From Explicit Communication to Tacit Cooperation: A Novel Paradigm for Cooperative MARL

Extended Abstract

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ABSTRACT
Centralized training with decentralized execution (CTDE) is a widely used learning paradigm that has achieved significant success in complex tasks. Drawing inspiration from human team cooperative learning, we propose a novel paradigm that facilitates a gradual shift from explicit communication to tacit cooperation. In the initial training stage, we promote cooperation by sharing relevant information among agents and concurrently reconstructing this information using each agent’s local trajectory in a self-supervised manner. We then combine the explicitly communicated information with the reconstructed information to obtain mixed information. Throughout the training process, we progressively decrease the proportion of explicitly communicated information, facilitating a seamless transition to fully decentralized execution without communication.

KEYWORDS
Reinforcement Learning; Multi-agent System; Tacit Cooperation.

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1 INTRODUCTION
Cooperative multi-agent reinforcement learning (MARL) has made significant progress in practical applications in recent years, such as traffic light control [1, 18], autonomous driving [11], game playing [2, 15], and multi-robot control [3, 8]. To effectively address multi-agent learning problems, various algorithms have emerged. Among these methods, the paradigm of centralized training with decentralized execution (CTDE) has gradually become the most concerned MARL paradigm due to its scalability and ability to handle non-stationary problems. The CTDE paradigm serves as a hybrid approach that combines the advantages of both centralized [5, 6] and decentralized [13] learning methods. The fundamental concept of the CTDE paradigm is that agents can access global information in a centralized manner during the training process while operating solely on local observations in a decentralized manner during execution. Based on this approach, many MARL algorithms [4, 7, 9, 12, 16, 17, 19] have demonstrated exceptional performance in some complex decision-making tasks [10].

Drawing inspiration from human teamwork, this paper proposes a novel paradigm that can transition from explicit communication to TACit COoperation (TACO). This paradigm enables agents to share relevant information via an attention mechanism during the initial training stage while simultaneously reconstructing this information using local observations in a self-supervised manner. We then obtain mixed information by weighted sums of the reconstructed information and true information. As training progresses, the accuracy of the reconstructed information steadily improves. Consequently, we can reduce reliance on communication by gradually decreasing its proportion in the mixed information, ultimately achieving the ability to infer teammate’s intentions without actual communication.
2 FROM EXPLICIT COMMUNICATION TO TACIT COOPERATION

2.1 The TACO Framework

Communication Abstract Module: The communication abstract module applies a self-attention mechanism [14] to aggregate highly relevant information from other teammates. Given the hidden state of agent $i$ and agent $j$, the attention weight $w_{i,j}^{att}$ for agent $i$ to agent $j$ can be computed by using a bilinear mapping and then normalizing it with a softmax function, as shown below:

$$w_{i,j}^{att} = \frac{\exp(h_i^T W_k^T W_q h_i)}{\sum\exp(h_j^T W_k^T W_q h_i)}.$$  (1)

Tacit Reconstruct Module: The tacit reconstruct module is responsible for approximating the relevant attention information based on the agent’s own local history trajectory. To achieve this, we use a two-layer fully connected network with the Relu activation function for simplicity. Specifically, the reconstruct network takes the hidden state $h_i$ of agent $i$ as input and outputs an approximation $\hat{v}_i$ of the actual relevant attention information $v_i$.

From Communication to Tacit Cooperation: To ensure a successful transition from communicate to tacit, we obtain the mixed information $\tilde{v}_i$ by taking the weighted average of the real attention information $v_i$ and the reconstructed information $\hat{v}_i$ as follows:

$$\tilde{v}_i = (1 - \alpha) v_i + \alpha \hat{v}_i.$$  (2)

The mixed weight $\alpha$ starts with an initial value $\alpha_{init}$ and using a simple linear decreasing schedule, given by $\alpha_t = \max(\alpha_{init} - t \Delta \alpha, \alpha_{min})$, which update during each training step. Therefore, as the training progresses, the proportion of explicit communication information in the mixed information gradually decreases. To make sure the agent can entirely transmit to fully tacit before training is completed, we usually set the $\alpha_{init} = 1$, $\alpha_{min} = 0$, and $\Delta \alpha \geq \frac{1}{\text{max}}$. The mixed information $\tilde{v}_i$ and the hidden state $h_i$ are concatenated to input MLP to obtain $Q_i(\tilde{v}, u, \tilde{a})$. The mixing network decomposes the joint action value function $Q_{tot}$ into the individual action value estimation $Q_i$.

2.2 Overall Learning Objective

We now introduce the learning objectives of TACO, which include two parts: the reinforcement learning part that tries to minimize the TD error, and the mixed information part that attempts to minimize the reconstruct error.

The reinforcement learning part end-to-end optimizes the same loss function as QMIX [9]:

$$L_{TD} = (Q_{tot}(s, a, s' ) - y_{tot})^2,$$  (3)

where $y_{tot} = r + \gamma \max_{u'} Q_{tot}(s', a', u')$. To achieve the goal of enforcing the reconstructed information $\hat{v}_i$ to be as close as possible to its corresponding true attention information $v_i$, TACO also includes a mixed information part that minimizes reconstruct loss. The similarity loss between the true relevant attention information $v_i$ and the reconstructed information $\hat{v}_i$ is measured by using the MSE loss function:

$$L_{Rec} = \frac{1}{n} \sum_{i=0}^{n} \text{MSE}(v_i, \hat{v}_i) = \frac{1}{n} \sum_{i=0}^{n} (v_i - \hat{v}_i)^2.$$  (4)

Both two parts are optimized simultaneously during training. Thus, the total loss function can be written as:

$$L_{tot} = L_{TD} + \beta L_{Rec}.$$  (5)

where the $\beta$ is a weighting term. For different complex scenarios, we can set different $\beta$ to change the proportion of reconstruct loss in the gradient update. It should be noted that the abstract module is updated by both the TD loss and the reconstruct loss gradients in Eq. (5).

3 EXPERIMENTS

We applied our method and baselines to the StarCraft II Multi-Agent Challenge benchmark, which includes a series of scenarios representing different levels of challenge.

As shown in Figure 1, there is not much difference between QMIX and QMIX-Attention in some relatively simple scenarios (5m_vs_6m and 2c_vs_64zg). However, the NDQ method performs poorly and has low learning efficiency, possibly due to its constraints on message passing and message instability. The performance of TACO is similar to that of QMIX-Attention and even exceeds QMIX-Attention in 5m_vs_6m. In the super hard scenarios, the classic TD3 method performs poorly due to a lack of effective communication, whereas QMIX-Attention performs well. However, QMIX-Attention’s success is mainly due to its lack of communication restrictions. The TACO method can achieve or even exceed the performance of QMIX-Attention without utilizing actual communication during the end of the training, which significantly enhances its practicality.

4 CONCLUSION

In this paper, we propose a simple and effective multi-agent collaboration training paradigm called TACO. This approach allows agents gradually replace explicit communication with reconstructed information, ultimately achieving efficient cooperation under fully decentralized execution. Experimental results show that the TACO method can achieve close or even better performance than the same baseline using communication or global information without sharing information.

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