Abstract

The exploitation of extra state information has been an active research area in multi-agent reinforcement learning (MARL). QMIX represents the joint action-value using a non-negative function approximator and achieves the best performance, by far, on multi-agent benchmarks, StarCraft II micromanagement tasks. However, our experiments show that, in some cases, QMIX is incompatible with A2C, a training paradigm that promotes algorithm training efficiency. To obtain a reasonable trade-off between training efficiency and algorithm performance, we extend value-decomposition to actor-critics that are compatible with A2C and propose a novel actor-critic framework, value-decomposition actor-critics (VDACs). We evaluate VDACs on the testbed of StarCraft II micromanagement tasks and demonstrate that the proposed framework improves median performance over other actor-critic methods. Furthermore, we use a set of ablation experiments to identify the key factors that contribute to the performance of VDACs.

Many complex sequential decision making problems that involve multiple agents can be modeled as multi-agent reinforcement learning (MARL) problems, e.g. the coordination of semi-autonomous or fully autonomous vehicles (Hu et al. 2019) and the coordination of machines in a product line (Choo, Adams, and Beling 2017). A fully centralized controller that applies single-agent reinforcement learning will suffer from the exponential growth of the action space with the number of agents in the system. Learning decentralized policies that condition on the local observation histories of individual agents is a viable way to attenuate this problem. Furthermore, partial observability and communication constraints, two common obstacles in multi-agent settings, also necessitate the use of decentralized policies.

In a laboratory or simulated setting, decentralized policies can be learned by a centralized fashion via enabling communication among agents or granting access to additional global state information. This centralized training and decentralized execution (CTDE) paradigm has attracted the attention of researchers. However, it remains an open research question how to best exploit centralized training. In particular, it is not obvious how to utilize joint action-value or global state value to train decentralized policies.

Recently, breakthroughs in Q-learning have been made using joint action-value factorization techniques. Value-decomposition networks (VDN) represents joint action-value as a summation of local action-value conditioned on individual agents’ local observation history (Sunehag et al. 2017). (Rashid et al. 2018), seen as a more general case of VDN, introduces a mixing network that approximates a broader class of monotonic functions to represent joint action-values called QMIX. QTRAN introduces a more complex factorization framework that consists of three modules and demonstrated the effectiveness of it theoretically (Son et al. 2019). While QMIX reports the best performance on StarCraft micromanagement games (Samvelyan et al. 2019), we find that QMIX, in some StarCraft II tasks, has issues learning good policies that can constantly defeat enemies under A2C training paradigm (Mnih et al. 2016), which is originally introduced to enable algorithms to be executed efficiently.

On the other hand, on-policy actor-critic methods, such as counterfactual multi-agent (COMA) (Foerster et al. 2018), can leverage the A2C framework to improve training efficiency at the cost of performance. (Samvelyan et al. 2019) point out that there is a performance gap between the state-of-the-art actor-critic method, COMA, and QMIX on the StarCraft II micromanagement testbed.

To bridge the gap between multi-agent Q-learning and multi-agent actor-critics, as well as offer a reasonable trade-off between training efficiency and algorithm performance, we propose a novel actor-critic framework called value-decomposition actor-critic (VDAC). Let $V^a, V_0 \in \{1, \ldots, n\}$ denote the local state value that is conditioned on agent $a$’s local observation, and let $V_{tot}$ denote the global state-value that is conditioned on the true state of the environment. VDAC takes an actor-critic approach but adds local critics, which share the same network with the actors and estimate the local state values $V^a$. The central critic learns the global state value $V_{tot}$. The policy is trained by following a gradient dependent on the central critic. Further, we propose two approaches for calculating $V_{tot}$.

VDAC is based on three main ideas. First, unlike QMIX, VDAC is compatible with a A2C training framework that enables game experience to be sampled efficiently. This is due to the fact that multiple games are rolled out independently during training. Second, similar to QMIX, VDAC enforces
the following relationship between local state-values $V^a$ and the global state-value $V_{\text{tot}}$:

$$\frac{\partial V_{\text{tot}}}{\partial V^a} \geq 0, \quad \forall a \in \{1, \ldots, n\}. \tag{1}$$

This idea is related to difference rewards (Wolpert and Tumer 2002), in which each agent learns from a shaped reward that compares the global reward to the reward received when that agents action is replaced with a default action. Difference rewards require that any action that improves an agent’s local reward also improves the global reward, which implies the monotonic relationship between shaped local rewards and the global reward. While COMA (also inspired by difference rewards) focuses on customizing gradients for each agent using predicted counterfactual action-value, it does not enforce the monotonic relationship between shaped local rewards and the global reward. Third, VDAC is trained by following a rather simple policy gradient that is calculated from a temporal-difference (TD) advantage. We theoretically demonstrate that the proposed method is able to converge to a local optimum by following this policy gradient. Despite the fact that TD advantage policy gradients and COMA gradients are both unbiased estimates of a vanilla multi-agent policy gradients, our empirical study favors TD advantage policy gradients over COMA policy gradients.

This study strives to answer the following research questions:

- **Research question 1**: Compared with COMA gradients, is TD advantage gradient sufficient to optimize multi-agent actor-critics?
- **Research question 2**: Does applying state-value factorization improve the performance of actor-critics?
- **Research question 3**: Compared with QMIX, does VDAC provide a reasonable trade-off between training efficiency and algorithm performance?
- **Research question 4**: What are the factors that contribute to the performance of the proposed VDAC?

This paper is organized as follows. In Related Work, we describe the prior art. In Background, we introduce preliminary information about MARL and RL. In Methods, we describe our proposed VDAC in detail and present a convergence proof. In Experiments, we present the competitive performance on cooperative environment against baselines. In Conclusions, we provide conclusions and possible areas of future work.

**Related Work**

MARL has benefited from recent developments in deep reinforcement learning, with the frameworks moving away from tabular methods (Bu et al. 2008) to deep neural networks (Foerster et al. 2018). Our work is related to recent advances in CTDE deep multi-agent reinforcement learning.

The degree of training centralization varies in the current literature of MARL research. **Independent Q-learning** (IQL) (Tan 1993) and its deep neural network counterpart (Tampuu et al. 2017) simply train an independent Q-learning model for each agent. Those that attempt to directly learn decentralized policies often suffer from the non-stationarity of the environment induced by agents simultaneously learning and exploring. (Foerster et al. 2017; Usunier et al. 2016) attempt to stabilize learning under the decentralized training paradigm. (Gupta, Egorov, and Kochenderfer 2017) propose a training paradigm that alternates between centralized training with global rewards and decentralized training with reshaped rewards.

Centralized methods, by contrast, naturally avoid the non-stationary problem at the cost of scalability. COMA (Foerster et al. 2016), takes advantage of CTDE, where actors are updated by following policy gradients that are tailored by their contributions to the system by the central critic. Multi-agent deep deterministic policy gradient (MADDPG) (Lowe et al. 2017) extends deep deterministic policy gradient (DDPG) (Lillicrap et al. 2015) to mitigate the issue of high variance gradient estimates exacerbated in multi-agent settings. (Wei et al. 2018), based on MADDPG, proposes multi-agent soft Q-learning in continuous action spaces to tackle the issue of relative overgeneralization. Probabilistic recursive reasoning (PR2) (Wen et al. 2019) is a method that uses a probabilistic recursive reasoning policy gradient that enables agents to recursively reason what others believe about their own beliefs.

More recently, value-based methods, which lie between the extremes of IQL and COMA, have shown great success in solving complex multi-agent problems. VDN (Sunehag et al. 2017), which represents joint-action value function as a summation of local action-value function, allows for centralized learning. However, it does not make use of extra state information. QMIX (Rashid et al. 2018) utilizes a non-negative mixing network to represent a broader class of value-decomposition functions. Furthermore, additional state information is captured by hypernetworks that output parameters for the mixing network. QTRAN (Son et al. 2019) is a generalized factorization method that can be applied to environments that are free from structural constraints. Other works, such as CommNet (Foerster et al. 2016), TarMAC (Das et al. 2019), ATOC (Jiang and Lu 2018), MAAC (Iqbal and Sha 2019), CCOMA (Su, Adams, and Beling 2020) and BiCNet (Peng et al. 2017) exploit inter-agent communication.

Similar to QMIX and VDN, VDAC applies value-decomposition, however, it differs in that VDAC is a policy-based method that decomposes global state-values whereas QMIX and VDN, which decompose global action-values, belong to the Q-learning family. (Nguyen, Kumar, and Lau 2018) addresses credit-assignment issue, however, under a different MARL setting, CDec-POMDP. COMA, which is also a policy gradient method inspired by difference rewards and has been tested on StarCraft II micromanage games, represents the body of literature most closely related to this paper.

**Background**

Decentralized Partially Observable Markov Decision Processes (Dec-POMDPs): Consider a fully cooperative multi-agent task with $n$ agents. Each agent identified by $a \in A \equiv \{1, \ldots, n\}$ take an action $u^a \in U$ simultaneously
at every timestep, forming a joint action $u \in U \equiv U^a, \forall a \in \{1, \ldots, n\}$. The function has a true state $s \in S$, a transition probability $P(s'|s, u) : S \times U \times S \rightarrow S$, and a global reward function $r(s, u) : S \times U \rightarrow \mathbb{R}$. In the partial observation setting, each agent draws an observations $z \in Z$ from the observation function $O(S, A) : S \times A \rightarrow Z$. Each agent conditions a stochastic policy $\pi(u^a|\tau^a) : T \times U \rightarrow [0, 1]$ on its observation-action history $\tau^a \in T \equiv Z \times U$.

Throughout this paper, quantities in bold represent joint quantities over agents, and bold quantities with the superscript $-a$ denote joint quantities over agents other than a given agent $a$. Similar to a single-agent RL, MARL aims to maximize the discounted return $R_t = \sum_{i=1}^{\infty} \gamma^i r_{t+i}$. The joint value function $V^\pi(s_t, u_t) = \mathbb{E}[R_t|s_t = s]$ is the expected return for following the joint policy $\pi$ from state $s$. The value-action function $Q^\pi(s_t, u_t) = \mathbb{E}[R_t|s_t = s, u_t]$ defines the expected return for selecting joint action $u$ in state $s$ and following the joint policy $\pi$.

### Single-Agent Policy Gradient Algorithms:

In the setting of RL, policy gradient methods directly adjust the parameters $\theta$ of the policy in order to maximize the objective $J(\theta) = \mathbb{E}_{s,u \sim \pi}[R(s,u)]$ by taking steps in the direction of $\nabla J(\theta)$. The gradient with respect to the policy parameters is

$$
\nabla_\theta J(\theta) = \mathbb{E}_\pi [\nabla_\theta \log \pi_\theta(a|s) Q^\pi(s, u)],
$$

where $p^\pi$ is the state transition by following policy $\pi$, and $Q^\pi(s, u)$ is an action-value. Policy gradient algorithms differ in how to evaluate $Q^\pi(s, u)$, e.g. the REINFORCE algorithm (Williams 1992) simply uses a sample return $Q(s_t, u_t) = \sum_{i=t}^{\infty} \gamma^i r_{i+t}$.

To reduce variations in gradient estimates, a baseline $b$ is introduced. In actor-critic approaches (Konda and Tsitsiklis 2000), an actor is trained by following gradients that are dependent on the critic. This yields the advantage function $A(s_t, u_t) = Q(s_t, u_t) - b(s_t)$, where $b(s_t)$ is the baseline ($V(s_t)$ or another constant is commonly used as the baseline). TD error $r_t + \gamma V(s_{t+1}) - V(s_t)$, which is an unbiased estimate of $Q(s_t, u_t)$, is a common choice for advantage functions. In practice, TD error that utilizes a n-step return $\sum_{k=0}^{n-1} \gamma^k r_{t+k} + \gamma^k V(s_{t+k}) - V(s_t)$ yields good performance (Mnih et al. 2016).

### Multi-Agent Policy Gradient (MAPG) Algorithms:

Multi-agent policy gradient algorithms are extensions of policy gradient algorithms with a policy $\pi_{\theta_a}(u^a|s^a), a \in \{1, \ldots, n\}$. Compared with policy gradient methods in RL settings, MAPG faces the issues of high variance gradient estimates (Lowe et al. 2017) and credit assignment (Foerster et al. 2018). Perhaps the simplest multi-agent gradient can be written as:

$$
\nabla_\theta J(\theta) = \mathbb{E}_\pi \left[ \sum_a \nabla_\theta \log \pi_\theta(u^a|s^a) Q^\pi(s, u) \right].
$$

Multi-agent policy gradients in the current literature often take advantage of CTDE by using a central critic to obtain extra state information $s_t$ and avoid using the vanilla multi-agent policy gradients (Equation 3) due to high variance. For instance, (Lowe et al. 2017) utilize a central critic to estimate $Q^\pi(s, (a_1, \ldots, a_n))$ and optimize parameters in actors by following a multi-agent DDPG gradient, which is derived from Equation 3:

$$
\nabla_\theta J(\theta) = \mathbb{E}_\pi \left[ \sum_a \nabla_\theta \log \pi_\theta(u^a|s^a) A^\pi(s, u) \right],
$$

where $A^\pi(s, u) = Q^\pi(s, u) - \sum_{a'} \pi_{\theta_a}(u'^a|s^a) Q^\pi(s, (u'^a, u'^{\alpha}))$ is the counterfactual advantage for agent $a$. Note that (Foerster et al. 2018) argue that the COMA gradients provide agents with tailored gradients, thus achieving credit assignment. However, they also prove that COMA gradients are unbiased estimates of the vanilla multi-agent policy gradients, and that COMA is a variance reduction technique.

### Methods

In addition to the previously outlined research questions, our goal in this work is to derive RL algorithms under the following constraints: (1) the learned policies are conditioned on agents’ local action-observation histories (The environment is modeled as Dec-POMDP), (2) a model of the environment dynamics is unknown (i.e. the proposed framework is task-free and model-free), (3) communication is not allowed between agents (i.e. we do not assume a differentiable communication channel such as (Das et al. 2019)), and (4) the framework should enable parameter sharing among agents (namely, we do not train different models for each agent as is done in (Tan 1993)). A method that met the above criteria would constitute a general-purpose multi-agent learning algorithm that could be applied to a range of cooperative environments, with or without communication between agents. Hence, the following methods are proposed.

#### Naive Central Critic Method

A naive central critic (naïve critic) is proposed to answer the first research question: is a simple policy gradient sufficient to optimize multi-agent actor-critics. As shown in Figure 1a, naïve critic’s central critic shares a similar structure with COMA’s critic. It takes input as $(s_t, u_{t-1})$ and outputs $V(s)$. Actors follow a rather simple policy gradient: a TD advantage policy gradients that is common in RL literature, which is given by:

$$
\nabla_\theta J(\theta) = \mathbb{E}_\pi \left[ \sum_a \nabla_\theta \log \pi_\theta(u^a|s^a) A(s, u) \right] = \mathbb{E}_\pi \left[ \sum_a \nabla_\theta \log \pi_\theta(u^a|s^a) (Q(s, u) - V(s)) \right],
$$

where $Q(s, u) = r + \gamma V(s')$. In the next section, we will demonstrate that policy gradients taking the form of Equation 6 under our proposed actor-critic frameworks, are also
unbiased estimates of the naive multi-agent policy gradients. The pseudo code is listed in Appendix.

**Value Decomposition Actor-Critic**

*Difference rewards* enable agents to learn from a shaped reward $D^a = r(s, u) - r(s, (u^a, c^a))$ that is defined by a reward change incurred by replacing the original action $u^a$ with a default action $c^a$. Any action taken by agent $a$ that improves $D^a$ also improves the global reward $r(s, u)$ since the second term in the difference reward equation does not depend on $u^a$. Therefore, the global reward $r(s, u)$ is monotonically increasing with $D^a$. Inspired by *difference rewards*, we propose to decompose state value $V_{tot}(s)$ into local states $V^a(o^a)$ such that the following relationship holds:

$$\frac{\partial V_{tot}}{\partial V^a} \geq 0, \quad \forall a \in \{1, \ldots, n\}. \quad (7)$$

With Equation (7) enforced, given that the other agents stay at the same local states by taking $u^{-a}$, any action $u^a$ that leads agent $a$ to a local state $o^a$ with a higher value will also improve the global state value $V_{tot}$.

Two variants of value-decomposition that satisfy Equation (7): VDAC-sum and VDAC-mix, are studied.

**VDAC-sum** VDAC-sum simply assumes that the total state value $v_{tot}(s)$ is a summation of local state values $V^a(o^a)$:

$$V_{tot}(s) = \sum_a V^a(o^a). \quad (8)$$

This linear representation is sufficient to satisfy Equation (7). VDAC-sum’s structure is shown in Figure [1c]. Note that the actor outputs both $\pi_\theta(o^a)$ and $V_{\theta_i}(o^a)$. This is done by sharing non-output layers between distributed critics and actors. In this paper, $\theta_i$ denotes the distributed critics’ parameters and $\theta$ denotes the actors’ parameters for generality. The distributed critic is optimized by minibatch gradient descent to minimize the following loss:

$$L_t(\theta_e) = \left( y_t - V_{tot}(s_t) \right) = \left( y_t - \sum_a V_{\theta_e}(o^a_t) \right), \quad (9)$$

where $y_t = \sum_{i=t}^{k-t-1} \gamma^i r_i + \gamma^{(k-t)} V_{tot}(s_k)$ is bootstrapped from the last state $s_k$ and $k$ is upper-bounded by $T$.

The policy network is trained by following the following policy gradient:

$$g = \mathbb{E}_\pi \left[ \sum_a \nabla_\theta \log \pi(u^a|s^a) A(s, u) \right], \quad (10)$$

where $A(s, u) = r + \gamma V(s') - V(s)$ is a simple TD advantage.

Similar to independent actor-critic (IAC), VDAC-sum does not make full use of CTDE in that it does not incorporate state information during training. Furthermore, it can only represent a limited class of centralized state-value functions.

**VDAC-mix** To generalize the representation to a larger class of monotonic functions, we utilize a feed-forward neural network that takes input as local state values $V^a(o^a), \forall a \in \{1, \ldots, n\}$ and outputs the global state value $V_{tot}$. To enforce Equation (7) the weights (not including bias) of the network are restricted to be non-negative. This allows the network to approximate any monotonic function arbitrarily well (Dugas et al. 2009).

The weights of the mixing network are produced by separate hypernetworks (Ha, Dai, and Le 2016). Following the practice in QMIX (Rashid et al. 2018), each hypernetwork takes the state $s$ as an input and generates the weights of one layer of the mixing network. Each hypernetwork consists of a single linear layer. An absolute activation function is utilized in the hypernetwork to ensure that the output weights are non-negative. The biases are not restricted to being non-negative. Hence, the hypernetworks that produce the biases do not apply an absolute non-negative function. The final bias is produced by a 2-layer hypernetwork with a ReLU activation function following the first layer. Finally, hypernetwork outputs are reshaped into a matrix of appropriate size. Figure [1c] illustrates the mixing network and the hypernetworks.

The whole mixing network structure (including hypernetworks) can be seen as a central critic. Unlike critics in (Foerster et al. 2018), this critic takes local state values $V^a(o^a), \forall a \in \{1, \ldots, n\}$ as additional inputs besides global state $s$. Similar to VDAC-sum, the distributed critics is optimized by minimizing the following loss:

$$L_t(\theta_e) = \left( y_t - V_{tot}(s_t) \right) = \left( y_t - f_{mix}(V_{\theta_e}(o^1_t), \ldots, V_{\theta_e}(o^n_t)) \right), \quad (11)$$

| Algorithm          | Central Critic | Value Decomposition | Policy Gradients |
|--------------------|----------------|---------------------|------------------|
| IAC (Foerster et al. 2018) | No             | -                   | TD advantage     |
| VDAC-sum           | No             | Linear              | TD advantage     |
| VDAC-mix           | Yes            | Non-linear          | TD advantage     |
| Naive Critic       | Yes            | -                   | TD advantage     |
| COMA (Foerster et al. 2018) | Yes           | -                   | COMA advantage   |

Table 1: Actor-Critics studied.
where $f_{\text{mix}}$ denotes the mixing network. Let $\theta^c$ denote parameters in the hypernetworks. The central critic is optimized by minimizing the same loss:

$$L^c(\theta^c) = (y_t - V_{\text{tot}}(s_t))^2.$$  

(12)

The policy network is updated by following the same policy gradient in Equation 6. The pseudo code is provided in Appendix.

Convergence of VDAC frameworks [Foerster et al. 2018] establish the convergence of COMA based on the convergence proof of single-agent actor-critic algorithms (Konda and Tsitsiklis 2000; Sutton et al. 2000). In the same manner, we utilize the following lemma to substantiate the convergence of VDACs to a locally optimal policy.

**Lemma 1:** For a VDAC algorithm with a compatible TD(1) critic following a policy gradient

$$g_k = \mathbb{E}_\pi \left[ \sum_a \nabla_{\theta_k} \log \pi(u^a|\tau^a) A(s, u) \right],$$

at each iteration $k$, \(\lim_{k \to \infty} \|\nabla J\| = 0\) w.p.1.

**Proof** The VDAC gradient is given by:

$$g = \mathbb{E}_\pi \left[ \sum_a \nabla_{\theta} \log \pi(u^a|\tau^a) A(s, u) \right],$$

(13)

$$A(s, u) = Q(s, u) - V_{\text{tot}}(s).$$

Similarly, we first consider the expected distribution of the baseline $V_{\text{tot}}$:

$$g_b = -\mathbb{E}_\pi \left[ \sum_a \nabla_{\theta} \log \pi(u^a|\tau^a) V_{\text{tot}}(s) \right]$$

$$= -\mathbb{E}_\pi \left[ \nabla_{\theta} \log \prod_a \pi(u^a|\tau^a) V_{\text{tot}}(s) \right].$$

(14)

where the distribution $\mathbb{E}_\pi$ is with respect to the state-action distribution induced by the joint policy $\pi$. Writing the joint policy as a product of independent actors:

$$\pi(u|s) = \prod_a \pi(u^a|\tau^a).$$

(15)

The total value does not depend on agent actions and is given by:

$$V_{\text{tot}}(s) = f(V_1(o^1), \ldots, V_n(o^n)),$$

(16)

where $f$ is a non-negative function. This yields a single-agent actor-critic baseline:

$$g_b = -\mathbb{E}_\pi \left[ \nabla_{\theta} \log \pi(u|s) V_{\text{tot}}(s) \right].$$

(17)

Now let $d^\pi(s)$ be the discounted ergodic state distribution as
defined by (Sutton et al. 2000):

\[ g_b = -\sum_s d^{\pi(s)} \sum_u \nabla_\theta \log \pi(u|s)V_{tot}(s) \]
\[ = -\sum_s d^{\pi(s)} V_{tot}(s) \sum_u \nabla_\theta \log \pi(u|s) \]
\[ = -\sum_s d^{\pi(s)} V_{tot}(s) \nabla_\theta \sum_u \log \pi(u|s) \]  \hspace{1cm} (18)
\[ = -\sum_s d^{\pi(s)} V_{tot}(s) \nabla_\theta 1 \]
\[ = 0 \]

The reminder of the gradient is given by:

\[ g = E_{\pi} \left[ \sum_a \nabla_\theta \log \pi(a|s)Q(s, a) \right] \]
\[ = E_{\pi} \left[ \nabla_\theta \log \prod_a \pi(a|s)Q(s, a) \right] . \]  \hspace{1cm} (19)

which yields a standard single-agent actor-critic policy gradient:

\[ g = E_{\pi} \left[ \nabla_\theta \log \pi(u|s)Q(s, u) \right] . \]  \hspace{1cm} (20)

(Konda and Tsitsiklis 2000) establish that an actor-critic that follows this gradient converges to a local maximum of the expected return \( J^\pi \), subject to assumptions included in their paper.

In the naive critic framework, \( V_{tot}(s) \) is evaluated by the central critic and does not depend on agent actions. Hence, by following the same proof in equation \( 18 \) we can show that the expectation of naive critic baseline is also 0, thus proves naive critic also converges to a locally optimal policy.

Experiments

In this section, we benchmark VDACs against the baseline algorithms listed in Table 1 on a standardized decentralised StarCraft II micromanagement environment, SMAC (Samvelyan et al. 2019). SMAC consists of a set of StarCraft II micromanagement games that aim to evaluate how well independent agents are able to cooperate to solve complex tasks. In each scenario, algorithm-controlled ally units fight against enemy units controlled by the built-in game AI. An episode terminates when all units of either army have died or when the episode reached the pre-defined time limit. A game is counted as a win only if enemy units are eliminated. The goal is to maximize the win rate, i.e., the ratio of games won to games played.

The action space of agents consists of the following set of discrete actions: move[direction], attack[enemy id], stop, and no operation. Agents can only move in four directions: north, south, east, or west. A unit is allowed to perform the attack[enemy id] action only if the enemy is within its shooting range.

Each unit has a sight range that limits its ability to receive any information out of range. The sight range, which is bigger than shooting range, makes the environment partially observable from the standpoint of each agent. Agents can only observe other agents if they are both alive and located within the sight range. The global state, which is only available to agents during centralised training, encapsulates information about all units on the map.

Note that all the algorithms have access to the same partial observation and global state in our implementation. We consider the following maps in our experiments: 2s_vs_1sc, 2s3z, 3s5z, 1c3s5z, 8m, and bane_vs_bane. The detailed configuration of each map can be found in table 2 located in Appendix.

Observation features and state features are consistent across all algorithms. All algorithms are trained under A2C framework where 8 episodes are rolled out independently during the training. Refer to Appendix for training details and hyperparameters.

Ablations

We perform the following ablations to answer the corresponding research questions:

- **Ablation 1:** Is the TD advantage gradient sufficient to optimize multi-agent actor-critics? The comparison between the naive critic and COMA will demonstrate the effectiveness of TD advantage policy gradients because the only significant difference between those two methods is that the naive critic follows a TD advantage policy gradient whereas COMA follows the COMA gradient (Equation 5).

- **Ablation 2:** Does applying state-value factorization improve the performance of actor-critic methods? VDAC-sum and IAC, both of which do not have access to extra state information, shares an identical structure. The only difference is that VDAC-sum applies a simple state-value factorization where the global state-value is a summation of local state values. The comparison between VDAC-sum and IAC will reveal the necessity of applying state-value factorization.

- **Ablation 3:** Compared with QMIX, does VDAC provide a reasonable trade-off between training efficiency and algorithm performance? We train VDAC and QMIX under A2C training paradigm, which is proposed to promote training efficiency, and compare their performance.

- **Ablation 4:** What are the factors that contribute to the performance of the proposed VDAC? We investigate the necessity of non-linear value-decomposition by removing the non-linear activation function in the mixing network. The resulting algorithm is called as VDAC-mix (linear) and it can be seen as a VDAC-sum with access to extra state information.

Overall Results

As suggested in (Samvelyan et al. 2019), our main evaluation metric is the median win percentage of evaluation episodes as a function of environment steps observed, over

https://github.com/hahayonghuming/VDACs
the 200k training steps. Specifically, the performance of an algorithm is estimated by periodically running a fixed number of evaluation episodes (in our implementation, 32) during the course of training, with any exploratory behaviours disabled. The median performance as well as the 25-75\% percentiles are obtained by repeating each experiment using 5 independent training runs. Figure 2 demonstrates the comparison among actor-critics across 6 different maps. In all scenarios, IAC fails to learn a policy that consistently defeats the enemy. In addition, its performance across training steps is highly unstable due to the non-stationarity of the environment and its lack of access to extra state information.

Noticeably, VDAC-mix consistently achieves the best performance across all tasks. On easy games (i.e., 8m), all algorithms generally perform well. This is due to the fact that a simple strategy to attack the nearest enemies, which is outputted by Heuristic AI, is sufficient to win. In harder games such as 3s5z and 2s3z, only VDAC-mix can match or outperform the heuristic AI.

It is worth noting that VDAC-sum, which cannot access extra state information, matches the naive critic’s performance on most maps.

Ablation Results

Ablation 1 Consistent with (Lowe et al. 2017), the comparison between the naive critic and IAC demonstrates the importance to incorporate extra state information, which is also revealed by the comparison between COMA and IAC (Refer to Figure 2 for comparisons between naive critic and COMA across different maps.). As shown in Figure 3, naive critic outperforms COMA across all tasks. It reveals that it is also viable to use a TD advantage policy gradients in multi-agent settings. In addition, COMA’s training is unstable, as can be seen in Figure 3a and 3b, which might arise due to its inability to predict accurate counterfactual action-value $Q^\pi(s, (u^{o}, u^{a}))$ for un-taken actions.

Ablation 2 Despite the similarity in structures of VDAC-sum and IAC, VDAC-sum’s median win rates at 2 million training step exceeds IAC’s consistently across all maps (Refer to Figure 2 for comparisons between VDAC-sum and IAC across 6 different maps.). It reveals that, by using a simple relationship to enforce equation 7, we can drastically improve multi-agent actor-critic’s performance. Furthermore, VDAC-sum matches naive critic on many tasks, as shown in Figure 3c, demonstrate that actors that are trained without extra state information can achieve similar performance to naive critic by simply enforcing equation 7. In addition, it is noticeable that, compared with naive critic, VDAC-sum’s performance is more stable across training.

Ablation 3 Figure 4a and 4b shows that, under A2C training paradigm, VDAC-mix outperform or match QMIX in map 2s_vs_1sc and 3s5z. Refer to Figure 5 in Appendix for comparisons between VDACs and QMIX over all maps. In easier games, QMIX’s performance can be comparable to VDAC-mix. In harder games such as 2s_vs_1sc and 3s5z, VDAC-mix’s median test win rates at 2 million training
Figure 3: Ablation 1 and 2

step outnumber QMIX’s by 38% and 71%, respectively. Furthermore, QMIX’s performance can be noticeably unstable across the training steps in some maps as shown in Figure 4a.

Ablation 4 Finally, we introduced VDAC-mix (linear), which can be seen as an more general VDAC-sum that has access to extra state information. Consistent with our previous conclusion, the comparison between VDAC-mix (linear) and VDAC-sum shows that it is important to incorporate extra state information. In addition, the comparison between VDAC-mix and VDAC-mix (linear) shows the necessity of assuming the non-linear relationship between the global state value $V_{tot}$ and local state values $V^a$, $\forall a \in \{1, \ldots, n\}$. Refer to Figure 6 in Appendix for comparisons between VDACs across all maps.

Conclusion

In this paper, we propose a new credit-assignment actor-critic frameworks based off our observation on difference rewards, which implies the monotonic relationship between the global reward and the reshaped rewards for agents. Theoretically, we establish the convergence of proposed actor-critics to a local optimal. Empirically, benchmark tests on StarCraft micromanage games demonstrate that our proposed actor-critics bridges the performance gap between multi-agent actor-critics and Q-learning, and our methods provide a balanced trade-off between training efficiency and performance. Furthermore, we identify a set of key factors that contribute to the performance of our proposed algorithms via a set of ablation experiments. In the future, we aim to implement our framework in real-world applications such as highway on-ramp merging of semi or full self-driving vehicles.


Figure 4: Ablation 3 and 4

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Appendix

SMAC
In this paper, we use all the default settings in SMAC. That includes: the game difficulty is set to level 7, very difficult, the shoot range, observe range, etc, are consistent with the default settings. The observation vector also follows the default implementation in (Samvelyan et al. 2019). It contains the following attributes for both allied and enemy units within the sight range: distance, relative x, relative y, health, shield, and unit type. In addition, the observation vector includes the last actions of allied units that are in the field of view. Lastly, the terrain features, in particular the values of eight points at a fixed radius indicating height and walkability, surrounding agents within the observe range are also included. The state vector includes the coordinates of all agents relative to the center of the map, together with units’ observation feature vectors. Additionally, the energy of Medivacs and cooldown of the rest of the allied units are stored in the state vector. Finally, the last actions of all agents are attached to the state vector.

Table 2: Map Descriptions.

| Map Name     | Ally Units                     | Enemy Units                     |
|--------------|--------------------------------|---------------------------------|
| 2s_vs_1sc    | 2 Stalkers                     | 1 Spine Crawler                 |
| 8m           | 8 Marines                      | 8 Marines                       |
| 2s3z         | 2 Stalkers & 3 Zealots         | 2 Stalkers & 3 Zealots          |
| 3s5z         | 3 Stalkers & 5 Zealots         | 3 Stalkers & 5 Zealots          |
| 1c3s5z       | 1 Colossus, 3 Stalkers & 5 Zealots | 1 Colossus, 3 Stalkers & 5 Zealots |
| bane_vs_bane | 20 Zerglings & 4 Banelings     | 20 Zerglings & 4 Banelings       |

Training Details and Hyperparameters
The agent networks of all algorithms resemble a DRQN (Hausknecht and Stone 2015) with a recurrent layer comprised of a GRU (Chung et al. 2014) with a 64-dimensional hidden state, with a fully-connected layer before and after. The exception is that IAC, VDAC-sum, and VDAC-mix agent networks contain an additional layer to output local state values and the policy network outputs a stochastic policy rather than action-values.

Algorithms are trained with RMSprop with learning rate $5 \times 10^{-4}$. During training, 8 games are initiated independently, from which episodes are sampled. Q-learning replay buffer stores the latest 5000 episodes for each independent game (In total, replay buffer has a size of $8 \times 5000 = 40000$). We set $\gamma = 0.99$ and $\lambda = 0.8$ (if needed). Target networks (if exists) are updated every 200 training steps.

The architecture of the COMA critic is a feedforward fully-connected neural network with the first 2 layers, each of which has 128 units, followed by a final layer of $|U|$ units. Naive central critic shares the same architecture with COMA critic with an exception that its final layer contains 1 units.

The mixing network in QMIX and VDAC-mix shares an identical structure. It consists of a single hidden layer of 32 units, whose parameters are outputted by hypernetworks. An ELU activation function follows the hidden layer in the mixing network. The hypernetworks consist of a feedforward network with a single hidden layer of 64 units with a ReLU activation function.

For naive central critic, IAC, and VDACs, $Q(s_t, u_k)$ is given by:

$$Q(s_t, u_k) = \sum_{i=0}^{k-1} \gamma^i r_{t+i} + \gamma^k V(s_{t+k})$$  \hspace{1cm} (21)

$,$ where $k$ can vary from state to state and is upper-bounded by $T$.

StarCraft II Results
Algorithm 1 Naive Central Critic

1: Initialize critic $\theta^c$, target critic $\hat{\theta}^c$, and actor $\theta$
2: for each training episode $e$ do
3:   Empty buffer
4:   for $e_c = 1$ to $\frac{\text{BatchSize}}{n}$ do
5:     $t = 0$, $h^o_t$ for each agent $a$
6:     while game not terminated and $t < T$ do
7:        $t = t + 1$
8:        for each agent $a$ do
9:           $h^a_t, \pi^a_t = \text{Actor}(o^a_t, h^a_{t-1}, u^a_{t-1}, a; \theta)$
10:          Sample action $u^a_t$ from $\pi^a_t$
11:        end for
12:        Get reward $r_t$ and next state $s_{t+1}$
13:     end while
14:     add experience to buffer
15:   end for
16: Collate episodes in buffer into single batch
17: for $t = 1$ to $T$ do
18:   Batch unroll RNN using states, actions and reward
19:   Calculate $y_t$ and $A_t$ using $\hat{\theta}^c$
20: end for
21: for $t = T$ down to 1 do
22:   Calculate gradient wrt $\theta^c$: $\Delta \theta^c \leftarrow \nabla_{\theta^c} (y_t - V(s_t, u_{t-1}; \theta^c))^2$
23:   Update critic $\theta^c \leftarrow \theta^c - \alpha \Delta \theta^c$
24:   Every C steps update target critic $\hat{\theta}^c \leftarrow \theta^c$
25: end for
26: for $t = 1$ down to $T$ do
27:   Accumulate gradient wrt $\theta$: $\Delta \theta \leftarrow \Delta \theta + \nabla_{\theta} \log \pi(u^o_t | o^o_t) A_t$
28: end for
29: Update actor weights $\theta = \theta + \alpha \Delta \theta$
30: end for
Algorithm 2 Value Decomposition Actor-Critic (VDAC-sum)

1: Initialize actor network $\theta$
2: for each training episode $e$ do
3:   Empty buffer
4:   for $e_c = 1$ to BatchSize do
5:     $t = 0$, $h_a^0$ for each agent $a$
6:       while game not terminated and $t < T$ do
7:         $t = t + 1$
8:           for each agent $a$ do
9:             $h_t^a, \pi_t^a, V_t^a = \text{Actor}(o_t, h_{t-1}^a, u_{t-1}^a; \theta)$
10:            Sample action $u_t^a$ from $\pi_t^a$
11:           end for
12:           Get reward $r_t$ and next state $s_{t+1}$
13:       end while
14:       add experience to buffer
15:   end for
16:   Collate episodes in buffer into single batch
17:   for $t = 1$ to $T$ do
18:     Batch unroll RNN using states, actions and reward
19:     Calculate $y_t$ and $A_t$
20:     Accumulate gradient wrt $\theta_v$: $\Delta \theta_v \leftarrow \Delta \theta_v + \nabla_{\theta_v} (y_t - \sum_a V_t^a)^2$
21:   end for
22:   for $t = 1$ to $T$ do
23:     Accumulate gradient wrt $\theta_\pi$: $\Delta \theta_\pi \leftarrow \Delta \theta_\pi + \nabla_{\theta_\pi} \log \pi(u_t^a | o_t^a)A_t$
24:   end for
25:   Update actor weights $\theta = \theta + \alpha_\pi \Delta \theta_\pi - \alpha_v \Delta \theta_v$
26: end for

Algorithm 3 Value Decomposition Actor-Critic (VDAC-mix)

1: Initialize hypernetwork $\theta^c$, and actor network $\theta$
2: for each training episode $e$ do
3:   Empty buffer
4:   for $e_c = 1$ to BatchSize do
5:     $t = 0$, $h_a^0$ for each agent $a$
6:       while game not terminated and $t < T$ do
7:         $t = t + 1$
8:           for each agent $a$ do
9:             $h_t^a, \pi_t^a, V_t^a = \text{Actor}(o_t^a, h_{t-1}^a, u_{t-1}^a; \theta)$
10:            Sample action $u_t^a$ from $\pi_t^a$
11:           end for
12:           Get reward $r_t$ and next state $s_{t+1}$
13:       end while
14:       add experience to buffer
15:   end for
16:   Collate episodes in buffer into single batch
17:   for $t = 1$ to $T$ do
18:     Batch unroll RNN using states, actions and reward
19:     Calculate $y_t$ and $A_t$
20:     Accumulate gradient wrt $\theta^c$: $\Delta \theta^c \leftarrow \Delta \theta^c + \nabla_{\theta^c} (y_t - V_{tot}(V_1^t, \ldots, V_n^t))^2$
21:     Accumulate gradient wrt $\theta_v$: $\Delta \theta_v \leftarrow \Delta \theta_v + \nabla_{\theta_v} (y_t - V_{tot}(V_1^t, \ldots, V_n^t))^2$
22:   end for
23:   for $t = 1$ to $T$ do
24:     Accumulate gradient wrt $\theta_\pi$: $\Delta \theta_\pi \leftarrow \Delta \theta_\pi + \nabla_{\theta_\pi} \log \pi(u_t^a | o_t^a)A_t$
25:   end for
26: Update actor weights $\theta = \theta + \alpha_\pi \Delta \theta_\pi - \alpha_v \Delta \theta_v$
27: Update hypernet weights $\theta^c = \theta^c - \alpha \Delta \theta^c$
28: end for
Figure 5: Overall results: VDACs vs QMIX

Figure 6: Overall results: VDAC-mix vs VDAC-mix(linear) vs VDAC-sum