domains of Figure 5(a), the two agents (blue and red squares) are assigned to collect the cans (green squares) and dump them into trash bin (yellow square) with impermeable walls (grey squares). Each agent has 7 actions, i.e., **up**, **down**, **left**, **right**, **pick-up**, **put-down** and **no-op**. For MATC-Room and MATC-Ring domains, each agent is given a reward of 0.5 when dumping a can into a trash bin. For Coordination domain, each agent has to coordinate with the other by picking up cans and dumping them into the same trash bin. A reward of 1/0.5 is given to each agent if successfully coordinating at the upper/lower trash bin, and 0.1 for non-coordination.

For all three domains, we decompose the MATC task into several navigation goals and two one-step operation goals, i.e., pick-up and put-down. For example, the navigation goals of MATC-Room are Moving-to-canal1, Moving-to-canal2, Moving-to-trashbin1 and Moving-to-trashbin2. Two agents share the same decomposition of tasks and learn hierarchical policies with the Ind-hDQN architecture. At
Figure 5: Multiagent Trash Collection. (a) MATC domains. Top-Left: MATC-Room, 11 × 11. Top-Right: MATC-Ring, 11 × 11. Bottom: Coordination, 15 × 7. (b)-(d) Averaged reward sums and step numbers of each episode for three tasks. Horizontal axes are training episode numbers. The results are training curves and are averaged over 5 random seeds.

5.2 Fever Basketball Defense

Fever Basketball Defense (FBD) is a team sports game which contains 3 defense players (i.e., C, SF, PG) competing against three mirror opponents. The agents (defense players) aim to learn cooperative defense strategies to prevent the offensive opponents from scoring. The opponents act by following the built-in offense policy, which is much powerful than common human game players. A screenshot of Fever Basketball is shown in Figure 6(a).

Environment Setup. At each timestep $t$, agent $i$ takes a 50-dimension vector as its own observation $o_i^t$ which consists of physical features of the entities in the game field, i.e., relative distances and angles (see in Appendix B), and chooses an action $a_i^t$ from 18 available actions, i.e., no-op, defense-still, move-[in 8 directions] and defense-move-[in 8 directions]. A reward of $-1$ or $+1$ is obtained at the end of each episode, depending on whether the opponent team scores or not. Defense skills like block and steal are built-in behaviors and can be triggered when defense agent is in a good defense position. Thus, the target of the agents is to keep good defense positions and decrease the score-rate of the opponents.

Temporal Abstraction and Intrinsic Rewards. To solve the problem with temporal abstraction, we decompose the 3v3 defense game into 6 goals, i.e., run-to-[C/SF/PG] and close-defense-[C/SF/PG], and each goal has an action space of 9 primitive actions. An illustration of the detailed decomposition for FSB can be seen in Appendix B. For low-level learning, the goal-related observation of agent $i$ contains 26-dimension features of current observation $o_i^t$ related to the opponent player in $g_i^t$, i.e., $\hat{o}_i = \phi(o_i^t; g_i^t) \subset o_i^t$. Besides, we use a minimal intrinsic reward function with a binary-value design for all goals. A reward of $+2/ -0.01$ is obtained depending on whether the agent is within the distance and angle thresholds, i.e., good defense area (see in Appendix B). For close-defense goals, an extra bonus of $+2$ is given if the agent successfully blocks or steals the ball. Each goal is executed for 15 timesteps and early terminations can only happen when an episode ends or the opponent players pass the ball. This is a synchronous hierarchical MARL case as agents always shift their goals concurrently. We also modify it into an asynchronous fashion by allowing the agent to
choose a new goal, as long as it reaches/leaves the defense area during the execution of move-to/close-defense goals.

### Ablations
We perform ablation experiments to evaluate our hierarchical deep MARL architectures. First, we demonstrate the significance of temporal abstraction by comparing Ind-hDQN with Ind-DQN. Another variant of Ind-hDQN which trains low-level policies only (low-level-only) is compared to see the contribution of hierarchical policies. Second, we evaluate our hierarchical MARL architectures, i.e., hCom and hQmix, by comparing with the baseline architecture Ind-hDQN. Figure 6(b) shows the average shoot miss rates of the opponent team against training episodes for each method under synchronous settings. The shoot miss rates are moving-averaged across 200 episodes and 5 random seeds.

The significance of temporal abstraction can be demonstrated by Ind-hDQN’s superior performance over Ind-DQN in Figure 6(b). Ind-DQN fails to learn effective defense strategies and can hardly hinder the offense of the opponent team, while Ind-hDQN achieves a near 30% increase in shoot miss rate. Interestingly, the low-level-only shows certain defense performance with a shoot miss rate of near 43%, even with a random high-level policy. This indicates that Ind-hDQN takes a two-step improvement by learning at different time scales. Low-level policy learning is the cornerstone for effective hierarchical learning. With high-quality low-level skills, i.e., move and defense, defense strategies can be efficiently learned at the high level.

Furthermore, hCom and hQmix achieve similar shoot miss rates of near 55%, clearly outperforming the baseline approach Ind-hDQN. For hCom, we credit the advantage to the communication among agents. With taking others’ reasoning into consideration through communication, agents make decisions and update their policies in a more coordinated fashion. In contrast to independent learning, it is more likely for cooperative policies to emerge in hCom. Besides, Ind-hDQN also suffers from the misleading of team reward, i.e., multiagent Credit Assignment. hQmix alleviates this issue by allowing decentralized agents to update their policies centrally, regarding to the contribution assigned by a joint Q-value function that learned over the team rewards. Thus, the hQmix agents can learn their policies efficiently with more accurate guidance on updates. Another interesting observation is that hCom and hQmix show different defense behaviors in our experiments. hCom learns aggressive strategies, e.g., joint defense and rapid shifts, while hQmix is relatively cautious and prefers to one-to-one defense. The demonstration videos can be seen in supplemental materials.

**Evaluation of ACER.** Next we move to the evaluation of our experience replay mechanism, i.e., ACER. Figure 6(c) illustrates the averaged shoot miss rates for Ind-hDQN/hCom with and without ACER under synchronous settings. The results show that ACER improves the defense performance for both Ind-hDQN and hCom. Note that we do not apply ACER on hQmix as it naturally ensures concurrent sampling by updating policies with the joint experiences of agents. Ind-hDQN-ACER shows an obvious advantage over Ind-hDQN with a near 5% increase in shoot miss rate, achieving a comparable level against hCom. As to hCom, hCom-ACER shows a slight improvement (near 3%) and we hypothesize that it is due to the stability nature of multiagent communication. This indicates that ACER is crucial for stabilizing multiagent experience replay and improving policy learning, especially when agents learn their policies independently.

We also performed experiments in asynchronous settings. The effects of our approaches are similarly demonstrated and comparable defense strategies are learned. Due to space limitation, the complete results can be found in Appendix B.

### 6 Conclusion
To the best of our knowledge, we are the first to study hierarchical deep MARL problem in the context of multiagent temporal abstraction. We propose several architectures, i.e., Ind-hDQN, hCom and hQmix, for both synchronous and asynchronous hierarchical deep MARL. A new experience replay mechanism, i.e., ACER, is also introduced to address the challenges of sparse experiences and non-stationarity in multiagent settings. Our results in Multiagent Trash Collection tasks and Fever Basketball Defense show that effective policies and collaborative defense strategies can be learned with our approaches. Future work will investigate special...
ization for asynchronous hierarchical MARL, extension to domains with cooperative or competitive goals (in contrast to independent goals), and evaluation on more complex domains with much larger numbers of tasks.

References

[Bacon, Harb, and Precup 2017] Bacon, P.; Harb, J.; and Precup, D. 2017. The option-critic architecture. In AAAI, 1726–1734.

[Dayan and Hinton 1993] Dayan, P., and Hinton, G. E. 1993. Feudal reinforcement learning. In NIPS, 271–278.

[Dietterich 2000] Dietterich, T. G. 2000. Hierarchical reinforcement learning with the maxq value function decomposition. Journal of Artificial Intelligence Research 13:227–303.

[Foerster et al. 2017] Foerster, J. N.; Nardelli, N.; Farquhar, G.; Afouras, T.; Torr, P. H. S.; Kohli, P.; and Whiteson, S. 2017. Stabilising experience replay for deep multi-agent reinforcement learning. In ICML, 1146–1155.

[Foerster et al. 2018] Foerster, J. N.; Farquhar, G.; Afouras, T.; Nardelli, N.; and Whiteson, S. 2018. Counterfactual multi-agent policy gradients. In AAAI, 1–8.

[Ghavamzadeh and Mahadevan 2004] Ghavamzadeh, M., and Mahadevan, S. 2004. Learning to communicate and act using hierarchical reinforcement learning. In AAMAS, 1114–1121.

[Gu et al. 2017] Gu, S.; Holly, E.; Lillicrap, T. P.; and Levine, S. 2017. Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates. In ICRA, 3389–3396.

[Kulkarni et al. 2016] Kulkarni, T. D.; Narasimhan, K.; Saeedi, A.; and Tenenbaum, J. 2016. Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. In NIPS, 3675–3683.

[Kumar et al. 2017] Kumar, S.; Shah, P.; Hakkani-Tür, D. Z.; and Heck, L. P. 2017. Federated control with hierarchical multi-agent deep reinforcement learning. arXiv preprint arXiv:1712.08266.

[Levine et al. 2016] Levine, S.; Finn, C.; Darrell, T.; and Abbeel, P. 2016. End-to-end training of deep visuomotor policies. Journal of Machine Learning Research 17:39:1–39:40.

[Levy, Jr., and Saenko 2017] Levy, A.; Jr., R. P.; and Saенко, K. 2017. Hierarchical actor-critic. arXiv preprint arXiv:1712.00948.

[Littman 1994] Littman, M. L. 1994. Markov games as a framework for multi-agent reinforcement learning. In ICML, 157–163.

[Makar, Mahadevan, and Ghavamzadeh 2001] Makar, R.; Mahadevan, S.; and Ghavamzadeh, M. 2001. Hierarchical multi-agent reinforcement learning. In IJCAI, 246–253.

[Mehta and Tadepalli 2005] Mehta, N., and Tadepalli, P. 2005. Multi-agent shared hierarchy reinforcement learning. In Workshop on Rich Representations for Reinforcement Learning, 45.

[Mnih et al. 2015] Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M. A.; Fidjeland, A.; Ostrovski, G.; Petersen, S.; Beattie, C.; Sadik, A.; Antonoglou, I.; King, H.; Kumaran, D.; Wierstra, D.; Legg, S.; and Hassabis, D. 2015. Human-level control through deep reinforcement learning. Nature 518(7540):529–533.

[Omidshafiei et al. 2017] Omidshafiei, S.; Pazis, J.; Amato, C.; How, J. P.; and Vian, J. 2017. Deep decentralized multi-task multi-agent reinforcement learning under partial observability. In ICML, 2681–2690.

[Palmer et al. 2018] Palmer, G.; Tuyls, K.; Bloembergen, D.; and Savani, R. 2018. Lenient multi-agent deep reinforcement learning. In AAMAS, 443–451.

[Parr and Russell 1997] Parr, R., and Russell, S. J. 1997. Reinforcement learning with hierarchies of machines. In NIPS, 1043–1049.

[Peng et al. 2017] Peng, P.; Wen, Y.; Yang, Y.; Yuan, Q.; Tang, Z.; Long, H.; and Wang, J. 2017. Multiagent bidirectionally-coordinated nets: Emergence of human-level coordination in learning to play starcraft combat games. arXiv preprint arXiv:1703.10069.

[Rashid et al. 2018] Rashid, T.; Samvelyan, M.; de Witt, C. S.; Farquhar, G.; Foerster, J. N.; and Whiteson, S. 2018. QMIX: Monotonic value function factorisation for deep multi-agent reinforcement learning. In ICML, 4292–4301.

[Schaal et al. 2015] Schaul, T.; Quan, J.; Antonoglou, I.; and Silver, D. 2015. Prioritized experience replay. arXiv preprint arXiv:1511.05952.

[Sukhbaatar, Szlam, and Fergus 2016] Sukhbaatar, S.; Szlam, A.; and Fergus, R. 2016. Learning multiagent communication with backpropagation. In NIPS, 2244–2252.

[Sutton, Precup, and Singh 1999] Sutton, R. S.; Precup, D.; and Singh, S. P. 1999. Between mdps and semi-mdps: A framework for temporal abstraction in reinforcement learning. Artificial Intelligence 112(1-2):181–211.

[Tan 1993] Tan, M. 1993. Multi-agent reinforcement learning: Independent vs. cooperative agents. In ICML, 330–337.

[Van der Pol and Oliehoek 2016] Van der Pol, E., and Oliehoek, F. A. 2016. Coordinated deep reinforcement learners for traffic light control. Proceedings of Learning, Inference and Control of Multi-Agent Systems (at NIPS 2016).

[van Hasselt, Guez, and Silver 2016] van Hasselt, H.; Guez, A.; and Silver, D. 2016. Deep reinforcement learning with double q-learning. In AAAI, 2094–2100.

[Vezhnevets et al. 2017] Vezhnevets, A. S.; Osindero, S.; Schaul, T.; Heess, N.; Jaderberg, M.; Silver, D.; and Kavukcuoglu, K. 2017. Feudal networks for hierarchical reinforcement learning. In ICML, 3540–3549.

[Zhang and Lesser 2013] Zhang, C., and Lesser, V. R. 2013. Coordinating multi-agent reinforcement learning with limited communication. In AAMAS, 1101–1108.
Appendix A

Multiagent Trash Collection

Environments For all three domains in Figure 7, the 2 agents (blue and red squares) are assigned to collect the cans (green squares) and dump them into trash bin (yellow square) with impermeable walls (grey squares). Each agent has 7 actions, i.e., up, down, left, right, pick-up, put-down and no-op. All cans and trash bins are equivalent and 7 actions are always available, which means that agents can pick up and put down cans at any time. Nothing happens if an illegal action is chosen, e.g., walk across walls, pick up or put down nothing and pick up when currently possessing.

Task Decomposition One example of task decomposition for MATC-Room is shown in Figure 8. Agents can shift their goals only when the current goal is achieved or a maximum goal length is reached. In our experiments, we set the max goal length to be 15 steps. The max episode horizon is set to 100 and 50 steps for MATC-Room/Ring and Coordination tasks respectively.

Training Details and Hyperparameters For Ind-hDQN, the high-level and low-level Q-networks are all 2-layer MLPs with 64/64 units. The learning rates are 0.00025/0.0005 and the discounted factors are 0.95/0.9 for high-level and low-level learning. The memory buffer sizes are 5000/5000 for both high level and low level. At the beginning of training, we keep high-level policy random and update low-level policies for 50000 times. After the warm-up period, agents learn their high-level policies and low-level policies together. For Ind-DQN and Ind-DDQN-PER, the networks are 2-layer MLPs with 128/128 units. The learning rates are 0.00025 and the discounted factors are 0.99. The memory buffer sizes are 10000. We render network updates every 20 steps. The exploration rates are annealed from 1 to 0.1 in 10000 updates for low-level learning and 100000 updates for others. We use parameter sharing for both high-level and low-level policies here.
Figure 7: Multiagent Trash Collection tasks.

Figure 8: An example of task decomposition for MATC-Room. Red dashed squares denote for primitive actions (one-step execution) and the blue dashed square is for abstract goals (multi-step execution).
Appendix B

Fever Basketball Defense

Task Decomposition  An illustration of decomposition for Fever Basketball Defense is shown in Figure 9(a).

State Features  The state features of FSD is almost the physical information about the game field. As illustrated in Figure 9(b), the position of an unit, i.e., defense/offense players or ball, is a tuple of \( \langle d, \cos(\theta), \sin(\theta) \rangle \), where \( d \) is the distance from the player to the basket rim and \( \theta \) is the angle from the horizontal axis and the line between the player and the basket rim. The high-level learner and low-level learner receive different input features. For an agent, its high-level observation is 50-dimension vector, consisting of the remaining time of current episode, the position of the ball, the types and positions of itself, teammates and opponents. Its low-level observation is 26-dimension vector consisting of the types and positions of itself and the defense target of current goal, e.g., the defense target is \( C \) if the current goal is run-to-C.

Good Defense Area  The good defense area is defined as a small area when a player has a defense target. For example, if player 2 is the current defense target of player 1, we say that player 1 is in the good defense area when the distance between them is less than 1.5 meters and the difference of their angles to the basket rim is less than 7.5 degrees, i.e., \( |\theta_1 - \theta_2| < 7.5 \).

Training Details and Hyperparameters  For Ind-hDQN, the high-level and low-level Q-networks are all 2-layer MLPs with 128/64 and 64/32 units respectively. The learning rates are 0.00025/0.00025 and the discounted factors are 0.95/0.9 for high-level and low-level learning. The memory buffer sizes are 20000 for both high level and low level. We build our hCom and hQmix architecture based on Ind-hDQN with the same hyperparameters. For hQmix, we use the same design for mixing networks and hypernetworks as the original paper. We update networks every step for low level and every 2 steps high level. The exploration rates are annealed from 1/1 to 0.01/0.1 in 100000/20000 updates for low-level and high-level learning respectively. We use parameter sharing for low-level networks and keep high-level policies independent. At the beginning of training, we keep high-level policy random and update low-level policies for 200000 times. After the warm-up period, agents learn their high-level policies and low-level policies together.

Complete Results

Demonstration Videos  We provide 2 game videos for demonstration in supplemental materials, i.e., hQmix-demo.mp4 and hCom-demo.mp4, for hQmix and hCom respectively. Note in the videos, our agents always control the team that is currently doing defense no matter how attack-defense relation changes, i.e., control team A if A is doing defense and control team B if team A gets the ball and team B starts to defense. Interestingly, we found that hCom and hQmix learns different defense strategies as shown in videos. hQmix agents prefer to one-to-one defense and almost always keep good defense positions. Besides, local cooperative defense can also been observed which means team spirits emerge among hQmix agents. The behaviors are quite reasonable as commonly seen in real-world basketball matches. In contrast, hCom learns relatively aggressive strategies. The agents show rapid shifts in defense target and joint defense behaviors happen a lot. In two aspects, this improves the quality of local defense but may cause the issue of defense leaking.
Figure 9: Fever Basketball Defense (FSD). (a) An illustration of decomposition for FSD. Red and blue dashed squares contain the goals/actions for movement and defense respectively. (b) An illustration of game field. Red and blue circles denote the game players of different teams. Green circle represents the basket rim.

| Methods          | BR-sync | SMR-sync | BR-async | SMR-async |
|------------------|---------|----------|----------|-----------|
| Ind-DQN          | 0.02    | 0.25     | 0.02     | 0.25      |
| low-level-only   | 0.18    | 0.43     | 0.18     | 0.43      |
| Ind-hDQN         | 0.27    | 0.50     | 0.24     | 0.48      |
| hCom             | 0.34    | 0.55     | 0.30     | 0.53      |
| hQmix            | 0.34    | 0.55     | N/A      | N/A       |
| Ind-hDQN-ACER    | 0.36    | 0.55     | 0.31     | 0.52      |
| hCom-ACER        | **0.37**| **0.58** | **0.31** | **0.54**  |

Table 1: Shoot miss rates (SMR) and block rates (BR) for all approaches in Fever Basketball Defense. The block rate is defined as \( \frac{\text{num of block} + \text{num of steal}}{\text{num of episode}} \). Results are averaged over recent 200 episodes and 5 random seeds.