

Fully Decentralized Cooperative Multi-Agent Reinforcement Learning is A Context Modeling Problem

Chao Li¹, Bingkun BAO¹, Yang Gao²

¹School of Computer Science, Nanjing University of Posts and Telecommunications

²School of Intelligence Science and Technology, Nanjing University

Abstract

This paper studies fully decentralized cooperative multi-agent reinforcement learning, where each agent solely observes the states, its local actions, and the shared rewards. The inability to access other agents' actions often leads to non-stationarity during value function updates and relative overgeneralization during value function estimation, hindering effective cooperative policy learning. However, existing works fail to address both issues simultaneously, due to their inability to model the joint policy of other agents in a fully decentralized setting. To overcome this limitation, we propose a novel method named Dynamics-Aware Context (DAC), which formalizes the task, as locally perceived by each agent, as an Contextual Markov Decision Process, and further addresses both non-stationarity and relative overgeneralization through dynamics-aware context modeling. Specifically, DAC attributes the non-stationary local task dynamics of each agent to switches between unobserved contexts, each corresponding to a distinct joint policy. Then, DAC models the step-wise dynamics distribution using latent variables and refers to them as contexts. For each agent, DAC introduces a context-based value function to address the non-stationarity issue during value function update. For value function estimation, an optimistic marginal value is derived to promote the selection of cooperative actions, thereby addressing the relative overgeneralization issue. Experimentally, we evaluate DAC on various cooperative tasks (including matrix game, predator and prey, and SMAC), and its superior performance against multiple baselines validates its effectiveness.

1 Introduction

Multi-agent reinforcement learning (MARL) has emerged as a powerful technique for addressing cooperative tasks, driving substantial advancements in both algorithms (*e.g.*, value decomposition methods (Sunehag et al. 2017; Rashid et al. 2020b; Son et al. 2019; Wang et al. 2020a) and multi-agent policy gradient methods (Lowe et al. 2017; Foerster et al. 2018; Yu et al. 2022; Zhong et al. 2024)) and applications (*e.g.*, traffic signal control (Wang et al. 2020b), autonomous vehicles (Zhou et al. 2021), and vaccine allocation task (Hao et al. 2023)). Most of these advances depend on the centralized training (often with decentralized execution) paradigm, where global information, particularly the joint actions of all agents, is accessible during training. However, such direct

access to other agents' actions is often unattainable in real-world domains. For instance, in industrial automation scenarios, robots from different companies can not share action information due to privacy concerns or limited communication capabilities. In such cases, the *fully decentralized learning* is necessitated, where each agent learns solely from its individual experiences, without access to the actions of other agents, during both training and execution periods.

However, developing efficient cooperative policies under the fully decentralized learning paradigm is challenging due to two key challenges arising from the lack of access to other agents' actions. The first is non-stationarity during per-agent value function updates. Since treating other agents as part of the environment, the task dynamics perceived by each agent becomes non-stationary due to the evolving policies of other agents, undermining the convergence of value function updates (Jiang, Su, and Lu 2024). The second is relative overgeneralization, wherein the value estimations of each agent's local cooperative actions may be biased by other agents' exploratory or sub-optimal action selections, hindering agents from selecting the optimal joint action (Matignon, Laurent, and Le Fort-Piat 2012). As a result, fully decentralized learning typically suffers from low efficiency and sub-optimal solutions, limiting efficient multi-agent cooperation.

Accordingly, we classify existing value-based MARL approaches into two categories. The first category aims to solve the non-stationarity issue. These methods either ensure stationary transition data by directly accessing other agents' actions (Sunehag et al. 2017; Rashid et al. 2020b), designing multi-agent importance sampling weights, fingerprints (Foerster et al. 2017), and constructing ideal transition probabilities (Jiang and Lu 2022), or enable stationary policy updates using alternative policy updates (Su et al. 2024). The second category primarily targets the relative overgeneralization issue, typically by rectifying the learned factored global action value function (Son et al. 2019; Wang et al. 2020a; Rashid et al. 2020a) or employing optimistic or lenient value function updates (Lauer and Riedmiller 2000; Matignon, Laurent, and Le Fort-Piat 2007; Omidshafiei et al. 2017; Panait, Sullivan, and Luke 2006; Wei and Luke 2016) to encourage the selection of optimal joint actions. Although both issues stem from the lack of other agents' action information, existing fully decentralized MARL methods address either the non-stationarity issue or the relative overgeneralization

problem in isolation, due to their inability to model the joint policy of other agents in a fully decentralized setting. Consequently, they fail to simultaneously resolve both challenges.

To overcome this limitation, we propose a novel method named Dynamics-Aware Context (DAC), which formalizes the task, as locally perceived by each agent, as an Contextual Markov Decision Process (CMDP) (Hallak, Di Castro, and Mannor 2015), and further addresses both non-stationarity and relative overgeneralization from a dynamics-aware context modeling perspective. Specifically, DAC attributes the non-stationary local task dynamics of each agent to switches between unobserved contexts, each corresponding to a distinct joint policy of other agents. Then, drawing upon ideas from concept drift literature (Lu et al. 2018), DAC employs a sliding window alongside per-agent local trajectory to model step-wise dynamics distribution using latent variables. Since each agent’s task dynamics is determined by the joint policy of other agents, these variables implicitly represent the other agents’ joint policy at each time step. Accordingly, we refer to them as contexts and learn a context-based value function for each agent to address the non-stationarity issue in value function updates. During value function estimation, an optimistic marginal value is derived to discard the effects caused by other agents’ sub-optimal actions, thereby facilitating the selection of optimal joint actions and addressing the relative overgeneralization problem. The above enables effective cooperative policy learning in a fully decentralized manner.

Empirically, we evaluate DAC across various cooperative tasks, including the matrix game, predator and prey, and the StarCraft Multi-Agent Challenge (SMAC) (Samvelyan et al. 2019). The results demonstrate significant performance gain against multiple baselines, validating DAC’s effectiveness.

2 Related Work

In this section, we classify current value-based MARL methods into two categories and give a brief introduction to them.

The first category of works addresses the non-stationarity problem by constructing stationary transition data or policy updates. Specifically, canonical value decomposition methods such as VDN (Sunehag et al. 2017) and QMIX (Rashid et al. 2020b)) assume direct access to agents’ joint actions to ensure stationary transitions during training. However, these methods often suffer from the relative overgeneralization issue due to the representational limitation of their learned factored global action value functions (Gupta et al. 2021). For independent Q-learning (IQL) (Tan 1993) agents, the multi-agent importance sampling (Foerster et al. 2017) technique assumes direct access to other agents’ policies and calculates an importance weight to decay obsolete data during experience replay. Multi-agent fingerprints (Foerster et al. 2017) uses the training iteration numbers and the exploration rates of other agents to estimate their policies, and augments per-agent local transitions with these estimations. However, such direct access to other agents’ information assumed in above methods is unattainable in practice. I2Q (Jiang and Lu 2022) addresses this by shaping ideal transition probabilities for each IQL agent in a fully decentralized manner, and guarantees convergence to the optimal joint policy. In comparison to I2Q’s approach of addressing non-stationarity and relative

overgeneralization issues by shaping ideal transition probabilities, this work aims for a novel context-aware framework to tackle both issues. In addition, to ensure stationary policy updates, MA2QL (Su et al. 2024) enforces sequential policy updates among IQL agents. When an agent updates its local policy, all others’ policies remain fixed. Despite its promise, the sequential policy update typically leads to sample inefficiency, as it lacks the capacity for parallel policy updates.

The second category of works addresses the relative overgeneralization issue by rectifying the learned factored global action value function or updating per-agent local value function in optimistic or lenient manners. Specifically, for value decomposition methods with representational limitations, weighted QMIX (Rashid et al. 2020a) places more weights on potentially optimal joint actions during value updates to exclusively recover correct value estimations for these critical actions. QTRAN (Son et al. 2019) and QPLEX (Wang et al. 2020a) incorporate additional complementary terms to correct the discrepancy between the learned factored global action value functions and the true joint ones. For IQL, distributed Q-learning (Lauer and Riedmiller 2000) employs an optimistic value function for each agent to discard the effect caused by other agents’ exploratory or sub-optimal actions. This enables agents to identify and select their local cooperative actions, thus addressing the relative overgeneralization problem. However, due to the high optimism, distributed Q-learning is vulnerable to stochasticity. Hysteretic Q-learning (Matignon, Laurent, and Le Fort-Piat 2007; Omidshafiei et al. 2017) avoids this by updating per-agent value function using two learning rates for positive and negative temporal difference errors, respectively. Lenient learning (Panait, Sullivan, and Luke 2006; Wei and Luke 2016) shifts from optimistic to standard value function update using gradually decreasing lenience. However, the optimistic update may cause value overestimation, particularly when the value function is approximated using neural networks. Moreover, the neglect of non-stationarity further hinders efficient policy learning.

In summary, existing fully decentralized MARL methods fail to address both non-stationarity and relative overgeneralization in a unified manner. To address this limitation, this work proposes to formalize the task perceived by each agent as an CMDP, and tackles both issues from a dynamics-aware context modeling perspective, thereby effectively promoting fully decentralized cooperative policy learning.

3 Preliminary

In this section, we formalize the task addressed by this work, and review the non-stationarity and relative overgeneralization issues in decentralized learning, as well as the CMDP.

3.1 Multi-Agent Markov Decision Process

We consider a cooperative multi-agent task that can be modeled as an Multi-Agent Markov Decision Process (MMDP) $\langle N, S, \mathbf{A}, P, R, \gamma \rangle$, where $N = \{1, 2, \dots, n\}$ is the agent set and S denotes the state space. $\mathbf{A} = A^1 \times A^2 \times \dots \times A^n$ is all agents’ joint action space and A^i is the local action space of agent $i \in N$. At each time step t , each agent i observes the state $s_t \in S$ and selects its local action $a_t^i \in A^i$ based on

its decentralized policy $\pi^i(a_t^i|s_t)$. Based on the joint action of all agents $\mathbf{a}_t = (a_1^1, a_2^1, \dots, a_t^n)$, the environment transits to the next state s_{t+1} according to the state transition function $P(s_{t+1}|s_t, \mathbf{a}_t)$ and provides all agents with the same reward $R(s_t, \mathbf{a}_t)$. The goal is to learn the optimal joint policy $\pi = (\pi^1, \pi^2, \dots, \pi^n)$ that maximizes the expected cumulative return $\mathbb{E}_{\pi, P}[\sum_{t=0}^{\infty} \gamma^t r_t]$, where γ is a discount factor.

We consider the fully decentralized learning, where each agent i observes only the state s_t , its local action a_t^i , and the shared reward r_t . For each decentralized agent i , the perceived task can be modeled as an MDP $\langle S, A^i, P^i, R^i, \gamma \rangle$ with dynamics defined as follows:

$$\begin{aligned} P^i(s_{t+1}|s_t, a_t^i) &= \sum_{a_{-i}} \pi^{-i}(a_t^{-i}|s_t) P(s_{t+1}|s_t, \mathbf{a}_t), \\ R^i(s_t, a_t^i) &= \sum_{a_{-i}} \pi^{-i}(a_t^{-i}|s_t) R(s_t, \mathbf{a}_t), \end{aligned} \quad (1)$$

where π^{-i} and a_t^{-i} respectively denote the joint policy and the joint action of other agents $-i$ except for agent i .

Non-stationarity. As illustrated in Eq. (1), each agent i 's local task dynamics, denoted by P^i and R^i , depend on other agents $-i$'s joint policy π^{-i} . Since other agents continually change their policies, the local task dynamics of each agent i becomes non-stationary. In addition, when employing off-policy experience replay, the sampled data can be viewed as following P^i and R^i with respect to the average joint policy $\bar{\pi}^{-i}$ of other agents $-i$ over the course of training. This non-stationarity undermines the convergence of value functions.

Relative overgeneralization. Due to the absence of other agents' action information, the value estimation of per-agent local cooperative actions may be biased by other agents' exploratory or sub-optimal actions. As a result, the sub-optimal joint actions are preferred over the optimal ones, a problem known as relative overgeneralization.

Specifically, for each decentralized agent i , its local value function $Q^i(s_t, a_t^i)$ can be regarded as a projection regarding the joint action value function $Q(s_t, a_t^i, a_t^{-i})$. IQL adheres to an average-based projection, which is defined as follows:

$$Q^{i,\pi}(s_t, a_t^i) = \sum_{a_{-i}} \pi^{-i}(a_t^{-i}|s_t) Q^\pi(s_t, a_t^i, a_t^{-i}), \quad (2)$$

where $Q^\pi(s_t, a_t^i, a_t^{-i})$ represents the joint action value function given a joint policy $\pi = (\pi^i, \pi^{-i})$. As shown in Eq. (2), Q^i following the average-based projection is easily affected by other agents' sub-optimal actions, thus suffering from the relative overgeneralization issue. In contrast, the maximum-based (optimistic) projection is defined below:

$$Q^{i,\text{opt}}(s_t, a_t^i) = \max_{a_{-i}} Q^*(s_t, a_t^i, a_t^{-i}), \quad (3)$$

where $Q^*(s_t, a_t^i, a_t^{-i})$ is the joint action value function of an optimal joint policy π^* . This optimistic projection assumes that other agents $-i$ always select their cooperative actions, thus eliminating their effects on agent i 's local value estimations. Both distributed Q-learning and hysteretic Q-learning approximate $Q^{i,\text{opt}}(s_t, a_t^i)$ by an optimistic value function update. In contrast, our method estimates it by an optimistic marginal value derived from a context-based value function. We detail the distinction between them in Appendix. A.

3.2 Contextual Markov Decision Process

A contextual Markov Decision Process (CMDP) is often defined as a tuple $\langle \mathcal{C}, S, A, M(c) \rangle$, where \mathcal{C} denotes the context space, S represents the state space, and A is the action space. For each context $c \in \mathcal{C}$, the function $M(c)$ specifies a MDP $\langle S, A, P^c, R^c, \gamma \rangle$. As a result, CMDP defines a family of MDPs that share the same state and action spaces but differ in the state transition and reward functions. In this work, we employ CMDP to model the non-stationary task dynamics locally perceived by each agent, where the contexts are associated with other agents' joint policies.

4 Methodology

In this section, we give a comprehensive introduction to our method, DAC. We begin by proposing the task formalization based on CMDP, and then delve into the process of modeling dynamics-aware contexts. Subsequently, for each agent, we learn a context-based value function and derive an optimistic marginal value, thereby addressing both non-stationarity and relative overgeneralization issues. Finally, we summarize the overall learning procedure of DAC.

4.1 Task Formalization

As detailed in Sec. 3.1, the task, as locally perceived by each agent i , can be modeled as an MDP $\langle S, A^i, P^i, R^i, \gamma \rangle$, where the state transition dynamics P^i and the reward function R^i depend on other agents $-i$'s joint policy π^{-i} . Considering all possible π^{-i} , the perceived task of agent i can be decomposed into a family of MDPs that share the same state and action spaces but differ in their transition and reward functions, each corresponding to an unique π^{-i} . By associating each context c with a specific π^{-i} , we propose to formalize the perceived task of each agent i as a CMDP below:

$$\langle \mathcal{C}, S, A^i, M(c) \rangle, M(c) : c \rightarrow \langle S, A^i, P_c^i, R_c^i, \gamma \rangle, \quad (4)$$

where S represents the state space and A^i is the local action space of agent i . Note that the state transition dynamics P_c^i and the reward function R_c^i are explicitly conditioned on the context $c \in \mathcal{C}$, each corresponding to an unique π^{-i} .

When each agent operates in a fully decentralized manner, under the above CMDP formalization, the task dynamics is determined by the underlying context, which corresponds to other agents' current joint policy. When an agent encounters different contexts at different time steps, the same states and local actions lead to different next states and rewards due to the distinct task dynamics. Consequently, the lack of context information hinders each agent from fully capturing the task dynamics, leading to the non-stationarity problem.

For each agent, this CMDP formalization attributes non-stationarity to switches between unobserved contexts, and provides a principled framework to address this problem by explicit context modeling. The context can be instantiated as either an estimate of the current joint policy of other agents or a representation of the current agent's task dynamics distribution. By augmenting per-agent local transitions with the inferred contexts, the resulting transitions become stationary and enable stationary fully decentralized policy learning.

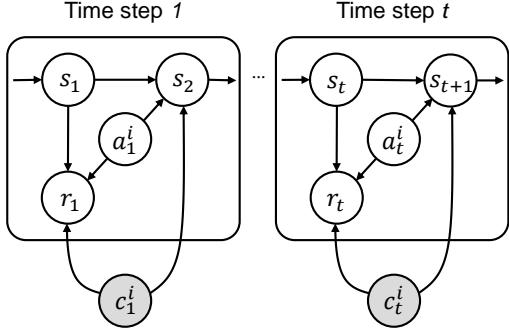


Figure 1: A general case where the context changes every (or every few) time steps within agent i 's local task, depending on the update interval of other agents' joint policy. In the above plot, the dynamics is determined by c_1^i at time step 1 and by c_t^i at time step t . Empty and solid circles respectively represent observable and unobservable stochastic variables.

The frequency of context changes directly determines the degree of non-stationarity. In this work, we consider a general case where contexts change between time steps, as illustrated in Fig. 1. In such case, other agents update their joint policy every (or every few) time steps, and the contexts shift accordingly within the current agent's CMDP over the same interval. We take a step toward explicitly modeling contexts within this case to address the non-stationarity problem.

4.2 Dynamics-Aware Context Modeling

For each agent, we propose to represent its real-time task dynamics distribution using latent variables, and refer to them as contexts. Since other agents may update their joint policy every (or every few) time steps, the task dynamics distribution within current agent's local trajectory changes over the same time interval. This parallels the setting of concept drift, where the underlying data distribution evolves over time. To address such shifts, maintaining a sliding window to hold the latest data within the data stream has proven effective in capturing the real-time data distribution, ensuring model adaptability and accuracy in dynamic settings (Lu et al. 2018).

Motivated by this insight, we cast the per-agent real-time task dynamics distribution modeling as a concept drift problem, and propose DAC as a solution. At first, DAC employs a sliding window alongside per-agent local trajectory to hold the latest k transitions. Specifically, at time step t , the sliding window is instantiated as the trajectory segment $\tau_{t-k+1:t}^i$ of agent i , which contains transitions from $t-k+1$ to t :

$$\tau_{t-k+1:t}^i = (s_{t-k+1}, a_{t-k+1}^i, r_{t-k+1}, s_{t-k+2}, \dots, s_t, a_t^i, r_t, s_{t+1}). \quad (5)$$

For modeling the task dynamics distribution of $\tau_{t-k+1:t}^i$, we assume that this distribution can be represented by a latent variable c_t^i , and the underlying mapping from the trajectory segment to the variable follows an unknown probability distribution $p^i(c_t^i | \tau_{t-k+1:t}^i)$. We learn an additional distribution $q^i(c_t^i | \tau_{t-k+1:t}^i)$ to approximate it, and optimize this

approximation by minimizing the KL-divergence between them (Detailed derivation can be found in Appendix. B):

$$\begin{aligned} & D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i | \tau_{t-k+1:t}^i)) \\ &= \log p^i(\tau_{t-k+1:t}^i) + D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i)) \quad (6) \\ & - \mathbb{E}_{q^i(c_t^i | \tau_{t-k+1:t}^i)} \log p^i(\tau_{t-k+1:t}^i | c_t^i), \end{aligned}$$

where $p^i(c_t^i)$ denotes the true prior distribution of the latent variable, and $\log p^i(\tau_{t-k+1:t}^i)$ is the evidence that can be regarded as a constant. Based on Eq. (6), to minimize the term $D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i | \tau_{t-k+1:t}^i))$, we aim to maximize the following equation:

$$\begin{aligned} & \max \underbrace{\mathbb{E}_{q^i(c_t^i | \tau_{t-k+1:t}^i)} \log p^i(\tau_{t-k+1:t}^i | c_t^i)}_{\textcircled{1}} \\ & - \underbrace{D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i))}_{\textcircled{2}}. \end{aligned} \quad (7)$$

In Eq. (7), term ① denotes the reconstruction likelihood that ensures the learned latent variable c_t^i contains sufficient information of the trajectory segment $\tau_{t-k+1:t}^i$, and term ② ensures the latent variable c_t^i is close to its prior distribution. For optimizing term ①, we expand it as follows:

$$\begin{aligned} p^i(\tau_{t-k+1:t}^i | c_t^i) &= p^i(s_{t-k+1}) \\ & \prod_{h=t-k+1}^t p^i(a_h^i | s_h) p^i(s_{h+1}, r_h | s_h, a_h^i, c_t^i), \end{aligned} \quad (8)$$

where the initial state distribution $p^i(s_{t-k+1})$ is determined by the environment and $p^i(a_h^i | s_h)$ denotes agent i 's decentralized policy only conditioned on the state. Therefore, we ignore these two components and rewrite Eq. (7) as follows:

$$\begin{aligned} & \max \mathbb{E}_{q^i(c_t^i | \tau_{t-k+1:t}^i)} \sum_{h=t-k+1}^t \log p^i(s_{h+1}, r_h | s_h, a_h^i, c_t^i) \\ & - D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i)). \end{aligned} \quad (9)$$

Accordingly, DAC is capable of representing the real-time task dynamics distribution using the latent variable c_t^i , which is derived by the learned distribution $q^i(c_t^i | \tau_{t-k+1:t}^i)$. Then, these variables are used as contexts to enable stationary policy learning, as detailed in subsequent sections.

Context-based value function. For each agent i , we learn a value function $Q^i(s_t, a_t^i, c_t^i)$, which is additionally conditioned on the context c_t^i , besides the state s_t and the local action a_t^i . The incorporation of contexts brings two benefits. On the one hand, the context is derived from each agent i 's local trajectory segment based on $q^i(c_t^i | \tau_{t-k+1:t}^i)$, enabling fully decentralized policy learning via $Q^i(s_t, a_t^i, c_t^i)$. On the other hand, the context alleviates the non-stationarity caused by other agents' evolving joint policy, therefore facilitating stationary update of $Q^i(s_t, a_t^i, c_t^i)$. Based on the augmented transition $(s_t, a_t^i, r_t, c_t^i, s_{t+1}, c_{t+1}^i)$, Q^i is updated as below:

$$\begin{aligned} \mathcal{L}_C(\theta^i) &= \mathbb{E}_{(s_t, a_t^i, c_t^i, r_t, s_{t+1}, c_{t+1}^i) \sim \mathcal{D}^i} \\ & (r_t + \gamma \max_{a_{t+1}^i} Q^i(s_{t+1}, a_{t+1}^i, c_{t+1}^i) - Q^i(s_t, a_t^i, c_t^i))^2, \end{aligned} \quad (10)$$

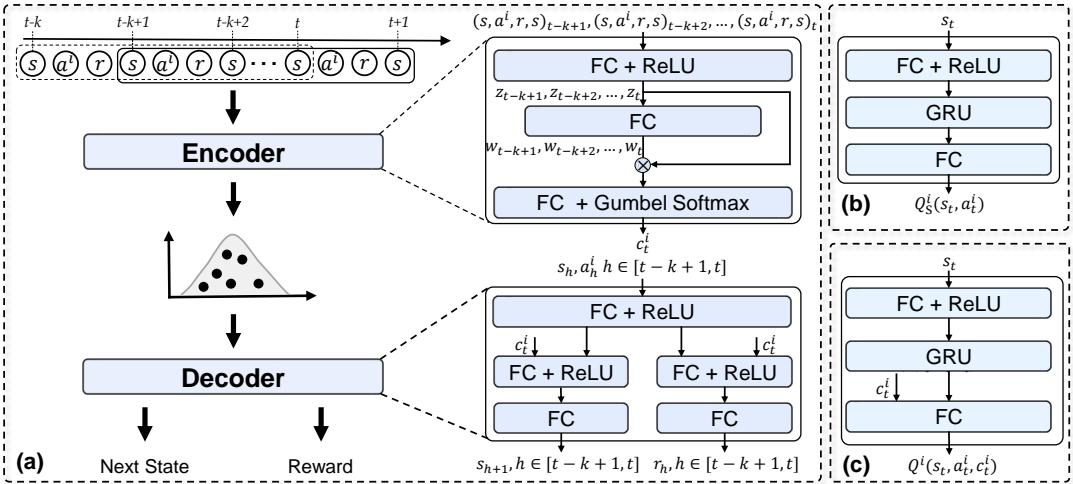


Figure 2: The architecture of DAC. (a) The VAE-like network which contains the encoder and decoder modules. (b) The value function Q_S^i . (c) The context-based value function Q^i . Note that DAC maintains a sliding window to hold the latest k transitions.

where θ^i represents the parameter of Q^i and we sample transitions from agent i 's replay buffer \mathcal{D}^i to conduct the update.

Optimistic Marginal Value. There are still two problems during value function estimation: (1) The relative overgeneralization hinders agents from identifying and selecting their local cooperative actions; and (2) Each agent can not select actions based on the context-based value function, where the context based on real-time task dynamics modeling is available only when the current transition (*i.e.*, $(s_t, a_t^i, r_t, s_{t+1})$) is finished. To deal with these two problems, we propose the optimistic marginal value for each agent, as defined below:

$$\phi^i(s_t, a_t^i) = \max_{c \in \mathcal{C}} Q^i(s_t, a_t^i, c), \quad (11)$$

where we shape marginal value functions of per-agent local actions using the maximum context-based value estimations across all possible contexts. Eq. (11) adheres to an optimistic belief that other agents always select their cooperative actions, and thus the optimistic marginal value of per-agent local action can reach the optimal (maximum) value over all possible contexts $\max_{c \in \mathcal{C}} Q^i(s_t, a_t^i, c)$. Consequently, for each agent, the optimistic marginal value discards the effects caused by other agents' exploratory or sub-optimal actions, and further enables accurate identifications and selections of per-agent local cooperative actions, therefore addressing the relative overgeneralization and leading to the cooperation.

Implementation. For efficiently enumerating all possible contexts in Eq. (11), we propose to construct a discrete context space by introducing a VAE-like network (Kingma and Welling 2014). As illustrated in Fig. 2, we achieve the mapping function (distribution) $q^i(c_t^i | \tau_{t-k+1:t}^i)$ by the encoder. For shaping discrete contexts, the learned contexts should be close to a discrete prior, *i.e.*, $D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i))$ in Eq. (7) and Eq. (9). We achieve this by using Gumbel Softmax as the activation function for the encoder's output. Such encoder directly generates discrete contexts, thus eliminating the need to optimize $D_{\text{KL}}(q^i(c_t^i | \tau_{t-k+1:t}^i) || p^i(c_t^i))$.

In addition, the decoder outputs reconstructed objectives

$\sum_{h=t-k+1}^t \log p^i(s_{h+1}, r_h | s_h, a_h^i, c_t^i)$ in Eq. (9). As a result, both encoder and decoder are optimized using the maximum reconstruction likelihood objective, which is defined below:

$$\mathcal{L}_V(\omega^i) = -\mathbb{E}_{\tau_{t-k+1:t}^i \sim \mathcal{D}^i, c_t^i \sim q^i(c_t^i | \tau_{t-k+1:t}^i)} \sum_{h=t-k+1}^t \log p^i(s_{h+1}, r_h | s_h, a_h^i, c_t^i), \quad (12)$$

where ω^i is the parameter of encoder and decoder. The Gumbel Softmax enables differentiable updates of the encoder.

4.3 Overall Learning Procedure

Based on the optimistic marginal value, each agent i can select its local cooperative action by $\arg \max_{a_t^i} \phi^i(s_t, a_t^i) = \arg \max_{a_t^i} \max_{c \in \mathcal{C}} Q^i(s_t, a_t^i, c)$. However, accurately learning the context-based value function necessitates a thorough coverage over the entire trajectory space, which is typically unavailable during the early training period and leads to sub-optimal outcomes. To address this issue, we separately learn a value function $Q_S^i(s_t, a_t^i)$ and update it as follows:

$$\mathcal{L}_S(\sigma^i) = \mathbb{E}_{(s_t, a_t^i, r_t, s_{t+1}) \sim \mathcal{D}^i} (r_t + \gamma \max_{a_{t+1}^i} Q_S^i(s_{t+1}, a_{t+1}^i) - Q_S^i(s_t, a_t^i))^2, \quad (13)$$

where σ^i is the parameter of Q_S^i . We make each agent select its actions based on Q_S^i to generate informative trajectories during the early training process and accordingly provide an efficient update of $Q^i(s_t, a_t^i, c_t^i)$ following Eq. (10). Furthermore, we propose an auxiliary supervision loss below:

$$\mathcal{L}_{\text{SUP}}(\sigma^i) = D_{\text{KL}}(\pi_S^i(\cdot | s_t) || \pi^i(\cdot | s_t)), \quad (14)$$

where $\pi_S^i(\cdot | s_t)$ and $\pi^i(\cdot | s_t)$ respectively represent the Boltzmann policy with respect to $Q_S^i(s_t, a_t^i)$ and $\phi^i(s_t, a_t^i)$, which

A^1	A^2	a^1	a^2	a^3
a^1	8	-12	-12	
a^2	-12	6	0	
a^3	-12	0	6	

(a) Payoff matrix.

A^1	c	0	1	2	3
$a^1(8.03)$	=0.7	-11	8.03	=5.0	
$a^2(5.96)$	0.01	-12	5.96	0.00	
$a^3(5.95)$	0.06	-12	5.95	-0.0	

(b) $Q^1(s, a, c)$ and $\phi^1(s, a)$.

A^2	c	0	1	2	3
$a^1(8.03)$	=0.7	-11	8.03	=5.0	
$a^2(5.96)$	0.01	-12	5.96	0.01	
$a^3(5.94)$	0.07	-12	5.94	-0.0	

(c) $Q^2(s, a, c)$ and $\phi^2(s, a)$.

Table 1: The payoff matrix and value functions learned by DAC. We set the number of discrete contexts to 4. The context-based value functions $Q^1(s, a, c)$ and $Q^2(s, a, c)$ for all contexts c are presented in (b) and (c), respectively. The optimistic marginal values, $\phi^1(s, a)$ and $\phi^2(s, a)$, appear in the first column. $Q^i(s, a, c)$ with unattainable value is marked by $Q^i(s, a, c)$.

are defined as follows:

$$\begin{aligned}\pi_S^i(a_t^i|s_t) &= \frac{\exp(Q_S^i(s_t, a_t^i))}{\sum_{a^i \in A^i} \exp(Q_S^i(s_t, a^i))}, \\ \pi^i(a_t^i|s_t) &= \frac{\exp(\phi^i(s_t, a_t^i))}{\sum_{a^i \in A^i} \exp(\phi^i(s_t, a^i))}.\end{aligned}\quad (15)$$

In comparison to π_S^i , π^i is capable of addressing both non-stationarity and relative overgeneralization, and we make π_S^i imitate it. As a result, we update Q_S^i using the loss function $\mathcal{L}(\sigma^i) = \mathcal{L}_S(\sigma^i) + \beta\mathcal{L}_{\text{SUP}}(\sigma^i)$, where β is a scaling factor.

As a summary, the learning processes of Q_S^i and Q^i form a positive feedback loop: Q_S^i generates informative trajectories to ensure effective updates of Q^i , while Q^i guides Q_S^i in selecting agents' local cooperative actions to produce more informative trajectories. This mutual reinforcement facilitates efficient, fully decentralized cooperative policy learning. More algorithmic details are available in Appendix C.

5 Experiment

In this section, we design experiments to answer the following questions: (1) Can DAC benefit fully decentralized cooperative policy learning by addressing non-stationarity and relative overgeneralization issues? (2) If so, which component contributes the most to its performance gain?

For question (1), we compare our method against multiple fully decentralized value-based MARL baselines, including IQL (Tan 1993), Hysteretic Q-learning (Matignon, Laurent, and Le Fort-Piat 2007), and I2Q (Jiang and Lu 2022), on the matrix game, predator and prey, and the StarCraft Multi-Agent Challenge (SMAC). For question (2), we conduct ablation studies to assess the effectiveness of each component in DAC. All results are illustrated with the median performance and the standard error across five random seeds. More experimental details can be found in Appendix D.

5.1 Comparison Results

Matrix Game. We begin by evaluating all methods in a didactic matrix game. As shown in Tab. 1a, two agents within this game need to select the optimal joint action (a^1, a^1) to achieve the best reward +8. However, under the fully decentralized learning paradigm, each agent maintains higher value estimations regarding its local actions a^2 and a^3 , when other agents uniformly select their actions. This leads to the relative overgeneralization problem where sub-optimal joint actions are preferred over the optimal one.

Fig. 3 (a) shows the comparison results of all methods in the matrix game. One can observe that IQL struggles in the sub-optimal joint actions with +6 rewards, demonstrating that the average-based projection (Eq. (2)) followed by IQL is susceptible to the relative overgeneralization problem. In contrast, DAC presents an optimistic marginal value for each agent and accordingly discards the effects caused by others' sub-optimal actions. As a result, DAC succeeds in selecting the optimal joint action with +8 reward. This also applies to Hysteretic Q-learning, which adheres to an optimistic value function update and demonstrates efficiency in simple tasks. However, when faced with complex cooperative tasks, such optimistic value function update typically leads to overestimation for value function approximated by neural networks, leading to poor performance. We validate this insight in subsequent experiments. Similarly, I2Q shapes ideal transitions by implicitly assuming other agents follow cooperative policies, which adheres to an optimistic belief, and learning policies on these transitions leads to the optimal joint policy.

Furthermore, to analyze the representational capabilities of the contexts, we present the per-agent context-based value function and optimistic marginal value learned by DAC. As depicted in Tab. 1b and Tab. 1c, for agent 1 or 2, the context-based value function accurately approximates the rewards of all possible joint actions, which validates the effectiveness of dynamics-aware contexts in representing other agents' joint policies. Furthermore, the optimistic marginal values of per-agent local actions satisfy the optimistic property, *i.e.*, equal to the highest rewards only achieved when other agents select their cooperative actions. By enforcing per-agent value function to imitate the optimistic marginal value by Eq. (14), the efficient selection of optimal joint actions are achieved.

Predator and Prey. To further assess the effectiveness of DAC in addressing relative overgeneralization, we adopt the modified predator-prey (Son et al. 2019), where two predators receive a team reward of +1 when they simultaneously capture the single prey, otherwise $-P$ penalty for sole hunting. P controls the degree of relative overgeneralization.

We test four settings $P = 0.0, 0.3, 0.5, 1.0$. In general, a small penalty ($P = 0.0$) does not induce relative overgeneralization, and thus all methods succeed in learning cooperative prey-capturing policies with high rewards, as illustrated in Fig. 3 (b). As P increases and relative overgeneralization becomes more severe, IQL fails to learn effective policies in scenarios with $P = 0.3, 0.5$, and 1.0. In contrast, Hysteretic Q-learning and DAC achieve high rewards in scenario with

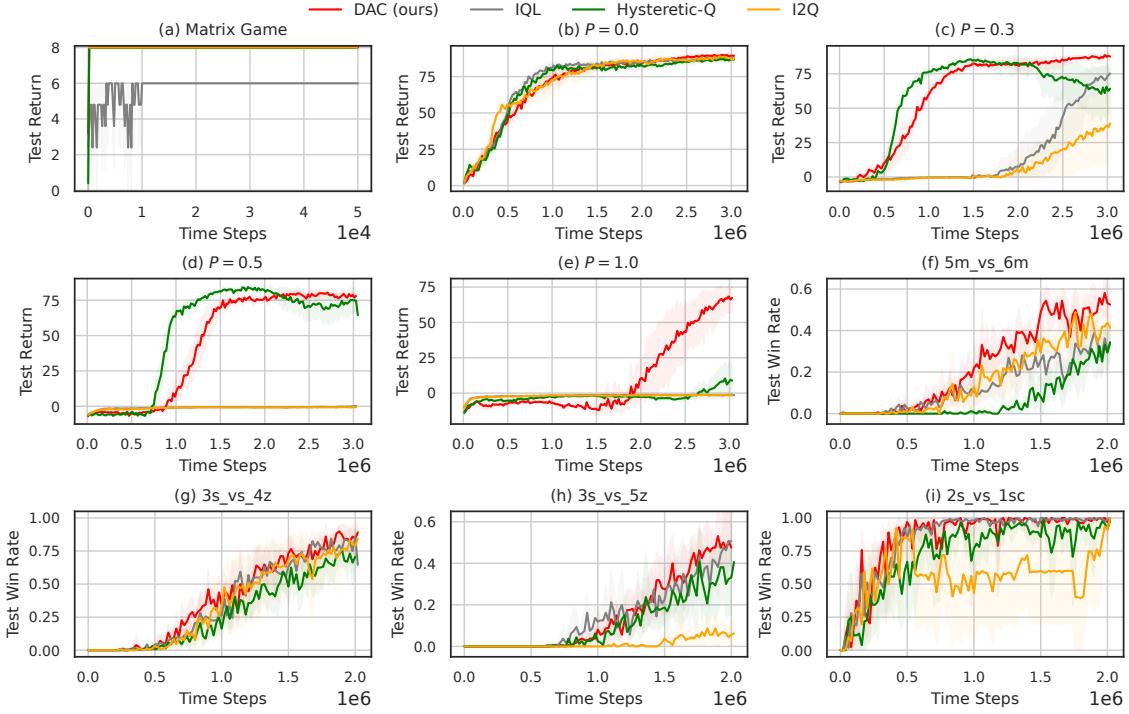


Figure 3: Comparison results in the matrix game, modified predator-prey, and several SMAC maps.

$P = 0.3$ and 0.5 , due to their capabilities of selecting cooperative actions based on optimistic value estimates. Notably, Hysteretic Q-learning suffers from degraded asymptotic performance due to the over-estimation issue. In the challenging scenario with $P = 1.0$, only DAC succeeds in learning an effective policy yielding high rewards, while all other baseline methods fail. We attribute DAC’s consistent superiority to its decoupled learning framework, which separately models the stationary context-based value function and the optimistic marginal value. I2Q demonstrates poor performance in scenarios with $P = 0.3, 0.5$, and 1.0 , suggesting that shaping ideal transition probabilities is difficult in certain tasks.

SMAC. To validate the scalability of DAC in more complex tasks, we evaluate all methods on several SMAC maps, including $2s_vs_1sc$, $3s_vs_4z$, $3s_vs_5z$, and $5m_vs_6m$. As depicted in Fig 3 (f) - (i), Hysteretic Q-learning exhibits poor performance across all maps, due to the overestimation and non-stationarity issues exacerbated in complex tasks. While IQL achieves competitive performance on most maps, DAC outperforms IQL on $5m_vs_6m$, $3s_vs_4z$, and $3s_vs_5z$, validating DAC’s effectiveness in complex tasks. On $2s_vs_1sc$, DAC performs comparably to IQL. We hypothesis that this map poses few challenges from non-stationarity and relative overgeneralization, and thus the benefit brought by DAC is not obvious. In addition, I2Q suffers from poor performance across all maps. We attribute this to its incapability of shaping ideal transition probabilities under partial observability.

5.2 Ablation Study

To examine the effects of DAC’s components: (1) the sliding window size (k), (2) the number of contexts (m), and (3) the scaling factor (β), we set k to $10, 15, 20, 30$, m to $5, 10, 20, 30$, and β to $0.001, 0.01, 0.1, 1.0$ as multiple baselines. The results, as presented in Appendix E, indicate that an excessively large m results in inefficient updates of the context-based value function due to the expanded context space. Regarding k , a small value may lead to abrupt fluctuations in the inferred dynamics distribution, while a large value may fail to capture timely distributional changes. We empirically identify $k = 20$ as a suitable choice for $5m_vs_6m$. The scaling factor is critical to maintain the positive feedback loop between Q_S^i and Q^i . Our experiments suggest that $\beta = 0.01$ performs effectively across complex SMAC maps.

6 Conclusion

This paper presents DAC as a unified framework to address both non-stationarity and relative overgeneralization inherent in fully decentralized cooperative MARL. DAC formalizes the local task, as perceived by each agent, as a CMDP, and constructs contexts by modeling step-wise task dynamics distribution. Subsequently, for each agent, DAC learns a context-based value function to enable stationary policy updates, and derives an optimistic marginal value to encourage the selection of cooperative actions. Extensive experiments across various cooperative tasks validate its effectiveness.

Limitation and Future Work. There are two limitations that warrant further exploration. First, DAC requires a com-

prehensive coverage of the trajectory space, while separately learning a decentralized value function and maintaining mutual reinforcement with the context-based value function can be challenging in complex tasks. We plan to address this by integrating DAC with efficient exploration techniques. Second, the optimistic marginal value computation becomes increasingly costly as the context space grows large. This can be alleviated by employing sampling-based heuristic search approaches to find approximate maxima and accordingly enable moderate complexity. We leave them for future work.

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