ABSTRACT

Cooperation between agents in a multi-agent system (MAS) has become a hot topic in recent years, and many algorithms based on centralized training with decentralized execution (CTDE), such as VDN and QMIX, have been proposed. However, these methods disregard the information hidden in the individual action values. In this paper, we propose HyperGraph CoNvolution MIX (HGCN-MIX), a method that combines hypergraph convolution with value decomposition. By treating action values as signals, HGCN-MIX aims to explore the relationship between these signals via a self-learning hypergraph. Experimental results present that HGCN-MIX matches or surpasses state-of-the-art techniques in the StarCraft II multi-agent challenge (SMAC) benchmark on various situations, notably those with a number of agents.

Index Terms— Hypergraph Convolution, Multi-Agent Reinforcement Learning, Coordination and Control

1. INTRODUCTION

In recent years, multi-agent reinforcement learning (MARL) has increasingly gained the attention of researchers as a result of its successful applications in gaming AI [1][2][3], robotics [4], networks and so on. Reinforcement learning (RL) requires the agent to correctly process the signals given by the environment in a Markov Decision Process (MDP) and make appropriate feedback based on this, so as to maximize the cumulative reward. However, in multi-agent systems, the existence of other agents renders the environment unstable from each agent’s perspective. How to deal with environmental signals in multi-agent tasks is still an open research question.

Currently, the centralized training with decentralized execution (CTDE) [5] paradigm is usually utilized in MARL. That is, during training, each agent can acquire global signals, including information from other agents, and interact with the environment only on the basis of signals relevant to themselves. Since many RL algorithms are constructed by using the Actor-Critic (AC) [6] structure and the critic is often only involved in the calculation during training, we can input the global signal into the critic during training and rely on the actor to produce the feedback during execution. Many methods based on communication CommNet [7] and BicNet [8], which mitigate the instability problem by transmitting signals between agents, have been the subject of intense research for some years. In addition, value decomposition [9] also plays an essential role in MARL community, which fuses the action values obtained by each agent according to the signal obtained by itself to calculate a global value. In this way, all the agents are regarded as a entirety. The methods based on this idea have achieved considerable success in the decentralized partially observable Markov Decision Process (Dec-POMDP) [10], which is a model for coordination and decision-making among multiple agents.

There are already some graph neural networks with graph representation learning to solve node or graph classification tasks. Similar to molecules, social, and financial networks, multi-agent systems can also be regarded as graph-structured networks. DGN [11] and Graph-MIX [12] introduce graph neural networks into MARL, enabling signals to be transmitted between agents, while DCG [13] demonstrate that hypergraphs can further explore the representation of the relationship between agents. These studies take the topological structure among agents into account by incorporating the idea of graph convolution into the CTDE structure. However, one major drawback of these studies is that the graph’s adjacency information is established manually, i.e., the graph’s edges are defined based on whether the agents are alive or can see each other. Because the aforementioned definitions frequently fail to accurately and fully describe the interaction between agents, it is critical to understand how to learn the inter-agent relationship. In this paper, we propose a novel end-to-end graph-based value-decomposition method, namely HyperGraph CoNvolution MIX (HGCN-MIX). In HGCN-MIX, the agent can determine the connections between itself and other agents based on the environmental signals it receives, which
analogous to most real-world situations. We believe that the dynamically adjusting the relationships between agents can remarkably argue the performance of the system in some complicated scenarios.

2. BACKGROUND

2.1. Dec-POMDP

Typically, a Dec-POMDP is used to describe the fully co-operative multi-agent tasks. A Dec-POMDP can be defined by a tuple \( G = (S, U, P, \mathcal{Z}, \tau, O, n, \gamma) \). \( s \in S \) denotes the true global state of the environment. Each agent \( a \in A := \{1, \ldots, n\} \) will take an individual action \( u_a \in U \) at each timestep. \( U \) is the action set. All the individual actions in the same timestep will form a joint action \( u \in U \equiv U^n \). \( P(s'|s, u) : S \times U \times S \rightarrow [0, 1] \) is the state transition function, which takes the current state and the joint action as input, generates the next state. All the agents share the same reward function \( r(s, u) : S \times U \rightarrow \mathbb{R} \).

Each agent \( a \) gets its own local individual partial observation \( z \in \mathcal{Z} \) according to the observation function \( O(s, a) : S \times A \rightarrow \mathcal{Z} \). Agent’s previous actions and observations make up its own action-observation history \( \tau_a \in T = (\mathcal{Z} \times U) \). Then, policy of agent policy is represented as: \( \pi_a(u_a|\tau_a) : T \times U \rightarrow [0, 1] \).

Similar to single agent reinforcement learning, the sum of discounted rewards \([14]\) is defined as \( R^t = \sum_{t=1}^{\infty} \gamma^{t-1} r_t \), and we aim to maximize the \( \mathbb{E}_{\tau \sim \pi}[R^0|s_0] \), where \( \tau \) is a trajectory and \( \gamma \in (0, 1) \) is the discount factor.

2.2. Value decomposition

In Dec-POMDP, agents share the same joint reward which makes it difficult to design a unique reward function for each agent. However, this way may lead to “lazy agents” \([9]\), some of which agent can never learn the optimal policies.

The core of CTDE is that a centralized critic will guide the agents during training. During execution, only agents will be retained. Based on CTDE, many algorithms have been proposed, such as Value-Decomposition Networks (VDN) \([9]\), QMIX \([13]\). These methods all follow the Individual-Global-MAX (IGM) equation:

\[
\arg \max_u Q_{tot}(\tau, u) = \left( \begin{array}{c}
\arg \max_{u_1} Q_1(\tau_1, u_1) \\
\vdots \\
\arg \max_{u_n} Q_n(\tau_n, u_n)
\end{array} \right)
\]

IGM assumes that the optimality of each agent is consistent with the global optimality.

2.3. Definition of hypergraph

A hypergraph \([16]\), denoted as \( \mathcal{G} \), is consisted of a vertex set \( \mathcal{V} = \{v_1, v_2, \ldots, v_N\} \), where \( N \) represents the number of vertices, and edge set \( \mathcal{E} \) with \( M \) hyperedges. An adjacency matrix of the hypergraph \( H \subseteq \mathbb{R}^{N \times M} \) is used to indicate the relationship between a vertex and a hyperedge. For a vertex \( v_i \in \mathcal{V} \) and a hyperedge \( e \in \mathcal{E} \), if \( v_i \) is connected by \( e \), \( H_{ie} = 1 \), otherwise 0. Besides, each hyperedge \( e \) has a non-negative weight \( W_{ee} \). All the \( W_{ee} \) form a diagonal matrix \( \mathcal{W} \in \mathbb{R}^{M \times M} \).

In a hypergraph, the vertex degree \( \mathcal{D} \in \mathbb{R}^{N \times N} \) and the hyperedge degree \( \mathcal{B} \in \mathbb{R}^{M \times M} \) are defined as \( D_{ii} = \sum_{e \in \mathcal{E}} W_{ee} H_{ie} \), \( B_{ee} = \sum_{i=1}^{N} H_{ie} \). Both \( \mathcal{D} \) and \( \mathcal{B} \) are diagonal matrices.

In a basic undirected graph, the degree of a edge is 2, which means each edge only connects 2 vertices. But in hypergraph, a edge maybe connect many vertices. This allows the hyperedge to obtain more information about the nodes. Furthermore, selecting various hyperedgeds makes it easy to incorporate prior knowledge.

2.4. Spectral convolution on hypergraph

Given a hypergraph \( \mathcal{G} = (\mathcal{V}, E, \Delta) \) with \( N \) vertices and \( M \) hyperedges, in which \( \Delta \in \mathbb{R}^{N \times N} \) is the hypergraph Laplacian semi-definite matrix. Then, \( \Delta \) can be factorized as \( \Delta = \Phi \Lambda \Phi^T \), in which \( \Phi = \text{diag}(\phi_1, \ldots, \phi_n) \) is the orthonormal eigen vectors and \( \Lambda = \text{diag}(\lambda_1, \ldots, \lambda_n) \) is the diagonal matrix whose diagonal elements are the corresponding eigenvalues. The Fourier transform for a signal \( x = (x_1, \ldots, x_n) \) is defined as \( \tilde{x} = \Phi^T x \). Then, the spectral convolution of signal \( x \) and filter \( g \) is defined as:

\[
g \ast x = \Phi g(\Lambda) \Phi^T x,
\]

where \( g(\Lambda) = \text{diag}(g(\lambda_1), \ldots, \lambda_n) \) is a function of the Fourier coefficients. However, the time complexity of this method arrives \( O(n^2) \). To solve this problem, Feng et al. \([17, 18, 19]\) derived spectral convolution as:

\[
g \ast x \approx \theta_0 x - \theta_1 D^{-\frac{1}{2}} \mathcal{H} \mathcal{W}^{-1} \mathcal{H}^T D^{-\frac{1}{2}} x,
\]

where \( \theta_0 \) and \( \theta_1 \) are the parameters of filters over all nodes. Further, with using a single parameter \( \theta \) is defined as:

\[
\begin{cases}
\theta_1 = -\frac{2}{\theta} \\
\theta_0 = \frac{1}{\theta} D^{-\frac{1}{2}} \mathcal{H} \mathcal{W}^{-1} \mathcal{H}^T D^{-\frac{1}{2}} - \frac{1}{\theta} x
\end{cases}
\]

Then, they derived the hypergraph convolution (HGCN) as:

\[
x^{(l+1)} = D^{-\frac{1}{2}} \mathcal{H} \mathcal{W}^{-1} \mathcal{H}^T D^{-\frac{1}{2}} x^{(l)} P,
\]

where \( P \) is called as the weight matrix between the \( l \)-th and \( (l+1) \)-th layer \([20]\). For each node in HGCN, more information can be accessed between those nodes connected by a common hyperedge, and the greater the weights, the more information is provided.
3. METHOD

3.1. Difficulties of traditional hypergraph

In section 2.3, we talk about the definition of hypergraph. Admittedly, traditional hypergraphs have three drawbacks: 1) prior knowledge is required to build hypergraph, but the prior knowledge is always hard to obtain; and 2) the hypergraph is fixed once it is established; and 3) the hypergraph only include two value, 1 and 0, which indicates whether the node is connected by the hyperedge. We rethink that agents need different levels of collaboration in various situations. Surely, fixed binary hypergraph can hardly solve this problem.

Instead of building a fixed binary hypergraph based on prior knowledge, we would like to generate a dynamic hypergraph via neural networks based on agents’ individual observations. Using real-value hypergraph rather than binary hypergraph to describe the connections between agents.

3.2. Building hypergraph

In hypergraph attention mechanism [20], a probabilistic model assigns non-binary and real values to measure the degree of connectivity. Besides, the incidence matrix $H$ can also flow Eq. [3] To better describe the degree of collaboration, we replace the original binary hypergraph with a non-binary hypergraph.

In HGCN-MIX, we utilize a linear function which takes individual observation $z_i \in Z, i \in \{1, \ldots, n\}$ as input, and generates a real values vector $A_i \in \mathbb{R}^m$, where $m$ represents the number of hyperedges. Then, under the ReLU operation, the negative weight will be changed to 0, meaning that the too week connections too weak are discarded. Each value in $A_i$, denoted as $\omega_{i,j}, j \in \{1, \ldots, m\}$, presents the weight for hyperedge $e_j$. The entirety of $\omega_{i,j}$ consist of the first part $H_1$ of our hypergraph $H$:

$$ H_1 = \text{ReLU} (\text{Linear} (Z)). $$

This part aims to make agents learn to collaborate with others in different observations.

3.3. Mixing network

As shown in Figure 1, the individual observations $Z$ are utilized to construct the hypergraph discussed in 3.2. Each agent applies a DRQN [21] to learn individual action value $Q_{a} \in Q$, where $a \in \{1, \ldots, n\}$. Then, the hypergraph convolution performs on $Q$. In convolution, we set $P$ to $\mathbb{I}_n$, and $W$ to the learned parameters. To keep Eq. [1] we use the absolute value of $W$ for HCGN. This means,

$$ Q' = \text{HGCN}(\text{HGCN}(Q, \text{abs}(W_1)), \text{abs}(W_2)), $$

where $W_i, i \in \mathbb{R}$ means the weight matrix in the $i$-th layer; $Q' \in \mathbb{R}^n$ is the transformed action values. Each action value $Q_a$ append the information contained in all the $Q_a$ by our method. Agents can strengthen their collaboration by doing so. Then, a mixing module attempts to add global state information.

$Q_{tot} = Q' + \sum_{i=1}^{n} Q_{a}.$
Table 1. Scenarios and maximum median win ratios

| Scenario (Difficulty) | Ally Units       | Enemy units       | Maximum Median Win Ratios(%) |
|-----------------------|------------------|-------------------|-------------------------------|
|                       |                  |                   | HGCN-MIX | QMIX | VDN | QTRAN | RODA | ROMA |
| 2s3z (Easy)           | 2 Stalkers       | 2 Stalkers        | 100      | 100  | 100 | 94    | 100  | 94   |
|                       | 3 Zealots        | 3 Zealots         |          |      |     |       |      |      |
| 5m vs 6m (Hard)       | 5 Marines        | 6 Marines         | 69       | 69   | 81  | 59    | 56   | 25   |
| 27m vs 30m (Super Hard)| 27 Marines       | 30 Marines        | 97       | 100  | 94  | 38    | 25   | 0    |
| MMM2 (Super Hard)     | 1 Medivac        | 1 Medivac         | 97       | 100  | 94  | 56    | 97   | 50   |
|                       | 2 Marauders      | 3 Marauder        |          |      |     |       |      |      |
|                       | 7 Marines        | 8 Marines         |          |      |     |       |      |      |
| 1c3s5z (Easy)         | 1 Colossus       | 1 Colossus        | 84       | 69   | 44  | 9     | 38   | 13   |
|                       | 3 Stalkers       | 3 Stalkers        |          |      |     |       |      |      |
|                       | 5 Zealots        | 5 Zealots         |          |      |     |       |      |      |
| 2c vs 64zg (Hard)     | 2 Cikissi        | 64 Zerglings      | 97       | 97   | 97  | 97    | 94   | 53   |
| 8m vs 9m (Easy)       | 8 Marines        | 9 Marines         | 100      | 100  | 94  | 100   | 100  | 81   |
| bane vs bane(Hard)    | 20 Zerglings     | 20 Zerglings      | 100      | 100  | 94  | 100   | 100  | 81   |
|                       | 4 Banelings       | 4 Banelings       |          |      |     |       |      |      |

3.4. Loss function

Our loss function follows the TD-error [14]:

\[
\mathcal{L}(\theta) = \frac{1}{2}\left(y_{tot} - Q_{tot}(\tau, u(\theta))\right)^2, \tag{5}
\]

where the joint action-value function is parameterized by \(\theta\), and \(y_{tot} = r + \gamma \max_{u'} Q_{tot}(\tau', u'(\theta))\). The target network is parameterized by \(\theta\).

4. EXPERIMENTS

4.1. Settings

We conduct the experiments with SMAC [22] as the testbed environments. SMAC, based on StarCraft II, is a popular experiment platform for Dec-POMDP problems. Our experiments are based on Pymarl [22]. The version of the Starcraft II is 4.6.2 (B69232) in our experiments. Our method is compared with several well-known baseline algorithms include RODE [23], ROMA [24], QMIX, QTRAN [25], and VDN. Note the fact that the original version of the Starcraft II in RODE and ROMA is 4.10, which maybe cause the different performance. Each experiment is conducted using five distinct random seeds, and the resulting curves are based on the median win ratios of the five random seeds. Besides, our experiments are carried out on Nvidia GeForce RTX 3090 graphics cards and Intel(R) Xeon(R) Platinum 8280 CPU. We perform 2M timesteps for training. In HGCN-MIX, the number of self-learning hyperedges is set to 32. Note that the hidden dim in MLP is set to 128. Other hyperparameters and the code of HGCN-MIX follows this link: [https://github.com/cugbbaiyun/HGCN-MIX](https://github.com/cugbbaiyun/HGCN-MIX)

4.2. Validation

In Figure 2, the solid line shows the median win ratio of the 5 random seeds, and the shaded area means the 25 – 75% percentiles of the win ratios. The experimental results present that HGCN-MIX outperforms QMIX significantly. So HGCN-MIX significantly improves the coordination between agents, in particular on the maps with large number of agents, such as 27m vs 30m and MMM2. Besides, in easy scenario 2s3z, HGCN-MIX converges faster than our baseline methods. Matrix multiplication and matrix inversion use the majority of the extra processing resources in HGCN-MIX as compared to QMIX. However, the significant improvement is still worthwhile.

4.3. Ablation

In ablation, the HGCN-MIX without self-learning hyperedges (only \(H_2\) in Eq. [4] reversed) is referred to as HGCN-MIX-OH. In fact, when hypergraph is set as an identity matrix, no matter what \(W\) is, the result of HGCN is: \(x^{(l+1)} = x^l\), which means
that nodes in this hypergraph hardly get information from others. Thus, we set the $W$ to ones to avoid floating point errors. We test HGCN-MIX and HGCN-OH on $MMM2$ and $2s3z$ and collect the average win ratios. The hyperparameters are set to the same as HGCN-MIX. As we shown in Figure 3 in $2s3z$, both HGCN-MIX and HGCN-MIX-OH have high performance. However, only HGCN-MIX has better performance in $MMM2$. This demonstrates self-learning hyperedges enhance the coordination, particularly in scenarios with a number of agents and tight cooperation.

5. CONCLUSION AND FUTURE WORK

In this paper, we propose a MARL algorithm named HGCN-MIX, which combines hypergraph convolution with value decomposition. The problems of decomposing joint state-action value functions in MARL using hypergraph convolution and generating hypergraphs without previous knowledge are solved by HGCN-MIX.

The results show that HGCN-MIX outperforms in some scenarios with a large number of agents. For the sake of HGCN-MIX only transforming the action values, it can be widely applied in many MARL algorithms which are based on value decomposition. Besides prior knowledge can be easily added via different hyperedges.

During experiments, we find that self-learning hyperedges tend to be all positive in some scenarios. It is a natural intuition that agents tend to connect with all other agents, revealing to us that there may be some relationship between self-learning hypergraph and hypergraph filled with the value one. We will explore it in the near future.

6. REFERENCES

[1] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al., “Human-level control through deep reinforcement learning,” nature, vol. 518, no. 7540, pp. 529–533, 2015.

[2] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al., “Mastering the game of go with deep neural networks and tree search,” nature, vol. 529, no. 7587, pp. 484–489, 2016.

[3] Chen Gong, Qiang He, Yunpeng Bai, Xinwen Hou, Guoliang Fan, and Yu Liu, “Wide-sense stationary policy optimization with bellman residual on video games,” in 2021 IEEE International Conference on Multimedia and Expo (ICME). IEEE, 2021, pp. 1–6.

[4] Sergey Levine, Chelsea Finn, Trevor Darrell, and Pieter Abbeel, “End-to-end training of deep visuomotor policies,” The Journal of Machine Learning Research, vol. 17, no. 1, pp. 1334–1373, 2016.
[5] Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, Pieter Abbeel, and Igor Mordatch, “Multi-agent actor-critic for mixed cooperative-competitive environments,” arXiv preprint arXiv:1706.02275, 2017.

[6] Richard S Sutton, David A McAllester, Satinder P Singh, et al., “Policy gradient methods for reinforcement learning with function approximation,” in Advances in neural information processing systems, 2000, pp. 1057–1063.

[7] Sainbayar Sukhbaatar, Rob Fergus, et al., “Learning multiagent communication with backpropagation,” Advances in neural information processing systems, vol. 29, pp. 2244–2252, 2016.

[8] Peng Peng, Ying Wen, Yaodong Yang, et al., “Multiagent bidirectionally-coordinated nets: Emergence of human-level coordination in learning to play starcraft combat games,” arXiv preprint arXiv:1703.10069, 2017.

[9] Peter Sunehag, Guy Lever, Audrunas Gruslys, et al., “Value-decomposition networks for cooperative multi-agent learning,” ArXiv, vol. abs/1706.05296, 2018.

[10] Frans A Oliehoek and Christopher Amato, A concise introduction to decentralized POMDPs, Springer, 2016.

[11] Jiechuan Jiang, Chen Dun, Tiejun Huang, et al., “Graph convolutional reinforcement learning,” arXiv preprint arXiv:1810.09202, 2018.

[12] Navid Naderializadeh, Fan H Hung, Sean Soleyman, et al., “Graph convolutional value decomposition in multi-agent reinforcement learning,” arXiv preprint arXiv:2010.04740, 2020.

[13] Wendelin Böhmer, Vitaly Kurin, and Shimon Whiteson, “Deep coordination graphs,” in International Conference on Machine Learning. PMLR, 2020, pp. 980–991.

[14] Richard S Sutton and Andrew G Barto, Reinforcement learning: An introduction, MIT press, 2018.

[15] Tabish Rashid, Mikayel Samvelyan, Christian Schroeder, et al., “Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning,” in International Conference on Machine Learning. PMLR, 2018, pp. 4295–4304.

[16] Claude Berge, Hypergraphs: combinatorics of finite sets, vol. 45, Elsevier, 1984.

[17] Yifan Feng, Haoxuan You, Zizhao Zhang, et al., “Hypergraph neural networks,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, vol. 33, pp. 3558–3565.