Promoting Coordination Through Electing First-move Agent in Multi-Agent Reinforcement Learning

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Abstract

Learning to coordinate among multiple agents is an essential problem in multi-agent systems. Multi-agent reinforcement learning has long been a go-to tool in the complicated collaborative environment. However, most existing works are constrained by the assumption that all agents take actions simultaneously. In this paper, we endow the hierarchical order of play for the agents through electing a first-move agent and other agents take the best response to the first-move agent to obtain better coordination. We propose the algorithm EFA-DQN to implicitly model the coordination and learn the coordinated behaviour in multi-agent systems. To verify the feasibility and demonstrate the effectiveness and efficiency of our algorithm, we conduct extensive experiments on several multi-agent tasks with different numbers of agents: Cooperative Navigation, Physical Deception, and The Google Football. The empirical results across the various scenarios show that our method achieves competitive advantages in terms of better performance and faster convergence, which demonstrates that our algorithm has broad prospects for addressing many complex real-world problems.

Keywords: Election Mechanism, Coordination, Multi-agent Reinforcement Learning

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1. Introduction

Recently we have witnessed the impressive achievement of deep reinforcement learning (DRL) for Atari [1], OpenAI Gym [2] and Go [3, 4]. The more complicated example, such as self-driving [5], traffic light control [6] and StarCraft II [7] can be modeled as multi-agent systems (MAS) [8]. The complexity and uncertainty of multi-agent systems make it imperative to study the coordination among the agents. For instance, there is only one single-plank bridge for two people standing opposite to cross the river. If two people act simultaneously, none of them can cross the river. The solution is one crosses the river first, and the other can’t act until the first-move person passes. Borrowing from the human society for the multi-agent system is essential for better collaboration and feasible solutions. However, learning coordination is abstract and how to design a mechanism to promote the coordination is extremely important.

The past few decades have seen increasingly rapid advances in the field of collaborative multi-agent reinforcement learning (MARL), where the agents learn to coordinate to achieve joint success. There is a growing body of literature that recognizes the importance of coordination. Among them, learning communication protocol [9, 10, 11, 12] has been proposed to learn the coordinated behaviour among multiple agents. Some works [13, 14] are goal-oriented, which employ a hierarchy with managers and workers to enforce the workers to achieve the goal generated by managers. There are also some works like [15, 16] that assign the agents with different roles in order to achieve better coordination to reach the final success. However, in these settings formulated by Markov Games [17], all agents are regarded symmetrically and take actions simultaneously, which would be stuck with the dilemma for some coordination tasks. Much of the research up to now has not fundamentally solved the coordination problem in multi-agent reinforcement learning.

In order to eliminate the coordination dilemma, we introduce a new framework for MARL to learn coordinated behaviour. The core idea is that we elect a first-move agent among all the agents to act first, and other agents take
their best response to the first-move agent. We break the symmetry and endow the hierarchical order of play for the agents to obtain better coordination. We develop our system in the context of cooperative multi-agent reinforcement learning, where there is a single goal to be optimized by maximizing a shared global cumulative return.

**Contributions.** In this paper, we give a novel problem formulation based on partially observable Markov games which can enable coordination due to the asymmetry of the agents. Under this formulation, we propose an algorithm called EFA-DQN that aims at promoting coordination through Electing the First-move Agent followed by an improved Deep Q-Network in cooperative multi-agent reinforcement learning. In the EFA sub-module, we construct a coordinated graph and use the graph convolutional network to aggregate the message from neighbours for a richer feature embedding used to elect the first-move agent. In the DQN sub-module, we use the weighted mixing network to places more emphasis on better joint action and impose a counterfactual constraint for the first-move agent to encourage more contribution of the first-move agent to the overall system. The empirical evaluations on several challenging MARL benchmarks show that our method can significantly achieve better performance and faster convergence over other related methods. These results provide a new perspective in understanding and promoting the emergence of coordination among agents and demonstrate that our algorithm has broad prospects for addressing many complex real-world problems.

The remaining part of the paper proceeds as follows: Firstly, we discuss the relevant literature in Section 2. Then we introduce the partially observable Markov game, graph convolutional network and value-based multi-agent reinforcement learning in Section 3. Next, Section 4 is concerned with the methodology used for this paper. We explain the problem formulation and present the detailed framework description. Afterwards, we explore our algorithm in several complex tasks and make an analysis. Finally, the conclusion is provided in Section 6.
2. Related Work

Recently, the centralized training with decentralized execution (CTDE) paradigm has attracted more and more attention from researchers due to its capacity of alleviating the non-stationarity brought by the decentralized approach and the poor scalability of the centralized approach. Combining the CTDE regime with value-based solutions, some works show great superiority in multi-agent reinforcement learning (MARL) tasks. The structural constraints in factorization such as the additivity of VDN [18], FQL [19] and the monotonicity of QMIX [20], WQMIX [21] naturally limit the scope of their applications. QTRAN [22], which is free from such structural constraints, guarantees more general factorization than VDN or QMIX. However, relaxing the optimization constraints by two penalties deviates QTRAN from exact solutions. Qatten [23] introduce multi-head attention to establish the mixing network. MAVEN [24] hybridizes value and policy-based methods by introducing a latent space for hierarchical control. QPLEX [25] takes a duplex duelling network architecture to factorize the joint value function and enables efficient value function learning. In this paper, we also utilize the value-decomposition popularized recently to address the complex multi-agent problems, which belongs to the Q-learning family.

Role-based works are broadly related to our method, but the difference is that we only elect the first-move agent. In some works [26], [27], roles are predefined using prior knowledge, which hurts generalization of the policy and requires prior knowledge that may not be available in practice. To alleviate this issue, the Bayesian Policy Search approach for MARL [28] is proposed to demonstrate the practical discovery of roles from supervised trajectories, and ROMA [16] learns a role encoder to generate the role embedding for the emergence of roles. RODE [15] learns a role selector based on action effects to make the role discovery much more accessible. However, our work aims to elect a role, i.e. the first-move agent, not to divide all agents into roles for better coordination.

Other works like learning coordinated behaviour in multi-agent systems are
studied extensively in the MARL community. Some previous works attempt to promote coordination by communication which can enhance the collective intelligence of learning agents further. RIAL, DIAL [9], CommNet [10], BiCNet [29], Message-Dropout [30], ATOC [11], MAGIC [31] and SchedNet [32] attempt to learn an efficient communication protocol in the decentralized execution phase for various multi-agent tasks. Some impressive work like [33, 34, 35, 36] try to figure out the possibility of the artificial emergence of language for communication. However, unlike the above work, we do not communicate explicitly but promote coordination through the information transmission from the first-move agent to other agents.

3. Preliminaries

In this section, we will introduce some fundamental theories of reinforcement learning for a better understanding of our framework.

3.1. Partially Observable Markov Game (POMG)

A partially observable Markov game described in [17] [37] is an appealing framework for dealing with sequential decision making problems for $N$ agents. It can formulated by a tuple $< i \in I, S, O, A, P, R >$. $I$ is a finite set of players or agents and $S$ is the global state. $O = \{O_1, O_2, ..., O_N\}$ is the set of local observations, $O_i$ is the observation space for agent $i$ and $o = < o_1, o_2, ..., o_N >$ denotes a joint observation. $A = \{A_1, A_2, ..., A_N\}$ is the set of actions and $A_i$ is the action space of agent $i$ and $a = < a_1, a_2, ..., a_N >$ denotes a joint action. The action $a_i$ of agent $i$ is generated by the policy $\pi_i$ which depends on the set of action-observation histories $H_i = (O_i \times A_i)^*$. The next state is generated according to the state transition function $P : S \times A_1 \times A_2 \times ... \times A_N \times S \rightarrow [0, 1]$. The reward function is: $R : S \times A_1 \times A_2 \times ... \times A_N \rightarrow \mathbb{R}$. After taking actions of all agents, the joint reward for each agent $r = < r_1, r_2, ..., r_n >$ and the local observation for agent $i$ is $o_i : S \rightarrow O_i$ are obtained. The agent $i$ aims to maximize its own discounted sum of future return $E_{s \sim p, a \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t r_i(s, a) \right]$.
where $\pi = (\pi_1, \pi_2, ..., \pi_N)$ and $a = (a_1, a_2, ..., a_N)$ are the set of policies and the joint action for all agents, $\rho_\pi$ is the state distribution and $\gamma$ is a discount factor.

3.2. Graph Convolutional Network (GCN)

Recently, Graph Neural Networks (GNNs) have received broad interest in various domains, such as natural language processing [38], computer vision [39] and social networks. GNNs typically operate by a message-passing mechanism aggregating the information from the neighbourhood of the node and modeling the dependencies between the neighbouring nodes. Graph Convolutional Network (GCN), the typical GNNs, aggregates graph-wise messages in the following way. The layer-wise propagation rule for multi-layer [40] motivated by the first-order approximation of localized spectral filters on graphs [41] is as follows:

$$H^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)})$$  \hspace{1cm} (1)

where $\tilde{A} = A + I_N$ is the adjacency matrix of the undirected graph $G$ with $N$ nodes and self-connections. $I_N$ and $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$ is the identity matrix and degree matrix respectively. The degree matrix is a diagonal matrix which contains the number of edges attached to each vertex. $W^{(l)}$ is a layer-specific trainable weight matrix, which is trained using gradient descent.

We can stack many convolutional layers to obtain multi-hop information. Taking a two-layer GCN for example:

$$\tilde{A} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}}$$
$$H^2 = f(H^0, \tilde{A}) = \sigma \left( \tilde{A} \sigma \left( \tilde{A} H^0 W^0 \right) W^1 \right)$$  \hspace{1cm} (2)

In addition, the per-layer propagation rules can be different variants as introduced in [40, 42, 43]. GCN exquisitely designs a structure to extract features from the graph data in the non-Euclidean space so that we can use these graph embedding to the downstream tasks.

In the field of multi-agent reinforcement learning, there are some works [44, 45, 46, 47] recently using GCN to encode the observations from the environment to obtain a richer representation. The multi-agent environment can be
constructed as a graph, where agents in the environment are represented by the
nodes of the graph, and each node has a set of neighbours constant or variable
over time. The neighbours can be determined by distance or other metrics,
which is specific to actual scenarios. Taking advantage of the natural topology
of graphs, applying graph neural networks in multi-agent reinforcement learning
is a promising approach to deal with large-scale complicated systems.

3.3. Value-based Multi-agent Reinforcement Learning

In the POMG, the joint-action value function (namely, the Q-function) de-
determining the expected return from undertaking joint action \( a \) in state \( s \) is as
follows:

\[
Q^\pi(s_t, a_t) = E^\pi \left[ \sum_{i=0}^{\infty} \gamma^i r_{t+i} | s_t, a_t \right]
\]

(3)

The value-based methods are introduced to find the optimal Q-function \( Q^* \)
that maximizes the expected return and the optimal policy can be derived from
\( \pi^* = \arg \max_a Q^*(s, a) \).

For agent \( i \) at time \( t \), the value of \( Q(s_t, a_t) \) is updated via temporal-difference
learning [48] as follows:

\[
Q^i(s_t, a_t) \leftarrow Q^i(s_t, a_t) + \alpha \left( R^i_t + \gamma \max_a Q^i(s_{t+1}, a) - Q^i(s_t, a_t) \right)
\]

(4)

The independent Q-learning (IQL) [49] is violent to learn an independent
action value function \( Q^i(s_t, a_t; \theta^i) \) and execute an updating process as Eq. 4
for each agent \( i \) that conditions only on its local action-observation history.
Tampuu et al. [50] combines IQL with deep learning techniques presented in
Deep Q-network (DQN) [51]. However, these algorithms are difficult to converge
due to the dynamically non-stationary environment.

For resolving the non-stationarity problem, some of the representative value-
based works like [18, 20, 22] are proposed which take advantage of the paradigm
of centralized training with decentralized execution (CTDE) by appropriately
transforming and factorizing the joint action-value function into individual action-
value functions.
4. Method

In this section, we give a new problem formulation and introduce the framework called EFA-DQN that promotes coordination through Electing First-move Agent followed by Deep Q-Network in cooperative multi-agent reinforcement learning at first. Then we further elaborate on the EFA sub-module and DQN sub-module in EFA-DQN respectively.

4.1. Formulation and Overview

4.1.1. Problem Formulation.

Based on POMG, we can extend it to $<i \in \mathcal{I}, S, O_f, O_s, A_f, A_s, \mathcal{P}, \mathcal{R}>$ for $N$ agents. $O_f$ denotes the observation of the first-move agent while $O_s$ denotes the second-move agents. $A_f$ denotes the action space of the first-move agent and $a_f$ is its action. $A_s$ the set of actions for second-move agents and $a_s = <a_1, a_2, ..., a_{N-1}>$ denotes the second-move agents’ actions. The joint action can be denoted as $a = <a_f, a_1, a_2, ..., a_{N-1}>$. $\mathcal{P}$ is the Markovian transition distribution with $P(s', a|s, a)$ being the probability of state $s$ transiting to $s'$ with result $o$ after taking action $a$. The reward function is $\mathcal{R}: S \times A_f \times A_s \rightarrow \mathbb{R}$. Noted that the number of the first-move agent can be expanded to multiple. However, in order to introduce the essential ideas more clearly, we shall only consider one first-move agent most of the time.

4.1.2. Approach Overview.

The proposed approach called EFA-DQN combines election sub-module and deep Q-network sub-module shown as Fig. [1]. The EFA module elects the first-move agent based on the current observations and the actions at the previous timestep. Due to the stability of Q-Learning methods as discussed in [52] [53], we choose DQN as the policy module to further promote coordination among agents.

4.2. Electing First-move Agent (EFA) Mechanism

In the partially observable Markov games, there may exist multiple equilibria with multiple values. To alleviate this phenomenon, we introduce an EFA
mechanism inspired by game theory. In game theory, the Stackelberg leadership model is a strategic game in which one firm moves first, and then the others move sequentially [54]. In this game model, the first-mover makes the decision first, and the remaining players called second-movers make their best responses based on the first-mover’s decision. Then the first-mover adjusts its own decision according to the responses of the second-movers. Repeating until it reaches the Stackelberg Equilibrium (SE) [55], which is defined as follows:

**Definition 1. Stackelberg Equilibrium (SE):** In a two-player game, $\pi^*_f$ is called Stackelberg equilibrium policy for the first-mover when it satisfies the following inequality, $\forall \pi_f \in \Pi_f$:

$$\inf_{\pi_s \in \Pi_s(\pi_f)} R_f(\pi_f, \pi_s) \geq \inf_{\pi_s \in \Pi_s(\pi_f)} R_f(\pi_f, \pi_s)$$

where $\Pi_s(\pi_f) = \arg \max_{\pi_s \in \Pi_s} R_s(\pi_f, \pi_s)$ denotes the rational policy set of the second-mover to take the best response to the first-mover’s policy. Known $\pi_f^*$ for the first-mover, any $\pi_s \in \Pi_s(\pi_f^*)$ will be referred to as an optimal policy for the second-mover that is in equilibrium with the Stackelberg policy of the
first-mover. Moreover, it’s also applicable when the second-movers expand to multiple players.

Moreover, the Stackelberg equilibria finding in Stackelberg games can generate better coordination because it can break the symmetry and endow the hierarchical order of the play. As discussed in [55], the Nash equilibria solved in Markov Game may not be the optimal solution due to the symmetry structure for some games like the bimatrix example. In general, the Stackelberg equilibrium policies in a Markov game are the stable solution for the original problems [56].

Inspired by the above mentioned, we assume the game can be constructed as the asymmetric Stackelberg model endowing the hierarchical order of the actions. Then we attempt to approach the Stackelberg equilibrium by electing the first-move agent, and the other agents take actions conditioned on the first-move agent’s action.

Figure 2: The overall network architecture of EFA module.

The EFA module depicted in Fig.2 consists of a triple of the following net-
works: message encoder, a message aggregator and a weight generator, as specified by:

Message Encoder: \(f^i_{ENC} : (o^i_t, u^i_{t-1}) \mapsto h^i_t\)

Message Aggregator: \(f^i_{AGG} : (h^i_t, h^{-i}_t) \mapsto m^i_t\)

Weight Generator: \(f^i_{WG} : m^i_t \mapsto w^i_t\)

**Message Encoder.** Here, the message encoder takes the all observations \(o = [o^i_t]_N\) and the last actions \(u = [u^i_{t-1}]_N\) for the agents as inputs and outputs the encoded information feature vectors \(h = [h^i_t]_N\), where \(o^i_t\) is the observation for the agent \(i\) at the time \(t\), including the position, the velocity and etc. We use a full connected layer followed by a GRU layer to capture the inherent and temporal information for each agent.

**Message Aggregator.** Then the encoded feature vectors \(h_t = f_{ENC}(o_t, u_{t-1})\) is fed into the GCN module [40] for exchanging the information with other agents to realize the aggregation of the messages. Convolution kernels integrate the feature in the receptive field to extract the latent feature. Further, convolution kernels should be able to learn how to abstract the relationship between agents so as to integrate their input features [44]. Here, we use multi-head dot-product attention as the convolutional kernel to realize message integration and abstraction.

The whole latent feature vector for the agent \(i\) aggregated from other agents \(j\) is given as:

\[
h^i_t' = \sigma(\sum_{j \in (1) - i} a^ij W^T h^j_t \oplus h^i_t)
\]

where \(\sigma\) denotes an optional nonlinearity activation function, and \(W\) represents trainable weights in the convolution layer. Note that residual connection applied here can speeds up the convergence and solve the degradation of deep neural networks [57]. \(a^ij\) is a relation weight that denotes how much the agent \(i\) should pay attention to the agent \(j\). Computing the attention coefficient between agent
and the agent $j$ using their feature vectors $h_i^t$ and $h_j^t$ as:

$$a_{ij}^t = \frac{\exp(h_i^t W (h_j^t W)^T / \sqrt{d_k})}{\sum_{k \in \{I\}^-i} \exp(h_i^t W (h_k^t W)^T / \sqrt{d_k})} \sum_{j \in \{I\}^-i} a_{ij}^t = 1$$ (6)

where $W \in R^{d_k' \times d_k}$ is a learnable weight matrix, $d_k'$ and $d_k$ denote the dimension of the input vector and the latent vector respectively. $k \in \{I\}^-i$ indexes neighbouring agents of agent $i$.

For each attention head, the latent features are generated by Eq.(5). Then, the outputs of $M$ attention heads for agent $i$ are concatenated as the final feature vector at time $t$(we drop $t$ for simplicity):

$$h_i'' = \text{concatenate} \left[ h_m', m \in [0, M] \right]$$ (7)

In this way, the message aggregator can obtain the richer feature vector:

$$h_i'' = f_{AGG}^i(h_i', h_{-i})$$.

**Weight Generator.** Finally, We consider a single-layer feed-forward neural network $f_{WG}$ as a weight generator to output the collection of all agents’ weight, which maps the aggregated feature vector $m_i^t$ to $w_i^t$. The agent with the largest weight is elected as the first-move agent. But using $\text{argmax}$ function directly to find the maximum value is not appropriate. The $\text{argmax}$ function is not differentiable, which means that the gradients will be truncated and cannot be back-propagated from the DQN module to the weight generator sub-module. We adopts the Gumbel-Softmax $[58]$ estimator with an inverse temperature parameter $\beta$ of 1 to generate the weight vector $W_i = \{w_1^t, ..., w_n^t\}$ in one-hot tensor format.

The Gumbel-Softmax function enables us to compute gradients of a sample from the categorical distribution. Given a categorical distribution with class probabilities $\pi$, we can reparameterize it as:

$$w_i^t = \frac{\exp((g_i + \log \pi_i)\beta)}{\sum_{j=1}^n \exp((g_j + \log \pi_j)\beta)}$$ (8)

for $i = 1, ..., n$, where $g_i$ is a Gumbel noise, sampled from $\text{Gumbel}(0, 1) = -\log(-\log(u))$ and $u \sim \text{Uniform}(0, 1)$. $\beta$ is an inverse temperature parameter.
Importantly, our model architecture allows for end-to-end differentiability via the Gumbel-Softmax trick so as to obtain a trainable weight representing the importance of the agents at timestep $t$. Improper weights would result in a poor coordination in the tasks and the choice of weights has a non-negligible impact on the final performance.

With the EFA module, it can elect a first-move agent by measuring the importance of the information of all agents. This can be explained in the real world: the player who contributes the most to the overall is often regarded as the leader of the game, and other players making their best response to the leader will usually achieve the best results for the long run. It is noteworthy that the EFA module can handle any number of agents and elect multiple agents for the demand of the specific scenario, which enables the method to learn more complex tasks and be applied in large-scale multi-agent systems.

Moreover, promoting coordination in the cooperative environment is a persistent and long-term process. Changing the first-move agent all the time is not conducive to stable collaboration. Thus, the first-move agent should be consistent and stable in a short period of time. We make the first-move agent maintain $K$ time steps. Here, $K$ is a tunable hyper-parameter, and we set $K = 5$. This will further promote the emergence of long-term cooperative behaviour among agents in the coordination process.

4.3. Improved Deep Q Network

In this section, we introduce the improved deep Q-network in our framework. To simplify the overall network for training in an end-to-end manner, we adopt the VDN [18] as the mixing network to generate $Q_{tot}$, which estimates the optimal joint action-value function. The decomposition of VDN can represented as: $Q_{tot}(s, a) = \sum_{i=1}^{n} Q_i(s, a_i)$, which factorises $Q_{tot}$ into a summation of the per-agent utilities. Based on VDN, in order to place more importance on better joint actions and alleviate the problem of misestimation, we propose the weighted mixing network and counterfactual constraints for the first-move agents.
4.3.1. Trick 1: Weighted Mixing Network

Inspired by [21, 23] that investigates the influence of weighted Q-values, we propose the weighted mixing loss for decreasing the mistakes of misestimating and suboptimal policy problems in MARL. The weightings for the Temporal Difference (TD) should satisfy the following principle: 1). This weighting should assign a higher weighting to the underestimated state-action value for the joint actions, which could be the true optimal actions, and vice versa. 2). The weight should change dynamically as the policy improves towards the optimal one. Therefore, our Weighted Mixing Operator is defined as follows:

\[ w(s, u) = \begin{cases} 1, & Q_{\text{tot}}(s, u) < Q^*(s, u) \\ \alpha, & \text{otherwise} \end{cases} \] (9)

where \( \alpha \in (0, 1] \) is the penalty factor that imposes the constraint on the overestimated action-value function. Intuitively, \( \alpha \) should increases as the training goes on due to the improvement of suboptimal policy for overestimation. Thus, we design the \( \alpha \) that dynamically changes once per batch (updating). In the next batch for updating, \( \alpha = \frac{1}{B} \sum_{i=1}^{B} w_i \), where \( B \) denotes the batch-size.

4.3.2. Trick 2: Counterfactual Constraints for the first-move agent

In the MARL, the reward \( r \) indicates the overall contribution after taking the joint action \( u \) at the given state \( s \). However, it does not reveal each agent’s contribution to the whole system. Our goal is to encourage the first-move agent to choose the greater action to demonstrate and guide the better choice for the entire joint action to achieve better coordination. Therefore, we consider imposing a counterfactual constraint for the first-move agent to encourage its contribution.

Inspired by [59], we find out the contribution of the first-move agent by conducting counterfactual experiments to obtain the Difference Rewards as follows:

\[ \Delta R^f(u^f | s, u^{-f}) = R(s, u) - R(s, \langle u^{-f}, a_{cf}^f \rangle) \] (10)

where the former term denotes the true global rewards and the latter indicates the reward of changing agent \( f \)’s action \( a_f \) to the default action \( a_{cf}^f \) while holding
other agents’ actions constant. But the choice of the default action can be problematic. Therefore we can marginalize out the first-move agent by computing its expected contribution to the reward given its current policy:

$$\Delta R^f (u^f | s, u^{-f}) = R(s, u) - E_{a^f \sim \pi_{af}} [R(s, \langle u^{-f}, a^f \rangle)]$$  \hspace{1cm} (11)$$

By adapting difference rewards to use the Q-function, approximated by a centralized critic $Q_\omega(s, a)$, we can obtain the tailored counterfactual advantage function for the first-move agent $f$ as [59]:

$$A^f (s, u) = Q_\omega(s, u) - \sum_{a' \in A^f} \pi_{af}(a'|s)Q_\omega(s, \langle u^{-f}, a' \rangle)$$  \hspace{1cm} (12)$$

The counterfactual policy gradient for the first-move agent is $\nabla_{\theta_f} \log(a_f|o_f)A^f (s, u)$, where the first-move agent’s policy is parameterized by $\theta_f$. This counterfactual term as the dedicated sub-objectives to be used as a regularizer is to constrain the first-move agent for better coordination.

In summary, rather than optimize the weighted temporal difference loss directly to learn the policy, we additionally regularize the behaviour by explicitly modeling the individual impact of the first-move agent. We optimize the regularized reinforcement learning objective as Eq.13. Moreover, we demonstrate our algorithm in Algorithm 1.

$$L(\theta) = \sum_{i=1}^{n} w(s, u)[r + \gamma \max_{u'} Q(s', u'; \theta^{-}) - Q_{tot}(s, u; \theta)]^2 + \alpha A^f (s, u) \log (\max a_f|o_f)$$  \hspace{1cm} (13)$$

To better understand the contribution of the weighted mixing network and counterfactual constraints for the first-move agents, we conduct the ablation experiments to investigate the impact of the two modules. We compare the improved DQN called EFA-DQN with the above two improvements and vanilla DQN labeled as EFA-naive with 2 and 5 agents in the Cooperative Navigation environment respectively. The experimental results are set out in Fig.3.

These results show the average episode rewards versus the number of full-episode games on the Cooperative Navigation tasks. The comparison of the two results indicates that our weighted mixing and counterfactual constraints can
Algorithm 1: Elect First-move Agent with Deep Q-Network (EFA-DQN)

**Initialize** \( \epsilon, \gamma, \alpha \) and replay buffer \( \mathcal{D} = \{ \} \);

**Initialize** \( \theta_1, \ldots, \theta_n \) for the parameters of agent networks;

\( \theta_i^- = \theta_i \) for \( i = 1, \ldots, n \);

\( \text{step} = 0, \text{episodes} = 0 \);

**for** each episode **do**

\( s_0 = \text{initial state} \);

**Initialize** \( h^{(1)}_0, \ldots, h^{(n)}_0 \) for RNN states;

**for** each \( t \) **do**

\( W_t = \text{EFA}(o_{t-1}^f, u_{t-1}, t); \) // The EFA is in Algorithm 2

\( o_t^f = W_t \cdot o_t; \) // The observation of the first-move agent

Sample the first-move action with \( \epsilon \)-greedy from \( Q^f_t(o_{t}^f, u_{t}^f; \theta^f) \);

Sample other actions with \( \epsilon \)-greedy from \( Q_i^t(o_{t}^i, u_{t}^i; \theta^i), i \in \{ I \} - f \);

Update RNN state \( h^{(1)}_{t-1}, \ldots, h^{(n)}_{t-1} \) to \( h^{(1)}_t, \ldots, h^{(n)}_t \);

receive reward \( r_t \) and observe a new state \( o_{t+1} \);

add transition \( \{ o_t, u_t, r_t, o_{t+1} \} \) in \( \mathcal{D} \);

**end**

**if** episodes > \( B \) **then**

sample a minibatch \( \{ o_j, u_j, r_j, o_{j+1} \}_{j=0}^M \sim \mathcal{D} \);

\( Q^\text{total}_j \leftarrow \text{Mix}(Q^1_j(\cdot; \theta^1), \ldots, Q^n_j(\cdot; \theta^n)); \)

\( \hat{Q}^\text{total}_j \leftarrow \text{Mix}(\hat{Q}_1^j(\cdot; \xi^1), \ldots, \hat{Q}_n^j(\cdot; \xi^n)); \)

set \( y_j = \begin{cases} r_j, & \text{if terminated} \\ r_j + \gamma \max \hat{Q}^\text{total}_{j+1}, & \text{else} \end{cases} \)

\( w(o_j, u_j) = \begin{cases} 1, & Q^\text{total}(o_j, u_j) < \hat{Q}^\text{total}(o_j, u_j) \\ \alpha, & \text{otherwise} \end{cases} \)

Compute the advantage for the first-move agent as \( A^f_t \) using COMA critic \([59]\);

update \( \theta \) to minimize: \( J(\theta) = \sum_j w(o_j, u_j)(y_j - Q^\text{total}_j)^2 + \alpha A^f_t(o_j, u_j) \log(\max A^f_t(a_j^f | o_j^f)) \);

Every \( C \) steps reset \( \theta_i^- = \theta_i \) for \( i = 1, \ldots, n \);

**end**

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**Algorithm 2: Elect First-move Agent (EFA) sub-module**

Initialize $K = 5$, $H = 4$;

Initialize $\theta_1, \theta_2, \theta_3$ for the Message Encoder, Message Aggregator, Weight Generator;

if $t \% K == 0$ then
  // $t$ is the input which denotes the current timestep
  Compute $h_t = f_{ENC}(o_t, u_{t-1}; \theta_1)$;
  Compute $m_t = f_{AGG}(h_t; \theta_2)$;
  Compute $eva_t = f_{WG}(m_t; \theta_3)$;
  Compute $W_t = \text{Gumbel – Softmax}(eva)$;
else
  $W_t = W_{t-1}$; //maintain the weight vector from the last timestep
end

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Figure 3: The ablation study between the improved DQN (EFA-DQN) and vanilla DQN (EFA-vanilla): (a). Cooperative Navigation with 2 agents. (b). Cooperative Navigation with 5 agents.

The model improve performance. However, the experimental results also reveal that our model is not very robust. As the number of agents increases, the variance of the results becomes larger, and the effect is slightly improved.
5. Experiment

To evaluate our model, we measured its performance with diverse MARL algorithms on several cooperative tasks including the Cooperative Navigation, the Physical Deception\textsuperscript{1}, Google Football 2-vs-6 scenario and Google Football 3-vs-1 scenario\textsuperscript{2}, which are shown in Fig.4.

![Figure 4](image.png)

Figure 4: Overview of experimental environments: (a). Cooperative Navigation with multiple agents trying to cover the same number of landmarks. (b). Physical Deception with multiple good agents trying to get higher reward to deceive the adversary. (c). The Google football tasks. We pick two scenario of \textit{academy}_3\textunderscore vs\textunderscore1\textunderscore with\textunderscore keeper and \textit{academy}_run\textunderscoreto\textunderscorescore\textunderscorewith\textunderscorekeeper in this paper.

5.1. Baselines

The baselines for evaluation are as follows. We consider the value-based methods including VDN and QMIX, the counterfactual policy gradient method COMA, the classical communication method CommNet and the graph-based method G2ANet for fully evaluating the superiority of our algorithm.

- **VDN**\textsuperscript{18}: Value Decomposition Network (VDN) imposes the structural constraints of the additivity in factorization, which represents $Q_{tot}$ as a sum of individual Q-values.

- **QMIX**\textsuperscript{20}: It is proposed to overcome the limitations that VDN has a strong assumption and ignores any extra state information available.

\textsuperscript{1}The environment code is at [https://github.com/openai/multiagent-particle-envs](https://github.com/openai/multiagent-particle-envs)

\textsuperscript{2}The environment code is at [https://github.com/google-research/football](https://github.com/google-research/football)
during training. QMIX enforces that $Q_{\text{tot}}$ is monotonic in the individual Q-values $Q^i$.

- **COMA [59]**: It updates stochastic policies using the counterfactual gradients and deals with the issue of credit assignment.

- **CommNet [10]**: It uses the continuous communication through broadcasting a communication vector representing the average of neighbors’ hidden states.

- **G2ANet [62]**: The two-stage attention network in G2ANet indicate whether there is an interaction between two agents and the importance of the interaction. The graph neural network aggregates the information of neighbors using the weights from the two-stage attention network.

5.2. Performance Validation

To validate the performance of the EFA-DQA, we conduct the experiments with multiple players on a public and comparable environment, the Cooperative Navigation and the Physical Deception, depicted in Fig. 4a ($N = 3$ for example) and Fig. 4a ($N = 3$ for example) respectively.

In the Cooperative Navigation, $n$ agents and $n$ landmarks are initialized with random locations, and the agents must cooperate to cover all landmarks by controlling their velocities with directions. The action set includes [up, down, left, right, stop]. Each agent only observes its velocity, position and displacement from other agents and the landmarks. The shared reward is the negative sum of displacements between each landmark and its nearest agent. Also, agents must also avoid collisions, as each agent incurs $-1$ shared reward for every collision against other agents.

In the Physical Deception, there are one adversary, $N$ good agents, and $N$ landmarks in which one is the ‘target landmark’. All agents can observe the position of landmarks and the other agents. Good agents are rewarded based on the closed distance from the target landmark but negatively rewarded on how close the adversary is close to the target landmark. The adversary is awarded
Figure 5: The initial 10 random seeds are used to validate the performance and convergence of EFA-DQN comparing with VDN, QMIX, COMA, CommNet, G2ANet on the Cooperative Navigation with multiple agents and landmarks.

Based on how close it is to the target, but it doesn’t know which landmark is the target landmark. So good agents have to learn to ‘split up’ and cover all landmarks to deceive the adversary.

Firstly, we explore our algorithm on the Cooperative Navigation with \( n = 2 \), \( n = 3 \), \( n = 5 \) to demonstrate that the EFA-DQN has the better convergence and efficiency. We average the episode rewards of the last 100 episodes for a total of 30000 episodes. Fig. 5 show the average rewards of various baselines, which are proposed for solving the credit assignment problem for the coordination, comparing with our EFA-DQN algorithm. It shows the quicker convergence and the lower variance in our EFA-DQN algorithm. In this pure cooperative environment, our algorithm suffers no drop in performance when trained in cases where the variance is minimal.

Moreover, we also test our algorithm in Physical Deception, a mixed cooperative-competitive environment. However, we solely apply our election mechanism to the good agents to elect the first-move agent. Our goal is to promote the emergence of cooperative behaviour among multiple agents in such an environment to achieve better coordination. The experimental results for a total of 10000 episodes are shown in Fig. 6. The good agents in the three environments act better, and the adversary obtains a lower reward than all the baselines. However, comparing with the baselines, our algorithm has a certain but not significant performance improvement, and it is unstable. It demonstrates that our algo-
algorithm is not very robust in such a mixed environment, which can be attributed to our election mechanism and weighted mixing network that are suitable for the fully cooperative settings.

Figure 6: The comparison among VDN, QMIX, COMA, CommNet, G2ANet and EFA-DQN on the Physical Deception with multiple good agents and one adversary. The initial 10 random seeds are used to validate the performance. The upper row represents the average reward of good agents, and the lower line is the average reward of the adversary in the corresponding environment.

5.3. The Google Football

For proving the feasibility of our algorithm in a realistically simulated complicated and dynamic environment, we explore our method on the Google Football environment without any obvious well-defined behavioural abstractions, a suitable testbed to study multi-agent decision making and coordination.

The environment exposes the raw observations, including ball information, the left and right team information, controlled player information, ball controlled information, game mode, etc. In addition, we use the wrappers called Simple115StateWrapper provided by the environment, which convert raw observations to 115 floats. The players are endowed with available actions at each
state from 19 actions over no-op, shoot and move and etc. Here, we pick the scenario of academy_3_vs_1_with_keeper for 3-vs-1 experiment and the scenario of academy_run_to_score_with_keeper for 2-vs-6 experiment. In the Google Football tasks, agents need to coordinate for better rewards and only scoring leads to rewards. We only control left-side players, which are against the rule-based built-in bots controlled by the game engine in our experiments.

In the scenario of academy_3_vs_1_with_keeper for the full-field game, three of our players try to score from the edge of the box, two players stand on each side, and the other stands at the center owning the ball. There is only an opponent keeper. Initially, the player at the center is facing the defender. The scenario is relatively simple and requires tacit cooperation with each other for scoring.

The scenario provided by google research called academy_run_to_score_with_keeper, with the starting point of the player set in the middle of the field, is a 2-vs-6 game. Our players need to score against a keeper and five opponent players who chase our players from behind. This is a complex and hard scenario due to the defense and hindrance of multiple opponent players.

![Graphs showing rewards for football games](image)

Figure 7: The initial 10 random seeds are used to validate the performance and convergence of EFA-DQN comparing with VDN, QMIX, COMA, CommNet and G2ANet on the football with scenario academy_3_vs_1_with_keeper for football 3_vs_1 and academy_run_to_score_with_keeper for football 2_vs_6.

The Google Football Environment, including the richness of possible be-
behaviours and the need to coordinate movement with respect to a dynamic context including ball, goals, and other players makes the coordinated strategies emerge harder. But the performance comparison against baselines in Fig.6 shows that EFA-DQN can still outperform all the baselines and also obtain a stable high episode reward within limited steps on both scenarios. The results demonstrate that our algorithm can be well adapted to the complex and dynamic practical environment.

5.4. Experiment Details and Supplementary

In our algorithm, the EFA module firstly elects the first-move agent according to the information aggregated from all agents. Then the first-move agent takes its action based on its history, and the second-move agents give their best response to the latter. The neural network structure of the agents’ policy includes a fully connected layer with 64 units, followed by a GRU recurrent layer and a fully-connected layer with $|A|$ outputs, where $|A|$ denotes the action dimension. We set $30 \times 64$ transitions for mini-batch training which are uniformly sampled from the experience replay buffer. The target network loads the parameters from the updated network every 200 optimizing steps. As for the EFA sub-module, we use the multi-head attention as the graph convolutional kernel and set the number of the attention head as $h = 4$. We construct the coordinated graph of all agents as a fully connected graph, and its adjacency matrix is symmetric with size $N \times N$ where $N$ is the number of the agents.

We set discount factor $\gamma = 0.99$. The optimization is conducted using RM-Sprop with a learning rate of $5 \times 10^{-4}$ and $\alpha = 0.99$ with no weight decay. Exploration for action selection is performed during training, during which each agent executes $\epsilon$-greedy policy over its actions. $\epsilon$ is annealed from 0.2 to 0.05 over 50k time steps and is kept constant afterwards.

Otherwise, the information regarding computational resources used is Enterprise Linux Server with 96 CPU cores and 6 Tesla K80 GPU cores(12G memory).
6. Conclusion

In this paper, we propose a framework that promotes coordination through electing the first-move agent followed by an improved deep Q-network (EFA-DQN) in cooperative multi-agent reinforcement learning. The EFA sub-module brings together benefits of graph convolutional network and attention mechanism for message aggregating, which is sent to the weight-based scheduler for the election. Then we introduce a customized deep Q-network for putting more emphasis on better joint actions and alleviate the problem of misestimation. Empirical results show that EFA-DQN can improve the agents’ performance and leads to faster convergence.
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