Group Actor-Critic - A Hybrid Approach For Cooperative Multi-agent RL

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Abstract

This paper explores cooperative multi-agent reinforcement learning (MARL) with a team reward. Many real-world problems require a team of agents to cooperatively optimize a single joint reward. Although, in theory, many of these problems could be treated using a centralized approach by reducing them to single-agent reinforcement learning (RL) problems to find a centralized policy, it is impractical to do so. Cooperative MARL, which has achieved great progress in recent years, provides a promising approach to these problems. However, as MARL deals with multiple agents learning concurrently, it suffers from several challenges in addition to those that arise in single-agent RL. The standard paradigm to address MARL challenges is centralized critic with fully decentralized actors, in which the goal is to find decentralized individual agent polices. Following this paradigm, many MARL methods require a fully centralized critic Q_{total} that conditions on the global state and joint action. As a result, these methods become impractical when there are more than a handful of agents. Value-Decomposition Networks (VDN) [1] addresses this issue by decomposing Q_{total} as the sum of individual critic Q_{agent}. This linear decomposition enables scalable learning but induces a limitation on the representational capacity of the centralized critic Q_{total}. This paper presents a hybrid approach between fully centralized and fully decentralized approaches mentioned above. The idea is to split agents into groups and operate group-wise - Each group has a centralized policy conditions on concatenated observations of agents within the group. The benefit of operating as groups is that we can decompose Q_{total} as the sum of the groups' critics Q_{group}. Each group critic is a non-linear combination of individual agent critic Q_{agent} of agents within that group. Therefore, by decomposing Q_{total} into Q_{group}, we create a non linear decomposition of Q_{total}. As a result, Q_{total} could represent a richer class of value functions. For this idea to work, agents within a group have to be able to communicate with each other. To evaluate this idea, we perform experiments on both partially and fully observable environments. We use actor-critic framework with an actor and a critic for each group. The actor outputs actions for all agents within the group, and the critic is the estimation of the group value function V_{group}. From our experiments, we found that as more complex behaviour is required, our approach works better than VDN, and as the number of agents increases, our approach scales better than the centralized methods.

1 Introduction

Cooperative MARL is a promising approach to help address a variety of cooperative multi-agent problems such as coordination of self driving cars, coordination of robot swarms, or optimizing the productivity of a system composed of many interacting parts.

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Although many of these problems could be treated in a centralized fashion by reducing them to single-agent reinforcement learning (RL) problems, single-agent RL methods require a central processing center which has some drawbacks such as lack of scalability and single point of failure (SPOF). Therefore, some local autonomy by learning decentralized policies which condition only on a subset of observations is necessary.

The simplest approach to learn decentralized policies is to use single-agent RL methods for each agent to optimize for the team reward as in *independent Q-learning* [2]. However, this method may not converge because agents can not distinguish other agents from the environment and so are faced with changing environment dynamics problem.

Another approach is to learn a centralized critic and use it to guide the learning of individual agent policies, an approach taken by ***MADDPG***[3] and ***COMA***[4]. However, learning a fully centralized critic is impractical if there are many agents. A way to improve the scalability of this approach is to learn a centralized but factorized critic as in *value decomposition networks* (VDN) [1]. VDN decomposes the centralized critic Q_{total} as the sum of individual action-value critic Q_{agent}. This linear decomposition structure enables scalable but severely limits the complexity of functions that Q_{total} can represent.

The approaches discussed so far either find a single fully centralized policy or multiple fully decentralized policies, a policy for each agent. In this paper, we present a hybrid approach that find policies between the two extremes - we split agents into groups and find a policy for each group. To find the group policies, we use multi-agent actor-critic framework and learn a centralized but factorized critic as in VDN. By learning decentralized policies at group level, many issues of both fully centralized approaches and fully decentralized approaches are addressed. The lack of scalability can be alleviated by increasing the number of groups. The SPOF problem in centralized approach can occur within each group, but we can create redundancy by having each agent keeps a copy of their group policy. The representational limitation from linear decomposition in VDN is alleviated because we decompose V_{total} as the sum of the groups' critics V_{group} . Each group value function is a non-linear combination of the individual agent value functions V_{agent} of agents within that group. Therefore, by decomposing V_{total} into V_{group}, we create a non linear decomposition of V_{total} and, in turns, increase the representation ability of V_{total}. However, note that agents within a group have to be able to communicate with each others for this approach to work.

2 Related Works

Independent Q-learning (IQL) [2] trains action-value functions for each agent independently using Q-learing. Inspired from IQL,[5] uses DQN to train the action-value function. Many methods use communication during execution such as CommNet [6], BicNet [7]. Some methods such as COMA [4], MADDPG [3] and [8] use centralized learning with fully decentralized paradigm. [9] and [10] explore individual reward shaping such that reward related more to agent observations.

3 Background

A fully cooperative multi-agent tasks can be modelled as a Dec-POMDP [(Oliehoeket al., 2016] consisting of $G = \langle I, S, A, P, R, Z, O, n, \gamma \rangle$. $s \in S$ is the true state of the environment. At each time step, each agent $i \in I$ receives an observation $o_i \in O$ according to observation function $Z(s, i)$ and selects an action $a_i \in A$, forming a joint action $\mathbf{a} \in \mathbf{A} \equiv A^n$. This causes a transition to a next state s' according to the transition function $P(s'|s, \mathbf{a})$ and a reward $r = R(s, \mathbf{a})$ shared by all agents. $\gamma \in [0, 1)$ is a discount factor.

VDN The main assumption in VDN is that the joint action-value function can be additively decomposed into value functions across agents

$$Q_{total}((h^1, h^2, ..., h^d), (a^1, a^2, ...a^d)) \approx \sum_{i=1}^{d} \tilde{Q}_i(h^i, a^i)$$

where the $\tilde{Q}_i$ depends on each agent's local observations. Note that $\tilde{Q}_i$ is relative and by itself does not estimate an expected return. The loss function for VDN is

$$\mathcal{L}(\theta) = \sum_{i=1}^{b} (y_i - Q_{total}(\mathbf{h}, \mathbf{a}))^2$$

where $y_i = r + \gamma \max_{\mathbf{a'}} Q(\mathbf{h'}, \mathbf{a'})$

Actor-Critic The actor, which is the policy, is trained using a gradient that depends on a critic, which usually is an approximation of the value function [11]. The actor's gradient is:

$$\nabla J(\theta) = E_{s_{0:T}, a_{0:T}} \left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a|s) R_t \right]$$

where R_t can be replaced by many expressions such as $R_t = \sum_{i=t}^{T} \gamma^{i-t} r_i$ or with the temporal difference (TD) error $R_t = r_t + \gamma V(s_{t+1}) - V(s)$

4 Method

Our method follows the standard paradigm of cooperative MARL - centralized training and decentralized execution, and uses actor-critic framework. Each group has its own actor and critic. Each group's actor outputs actions for all agents within the group given the group's local concatenated observations. Each group's critic is learned using only the group's local observations and guides the group's actor.

4.1 Train the critics

In training, we use a centralized but factorized critic as in VDN. The linear decomposition that VDN proposes is:

$$Q_{total}((h^1, h^2, ..., h^d), (a^1, a^2, ...a^d)) \approx \sum_{i=1}^{d} \tilde{Q}_i(h^i, a^i)$$

Therefore, we get

$$V_{total}((h^1, h^2, ..., h^d)) \approx \sum_{i=1}^{d} \tilde{V}_i(h^i) \tag{1}$$

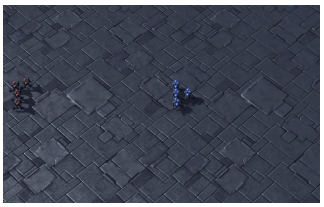
where d is the number of agents. As linear decomposition of V_{total} limits the representational capacity of the function, we divide agents into groups so equation (1) becomes:

$$V_{total}((h^1, h^2, ..., h^d)) \approx \sum_{g=1}^{G} \tilde{V}_g(h^g) \tag{2}$$

where G is the number of groups which is a hyperparmeter. We learn $\tilde{V}_g$ by backpropagating gradients from the following loss:

$$\mathcal{L}(\phi) = \sum_{i=1} \left\| V_{total}^{\phi}(\mathbf{h}_t) - y_i \right\|^2$$

where $y_i = r + \gamma V_{total}^{\phi}(\mathbf{h}_{t+1})$.



(a) 4 Marines

(b) 2 Stalkers and 2 Zealots

(c) 3 Stalkers and 5 Zealots

Figure 1: Snapshots of SMAC maps that we consider

4.2 Train the actors

After updating the group critics, we use $\tilde{V}_g$ to derive the on-policy gradients for the group policies:

$$\nabla J(\theta_i) = E_{\pi_i}\left[\sum_{t=0}^{T} \nabla_{\theta_i} \log \pi_{\theta_i}(a_i|h_i) A(h_{i,t}, a_{i,t})\right]$$

where $A(h_{i,t}, a_{i,t}) = r_t + \gamma \tilde{V}_i(h_{t+1}) - \tilde{V}_i(h_t)$ and $i \in [1, G]$. The reason that we can update each group policy independently is because of the linearly decomposed centralized critic [12]. Training requires some centralization, but during execution,only the learned group policies π_{θ_i} are used.

5 Experiments

In order to investigate the influence of dividing agents into groups, we run experiments on multiple environments and compare the average return of our method, VDN, and a centralized approach. As noted in the VDN paper, their approach is also applicable to policy gradient, therefore, we use the same implementation as our method but adjust the number of groups to N, the number of agents. We also use the same implementation for the centralized approach but adjust the number of groups to 1. For all experiments, we use groups of 2. We group agents in order using their ID number, agent 1 with agent 2, agent 3 with agent 4, and so on.... Moreover, we assume that each actor and critic is trained by an agent in the environment, and all agents have the same processing power. Therefore, we use the same neural net architect and hyperparameters for all actors and critics. The reason we impose this assumption is to avoid single point of failure problem and also ensure a fair comparison of the methods.

5.1 Decentralized StarCraft II Micromanagement - Partially Observable Environment

We perform some experiments on the The StarCraft Multi-Agent Challenge (SMAC). We use combat scenarios where two groups, red and blue, of identical units are placed symmetrically on the map. The red group is controlled by RL policies. The blue group is controlled by a built-in StarCraft II AI, which uses handcrafted heuristics. The difficulty of the AI units is set to default which is *very difficult*. The action space of agents consists of *move[direction]* (four directions: north, south, east, or west), *attack[enemy_id]*, *stop* and *noop*. Dead agents can only take *noop* action while live agents cannot. The observation of an agent consists of *distance*, *relative x*, *relative y*, *health*, *shield*, and *unit_type* for each unit within the agent's sight range. An agent can use *attack[enemy_id]* only towards enemies in their *shooting range*. All agents have *sight range* larger than their *shooting range*. Agents can only observe other agents within their *sight range* that are not dead.
At each time step, the agents receive a shared positive reward from the hit-point damage dealt to the enemies or from killing the enemies. The maximum cumulative reward achievable in an episode is 20. We compare the methods on a set of maps (showed in figure 1) consists of 4 Marines (4m), 2 Stalkers and 2 Zealots (2s_2z), 3 Stalkers and 5 Zealots (3s_5z) .

(a) 4 Marines (4m) (b) 2 Stalkers and 2 Zealots (2s2z) (c) 3 Stalkers and 5 Zealots (3s5z)

Figure 3: Average return on SMAC maps that we consider

5.2 Multi-Agent Particle Environments - Fully Observable Environment

We also perform an experiment using OpenAI's multi-agent particle environment. We use Cooperative Navigation environment. In this environment, N agents must cooperate to reach a set of N landmarks, N = 4 in our experiment. Agents can observe the relative positions of other agents and landmarks and share a team reward based on how far any agent is from each landmark. Agents are penalized if they collide with other agents. Therefore, agents have to learn to cover all landmarks while avoiding collision.

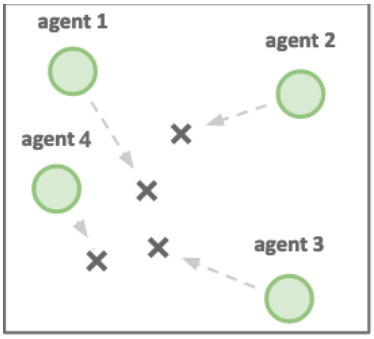


Figure 2: Cooperative Navigation

6 Results

In order to evaluate each method's performance, for every 20 iterations (around 16000 environment steps in SMAC, and 25000 environment steps in particle environment), we run a batch of independent episodes (at least 800 environment steps in SMAC and 1250 in particle environment) and record the average return of each method.

6.1 SMAC - Partially Observable Environment

Showed in Figure 3

4m map In this map, the agents are homogeneous, so a simple greedy strategy is sufficient for good performance, as evidenced by VDN's upward return trend. The centralized policy is the best performer in this map as the number of agents is relatively small, and it has the advantage of receiving concatenated observations from all agents. Our method converges to a less desirable policy which suggests that for tasks that require simple greedy strategy, VDN may be the better option.

2s2z map The centralized method is still the strongest performer in this map for the same reasons as mentioned above. Since this map has heterogeneous agents, VDN is unable to learn complex coordinated behaviour so it has the worst performance out of all the methods.

3s5z map For the previous 2 maps, the centralized method converges faster and to a better policy than the our method. However, in this map, our method has performance comparable to the centralized policy. One explanation is that there are a lot more agents in this map, which results in a big increase in the observation space and action space. Out of all methods, the centralized method is impacted the most as evidenced in the slower convergence rate. We suspect that as the number of agents increases, the performance of the centralized policy will decrease due to the bottleneck in computing. Whereas, our method which has the advantage of decentralized execution will scale better.

6.2 Multi-agent Particle Environment - Fully Observable Environment

Showed in figure 4
In fully observable environment, all methods converge to policies that are equally good. As for the convergence rate, the centralized method converges the fastest, then to ours and then VDN, which suggests that as the number of actors decreases, the convergence rate increases.

7 Future Work

Through our experiments, we think that dividing agents into groups is a promising approach. The number of groups and the number of agents in each group could be viewed as hyperparameters. Depending on the problems, we could tune these hyperparameters to get the optimal tradeoff between the advantages of fully centralized and fully decentralized approaches. By decomposing the centralized critic, we address the problem of scalability. However, our method is on-policy. With problems that have many agents, sample efficiency is also a tough issue that needs to be addressed. Using value-based methods or changing our implementation to off policy are possible approaches that should be investigated.

Figure 4: Cooperative Navigation Average Return

8 Conclusion

In this paper, we presented a novel group actor-critic method. We found that, for cooperative MARL, optimizing at group level is scalable and could give a better performance than at individual level.

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