ACCNet: Actor-Coordinator-Critic Net for “Learning-to-Communicate” with Deep Multi-agent Reinforcement Learning

Hangyu Mao¹, Zhibo Gong²*, Yan Ni¹*, Xiangyu Liu¹*
Quanbin Wang¹, Weichen Ke¹, Chao Ma¹, Yiping Song¹ and Zhen Xiao¹
¹ Peking University
² Huawei Technologies Co., Ltd.

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Abstract

Communication is a critical factor for the big multi-agent world to stay organized and productive. Typically, most multi-agent “learning-to-communicate” studies try to predefine the communication protocols or use technologies such as tabular reinforcement learning and evolutionary algorithm, which can not generalize to changing environment or large collection of agents.

In this paper, we propose an Actor-Coordinator-Critic Net (ACCNet) framework for solving multi-agent “learning-to-communicate” problem. The ACCNet naturally combines the powerful actor-critic reinforcement learning technology with deep learning technology. It can learn the communication protocols efficiently even from scratch under partially observable environment. We demonstrate that the ACCNet can achieve better results than several baselines under both continuous and discrete action space environments. We also analyse the learned protocols (communication messages) and discuss some design considerations.

Introduction

Communication is an important factor for the big multi-agent world to stay organized and productive. For applications where individual agent has limited capability and visibility of the world, it is particularly critical for multiple agents to learn communication protocols to work in a collaborative way. Name a few applications as example: data routing [1], congestion detection [2] and air traffic management [3].

However, most previous multi-agent “learning-to-communicate” studies try to predefine the communication protocols or use technologies such as tabular reinforcement

*These authors contribute equally to this study.
learning (RL) and evolutionary algorithm, which can not generalize to changing environment or large collection of agents as [4] points out. We argue that this field requires more in-depth studies with new technology.

Recently, we researchers have seen the success of the combination of deep learning (DL) and multi-agent reinforcement learning (MARL) in many applications, such as self-play Go [5], two-player Pong [6], multi-player StarCraft [7] and joint object search [8]. However, those work either assume full observability of the environment or lack communication among multiply agents.

Naturally, in this paper, we ask and try to answer a question: can we learn multi-agent communication protocols even from scratch under partially observable distributed environment with the help of DL and MARL.

We consider the setting where multiple distributed agents are fully cooperative with the same goal to maximize the shared discounted sum of rewards $R$ in a partially observable environment. Full cooperation means that all agents receive the same $R$ independent of their contributions. Partially observable environment means that no agent can observe the underlying Markov states and they must learn effective communication protocols via a limited bandwidth channel to coordinate their behaviors without collision.

The limited channel capacity is a common setting for “learning-to-communicate” studies [17, 5, 20, 4]. Traditional cooperative agents can share sensations, learned policies or even training episodes [16], which will take up a lot of bandwidth for communication itself and it is not suitable for real-word applications.

To this end, we propose a Actor-Coordinator-Critic Net (ACCNet) framework, which combines the powerful actor-critic RL technology with DL technology. The ACCNet has two paradigms. The first one is AC-CNet, which learns the communication protocols among actors with the help of coordinator and keep critics being independent. However, the actors of AC-CNet inevitably need communication even during execution, which is impractical under some special situations [9]. The second one is A-CCNet, which learns the communication protocols among critics with the help of coordinator and keep actors being independent. As actors are independent, they can cooperate with each other even without communication after A-CCNet is trained well. Note that, actor and critic are not two different agents but two services in one agent.

We explore the proposed ACCNet under different partially observable environments. Preliminary empirical studies show that: (1) both AC-CNet and A-CCNet can achieve good results for simple multi-agent environments; (2) for complex environments, A-CCNet has a better generalization ability and performs almost like the ideal fully observable models. To the best of our knowledge, this is the first work to investigate multi-agent “learning-to-communicate” problem based on deep actor-critic RL architecture under partially observable environment.

The rest of this paper starts from a brief review of RL and the most relevant multi-agent “learning-to-communicate” work. After that, we present the proposed ACCNet, followed by experiments and conclusion.
Reinforcement learning (RL) [10] is a machine learning approach to solve sequential decision making problem. At each timestep $t$, after receiving a state $s_t$, the agent takes an action $a_t$ and receive a feedback reward $r_{t+1}$ and a new state $s_{t+1}$ from the environment $E$. The goal of RL is to learn a policy $\pi(a | s)$, i.e., a mapping from state to action, which can maximize the discount cumulative future reward $R = \sum_{t=0}^{T} \gamma^t r_t$.

Several types of RL algorithms have been introduced and they can be divided into three groups [11, 12]. (1) Actor-only methods directly learn the parameterized policy $\pi(a | s; \theta)$. It can generate continuous action but suffer from high variance in the estimation of policy gradient. (2) Critic-only methods use low variance temporal difference learning (TD-Learning) to estimate the expected reward $Q(s, a; w) = E[R_t | s, a]$ for each $s-a$ pair. The policy can be derived using greedy action selection, i.e., $\pi(a | s) = a^* = \arg \max_a Q(s, a; w)$. But critic-only methods can only be used for discrete action as finding $a^*$ is computationally intensive in continuous action space. (3) Actor-critic methods jointly learn $\pi(a | s; \theta)$ and $Q(s, a; w)$. It combine the advantages (i.e., generating continuous action and reducing learning variance) of actor-only and critic-only methods.

Figure 1: Schematic overview of actor-critic algorithms. The dashed line indicates that the critic is responsible for updating the actor and itself.

The schematic structure of actor-critic methods is shown in Figure 1. Two functions reinforce each other: correct actor $\pi(a | s; \theta)$ gives high rewarding trajectory $(s, a, r, s')$, which updates critic $V(s; w)$ or $Q(s, a; w)$ towards the right direction; correct critic $V(s; w)$ or $Q(s, a; w)$ picks out the good action for actor $\pi(a | s; \theta)$ to reinforce. This mutual reinforcement behavior makes actor-critic methods converge faster and prone to converge to bad local minima, in particular for on-policy methods that follow the very recent policy to sample trajectory during training [7]. Specifically, if actor uses stochastic policies for action selection, the actor and critic are updated based on the following TD-error and stochastic policy gradient theorem [10]:

$$\delta_t = r_{t+1} + \gamma V(s_{t+1}; w) - V(s_t; w)$$  
(1)

$$\theta_{t+1} = \theta_t + \alpha * \delta_t * \nabla_{\theta} \log \pi(a_t | s_t; \theta)$$  
(2)

If actor uses deterministic policies for action selection, they are updated based on the
following TD-error and deterministic policy gradient theorem \[13\]:

$$
\delta_t = r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}; w) - Q(s_t, a_t; w)
$$

(3)

$$
\theta_{t+1} = \theta_t + \alpha \nabla_a Q(s_t, a_t; w) * \nabla_\theta \pi(a_t|s_t; \theta)
$$

(4)

As ACCNet is based on actor-critic methods, the following articles are strongly recommended to read: 10, 13, 14 and 15.

Deep reinforcement learning (DRL) uses deep neural networks to approximate one or more of the following entities: \(\pi(a|s; \theta)\), \(Q(s, a; w)\), \(V(s; w)\) and the environment.

**Related Work**

How to efficiently learn communication protocols is critical for the success of multi-agent systems. Most previous work predefine the communication protocols \[16, 17\] and some others use technologies such as tabular RL \[18\] or evolutionary algorithm \[19\], which can not generalize to the changing environment and large collection of agents as \[4\] points out.

Recently, end-to-end differentiable communication channel embedded in deep neural networks has proven to be useful for learning communication protocols from scratch. Generally speaking, the protocols can be optimized simultaneously while the networks are optimized. This work is an instance of this method. The most relevant solutions include the CommNet \[20\], DIAL \[4\] and BiCNet \[7\].

CommNet. CommNet is a single network designed for all agents. The input to the controller is the concatenation of all states from each agent. The communication channel is embedded between network layers. Each agent sends its hidden state as communication message to the current layer channel. The channel then send the averaged message from other agents to the next layer of a specific agent. However, single centralized network for all agents is not so elegant for naturally distributed multiple agents.

DIAL. DIAL trains a single network for each individual agent. At each timestep, the agent outputs its message as the input of other agents for the next timestep. To learn the communication protocols, it also push gradients from one agent to another through the communication channel. However, as we can see, the message is delayed for one timestep, the environment will keep changing before action is made.

BiCNet. Both CommNet and DIAL are based on DQN \[21\] for discrete action space environment. BiCNet is based on actor-critic methods for continuous action space environment. It uses a bi-directional recurrent neural network as the communication channel among agents. This approach allows single agent to maintain its own internal state and share information with other collaborators at the same time. However, it assumes agents can know the global observation of entire (game) environment, which is not so realistic for real-world applications. Besides, BiCNet also trains a single centralized network for all agents as CommNet.
Actor-Coordinator-Critic Net Framework

In this section, we present two paradigms of ACCNet framework for learning communication protocols based on actor-critic models.

AC-CNet

The most straightforward approach is to build a communication channel among actors while keep critics being independent. As shown in Figure 2(b), a coordinator communication channel is used for coordinating the actors to generate coordinated actions, so we call this paradigm AC-CNet. Specifically, each agent encodes its local state into a local message and sends it to the coordinator that further generate the global communication signal for this agent considering messages from all other agents. As the global signal is an encoding of all local messages, we hope it can catch the global information of the system. The integrated state is the concatenation of local state and global signal, which will be fed as input into the actor-critic models. Then the whole AC-CNet is trained as the original actor-critic model.

However, the AC-CNet inevitably need communication between actor and coordinator to get the global information even during execution, which is impractical under some special situations [9].

A-CCNet

Can those agents generate actions as if they have shared the global knowledge even without communication during training? What about during execution? The answer may be NO at the first glance and we also think so. Fortunately, machine learning has a fascinating property that we can do prediction after one model is trained and the auxiliary data on which the model is trained need no longer be kept! We ask ourselves that can we move the communication among actors into critics so that the actors can independently take actions according to their specific input states during execution after trained well (and the auxiliary critics as well as the communications among critics need no longer be kept at execution time).
As shown in Figure 2(c), a coordinator communication channel is used for coordinating the critics to generate better estimated Q-values, so we call this paradigm A-CCNet. Specifically, the actor is the same as the original actor-critic model shown in Figure 2(a), but the critics can communicate with each other through coordinator before they generate the estimated Q-values. Compared to AC-CNet where communication occurs among actors and the communication signal can only encode local state, A-CCNet put communication among critics where both local state and action can be encoded into the communication signal. So we hope A-CCNet can generate better policies (which has been confirmed by the experiments).

Besides, there are two designs for critic, critic1 use the global signal to generate Q-values directly while critic2 combine global signal and local message to generate Q-values. For both of the two designs, actors can directly generate their actions without communication during execution.

**Formal Formulation of ACCNet**

Consider N agents with parameterized actor network $\pi_i(a|s; \theta^i)$ and critic network $V_i(s; w^i)$ or $Q_i(s, a; w^i)$. For AC-CNet, as critics are independent, we can update each agent based on Equation (1)(2)(3)(4) just like updating single actor-critic agent. One key difference is that we need push the gradients of actors into the coordinator communication channels so that the communication protocols can also be optimized simultaneously. For A-CCNet, as critics communicate with each other, the critic network is now $V_i(s_t, s_{N}, a_t, a_{N}; w^i)$ or $Q_i(s_1, s_{N}, a_1, a_{N}; w^i)$. We can extend Equations (1)(2)(3)(4) into multi-agent formulations as following:

$$\delta_t^i = r_{t+1} + \gamma V_t^i(s_{t+1}^i,..., s_{t+1}^N; w^i) - V_t^i(s_t^i,..., s_t^N; w^i)$$ (5)

$$\theta_t^i = \theta_t^i + \alpha * \delta_t^i * \nabla_\theta \log \pi_i(a_t^i|s_t^i; \theta^i)$$ (6)

$$y_t^i = r_{t+1} - Q_t^i(s_t^i,..., a_t^N; w^i)$$ (7)

$$\delta_t^i = y_{t+1}^i - \gamma Q_t^i(s_{t+1}^i,..., s_{t+1}^N, a_{t+1}^1,..., a_{t+1}^N; w^i)$$ (8)

$$\theta_t^i = \theta_t^i + \alpha * \nabla_\theta Q_t^i(s_t^i,..., a_t^N) * \nabla_\theta \pi_t^i(a_t^i|s_t^i; \theta^i)$$ (9)

Our primary insight about ACCNet (especially A-CCNet) is that once each agent knows the states and actions from all other agents, the environment could be treated stationary regardless of the changing policies. More formally, the following equations always keep true for any agent (indexed by $i$) with any changing policies $\pi_i \neq \pi^i$:

$$P^i(s_t^i, s_{t+1}^i|s_t^i, s_{t+1}^i, a_t^i, ..., a_{t+1}^N, \pi_1, ..., \pi^N)$$ (10)

$$P^i(s_t^i|s_t^i, s_{t+1}^i, a_t^i, ..., a_{t+1}^N)$$ (11)

$$P^i(s_t^i, s_{t+1}^i|s_t^i, s_{t+1}^i, a_t^i, ..., a_{t+1}^N, \pi_1, ..., \pi^N)$$ (12)

**Comparison between ACCNet and Related Work**

Now, we are ready to give a brief comparison between the proposed ACCNet and other related work as shown in Table 1.
Table 1: The comparison between ACCNet and other related methods. ACCNet has more wider uses.

|                     | CommNet | DIAL | BiCNet | ACCNet |
|---------------------|---------|------|--------|--------|
| fully cooperative   | Y       | Y    | Y      | Y      |
| discrete action     | Y       | Y    | Y      | Y      |
| continuous action   | N       | N    | Y      | Y      |
| parti. observable   | Y       | Y    | N      | Y      |
| distri. agents      | N       | Y    | N      | Y      |
| limited bandwith    | N       | Y    | N      | Y      |
| indep. execution    | N       | N    | N      | Y      |

Experiments

[Two environment is enough? Our title is a general one!!]

In this section, we test the proposed ACCNet on both continuous action space and discrete action space environments.

Continuous Action Space Environment

Problem Definition. For continuous action space environment, we focus on the Network Routing Domain problem modified from [22]. Currently, the Internet is made up of many ISP networks. In each ISP network, as shown in Figure 3 there are several edge routers. Two edge routers are combined as ingress-egress router pair (IE-pair). The i-th IE-pair has a input flow demand \( F_i \) and \( K \) available paths that can be used to deliver the flow from ingress-router to egress-router. Each path \( P_k^i \) is made up of several links and each link can belong to several paths. The l-th link \( L_l \) has a flow transmission capacity \( C_l \) and a link utilization ratio \( U_l \).

As we know, high link utilization ratio is bad for dealing with burst traffic, so we want to find a good traffic splitting policy \( \pi(a|s) \) jointly for all IE-pairs across their available paths to minimize the maximum link utilization ratio in the network [24], i.e.:

\[
\min U_{l^*}
\]

subject to the constraints:

\[
l^* = \arg \max_l U_l
\]

\[
U_l = \sum_{F_i} \sum_{L_l \in P_k^i} \frac{F_i \times y_k^l}{C_l}
\]

\[
y_i = \sum_k y_k^l
\]

\[
0 \leq y_k^l
\]
where \( F_i \ast y_k^i \) is the flow transmitted along path \( P_k^i \) and \( y_k^i \) is the corresponding ratio of \( F_i \). Here, \( \pi(a|s) = f(y_k^i|s; \theta) \) and we need \( y_k^i \) for the flow routing.

**Network Topology.** Figure 3 shows two classical network topologies for network flow control studies [23, 24]. We use those two topologies too. Besides, we also test the scalability of ACCNet on a more complex topology as shown in Figure 4.

![Figure 3](image1.png)

Figure 3: The classical network topologies for research purpose. Link L1/L2/L3 are bottleneck links in both topologies. Left (TwoIE): There are two IE-pairs. Router A send packets to router C through path AC and AEFC. Router B send packets to router D through path BD and BEFD. Path AEFC and BEFD share the same link EF. Right (ThreeIE): Each bottleneck link is shared by two IE-pairs and each IE-pair has two paths.

![Figure 4](image2.png)

Figure 4: A “FiveIE” network topology for scalability test. IE-1/5 has two paths and IE-2/3/4 has three paths. Link L1~L9 are bottleneck links.

**Setting.** This network routing task introduces several main challenges of MARL. Firstly, multiple ingress-routers are fully cooperative to maximize \( R \). Besides, Markov states are partially observable because routers are located at different places. Specially, resources are interdependent such that using one resource impacts the load of others. Take TwoIE topology as example, as link EF is shared by path AEFC and BEFD, if router A send more packets through path AEFC, router B should send less packets through path BEFD; otherwise, link EF will be either overused or underused. Base on this setting, we design the following basic RL elements.

**State.** Current traffic demand and static network topology information are available. We also encode the estimated link utilization ratio into the state. Specifically, the local state is \( s = [F_i, U_i^1, max(0, 1 - U_i^1), max(0, U_i^1 - 1)] \).

**Action.** The ingress-router should generate a splitting ratio \( y_k^i \) with a constraint \( \sum_k y_k^i = 1 \) for current traffic demand \( F_i \). So the softmax activation is chosen as the final layer of actor network. This design is natural for the continuous action with sum-to-one constraint.

**Reward.** As we want to minimize the maximum link utilization ratio, so we set
reward signal to $r = 1 - \max(U_l)$.

**Baselines.** The following “learning-to-communicate” deep MARL models are usually used as baselines [20, 7].

Independent controller (IND): In IND model, each agent independently learns its own traffic splitting policy without any communication. This is the worst situation.

Fully-connected (FC): In FC model, all agents are controlled by a big fully-connected neural network to learn their traffic splitting policies jointly. The communication channel is embedded in the network without any bandwidth limitation. This can be seen as the ideal situation.

Besides, two kinds of communicating critics are designed: all critics share the same $Q(s,a)$ or each critic separately learns its own $Q(s,a)$. So we have the following models: IND, FC-sep, FC-sha, AC-CNet, A-CCNet-sep, A-CCNet-sha.

**Experiment Results.** In this environment, we care about the following performance metrics: convergence ratio (CR) of all independent experiments and maximum link utilization ratio (max-LU) of bottleneck links after convergence. All results on those performance metrics are shown in Table 2 and 3. See results of ThreeIE in the supplementary material.

For simple TwoIE topology, all models have high CR and low max-LU. But A-CCNet has a better performance than AC-CNet and IND. It even has a similar performance with the ideal fully observable FC model. For complex FiveIE topology, the performances of AC-CNet and IND drop severely, while A-CCNet can still keep its ability of performing almost like the ideal FC model. The reason may be that A-CCNet has more global information than other models (except for FC model): A-CCNet put communication among critics where both local state and action can be encoded into the communication signal while the communication signal of AC-CNet can only encode local state and IND does not exchange information at all. More information (in this case) means that the environment could be seen stationary as illustrated in equation (10)(11)(12).

Table 2: The CR and max-LU of TwoIE topology. Results of CR are averaged over 30 independent experiments. Results of max-LU are averaged over independent convergent experiments, so a little reducing of max-LU means big improvements.

|        | CR   | max-LU1 | max-LU2 | max-LU3 |
|--------|------|---------|---------|---------|
| IND    | 0.655| 0.713   | 0.724   | 0.716   |
| AC-CNet| 0.433| 0.712   | 0.713   | 0.733   |
| A-CCNet-sep | 0.9 | 0.708   | 0.698   | 0.714   |
| A-CCNet-sha | 0.9 | 0.734   | 0.707   | 0.718   |
| FC-sep | 0.967| 0.707   | 0.704   | 0.709   |
| FC-sha | 0.967| 0.710   | 0.702   | 0.715   |

Besides, for both topologies, we see that separate-$Q(s,a)$ is a little better than shared-$Q(s,a)$. As separate-$Q$ is more flexible for critics to fit different local observations than shared-$Q$, especially when the network topology is asymmetric and the agents have different local observations, such as situations in Figure 4. We also notice
Table 3: The CR and max-LU of FiveIE topology. Results of CR are averaged over 30 independent experiments. Results of max-LU are averaged over independent convergent experiments, so a little reducing of max-LU means big improvements.

|         | CR | max-LU2 | max-LU4 | max-LU6 | max-LU8 |
|---------|----|---------|---------|---------|---------|
| IND     | 0.1| 0.817   | 0.879   | 0.891   | 0.828   |
| AC-CNet | 0.0| -       | -       | -       | -       |
| A-CCNet-sep | 0.567 | 0.751 | 0.809   | 0.800   | 0.799   |
| A-CCNet-sha | 0.467 | 0.799 | 0.810   | 0.810   | 0.805   |
| FC-sep  | 0.8 | 0.818   | 0.8     | 0.797   | 0.822   |
| FC-sha  | 0.767 | 0.817  | 0.767   | 0.836   | 0.835   |

that even though separate-$Q(s, a)$ is more flexible to fit good models, but if different agents have totally different $Q$-values, the experiment is more likely to be divergence. Figure 5 shows two examples. That is to say, agents must have similar changing $Q$-values to coordinate their behaviors.

![Figure 5: Q-value comparisons for convergence and divergence experiments on topology TwoIE.](image)

**Communication Message Analysis.** We show the state-message-action changing of one convergence experiment in Figure 6. As the value of state become large (for example, more packets should be transmitted), agent1 will emit large message value while agent2 usually emits small message value. For action, if agent1 split more traffic to L1, agent2 will split more traffic to L2 because L2 is now underused. Besides, agent1 has a wider range of state value, so the message value and action value generated by agent1 are also wider than agent2. Those sophisticated and coordinated behaviors are critical for MARL system to stay organized.

**Discrete Action Space Environment**

**Problem Definition.** We consider the Traffic Junction problem modified from [25, 20]. As shown in Figure 7, four cars are deriving on the 4-way junction road. New car will be generated if one car reaches its destination at the edge of the grid. The simulation will be classified as a failure if location overlaps have occurred in 40 timesteps. Our target is to learn a car driving policy so that we can get low failure rate (FR).
Figure 6: The state-message-action changing of one convergence experiment on topology TwoIE with model AC-CNet. Only the 2D PCA projections of the original data are shown.

Figure 7: The environment of traffic junction task.

**Setting.** We use the same RL elements as in CommNet.

**State.** All cars can only know its location and driving direction. They can not see other cars. So we represent the local state as a one-hot vector set \( \{\text{location, direction}\} \).

**Action.** A car has two possible actions: gassing itself by one cell on its route or braking to stay at its current location.

**Reward.** A collision incurs a reward \( r_{\text{coll}} = -10.0 \), and each car gets reward of \( r_{\text{time}} = -0.01\tau \) at each timestep to discourage a traffic jam, where \( \tau \) is the timesteps passed since the car arrived. So the total reward at time \( t \) is: \( r(t) = C^t r_{\text{coll}} + \sum_{i=1}^{N^t} r_{\text{time}}^i \), where \( C^t \) is the number of location overlap at time \( t \), and \( N^t \) is number of cars present.

**Experiment Results.** Table 4 shows the results of this task. After training the models 300 episodes as CommNet, the proposed A-CCNet can get better results than both CommNet and Discrete-CN. When the training episode increases to 600, A-CCNet can still get a lower FR and a higher CR, while other models (except for the ideal FC models) can not get the same results. In fact, A-CCNet-sha gets the lowest FR and the highest CR.

**Communication Message Analysis.** We find a special car driving policy where the left car0 and the right car2 always brake to make space for the above car1 and the below car3. We illustrate the emitted messages by different cars under this policy in Figure 8. As we can see, messages for braking and gassing are naturally separated. For the same type (no matter braking or gassing) of messages, they can also be separated by different cars so that the ACCNet can distinguish them. Besides, gassing message
Table 4: Averaged results on 30000 experiments of traffic junction task. The results
of model CommNet and Discrete-CN are directly cited from [20], and please note that
those two environments have some nuances.

| Model         | CR   | FR (%) | CR   | FR (%) |
|---------------|------|--------|------|--------|
| IND           | 0.57 | 11.18  | 0.6  | 18.35  |
| AC-CNet       | 0.47 | 12.04  | 0.73 | 14.25  |
| A-CCNet-sep   | 0.6  | 15.82  | 0.73 | 10.48  |
| A-CCNet-sha   | 0.53 | 12.69  | 0.76 | 10.05  |
| FC-sep        | 0.8  | 12.76  | 0.8  | 11.95  |
| FC-sha        | 0.73 | 10.08  | 0.83 | 4.96   |
| CommNet (CN)  | -    | 10.0   | -    | -      |
| Discrete-CN   | -    | 100.0  | -    | -      |

is more diverse than braking message. The reason may be that braking positions are a
few (near the junction) while each position of the grid road needs a different gassing
message.

Figure 8: The emitted messages by different cars of one special learned car deriving
policy. Only the 2D PCA projections of the original messages are shown.

Design Discussion of ACCNet

As we know, some tricks are very important for the success of DRL in real applications.
For example, experience replay, frame-skipping, target network, reward-clipping, asyn-
chronous training, auxiliary task and even tricks of DL such as batch normalization, at-
tention mechanism as well as skip connection are becoming standard configurations of
DRL [21, 26, 27, 28, 15, 29, 20]. In this section, we briefly present a few tricks used in
ACCNet, hoping other researchers can confirm their usefulness. Detailed discussions
can be found in the supplementary material.

(1) The embedded communication channel. We suggest to use deep neural net-
works to encode the communication message so that the message dimension is con-
trolled independent of the dimension of original communication message. And most
importantly, as the communication channel is embedded in deep neural network, the
communication protocols can be learned even from scratch in an end-to-end differentiable way.

(2) [Do I need introduce [2017-ICML-Deep Decentralized Multi-task Multi-Agent Reinforcement Learning under Partial Observability], which propose the same replay methods for MARL.] The current episode experience replay (ER). Traditional ER uniformly sample a batch of $e_t = (s_t, a_t, r_{t+1}, s_{t+1})$ from replay buffer as the training example for model updating, which can increase data efficiency and remove correlation in the $e_t$ sequences. [26] introduces prioritized experience replay based on the magnitude of TD-error to accelerate learning. We propose current episode experience replay (CEER) which is a time-prioritized replay method. CEER keeps all $e_t$ of current episode in a temporary buffer, which will be combined with data from the main replay buffer as the training data at the end of this episode. Our preliminary experiments show the effectiveness of this method. See detail analyses in the supplementary material.

(3) Full-information activation function for sensitive (continuous) action. Ideally, the policy $\pi(a|s)$ is a one-to-one function mapping between state $s$ and optimal action $a^*$. If we use a neural network $\pi(a|s; \theta)$ to approximate $\pi(a|s)$ to meet one-to-one mapping requirement, we should not throw away any (useful) information in state $s$ at any layer of the network $\pi(a|s; \theta)$. Otherwise, similar states may be encoded into identical hidden vector and get the same optimal action $a^*$. So we suggest to use sigmoid, elu etc. rather than relu as the activation function for sensitive continuous action space applications. Similarly, we suggest to use relu for discrete action space applications because action is finite and similar states often correspond to the same optimal action $a^*$ in those applications. Our preliminary experiments show relu will give an average optimal action but not the exactly optimal action in Network Routing Domain problem where action is continuous. See detail analyses in the supplementary material.

(4) Centralized coordinator. Is there single point failure? As ACCNet is fully distributed, any agent (or special agents) can act as the coordinator. Besides, the A-CCNet model does not need the coordinator during execution and centralized training in simulator is common as [4] points out.

(5) Disable experience replay for discrete action space environments! See [2017-ICML-Stabilising Experience Replay for Deep Multi-Agent Reinforcement Learning] for more detail discussions (I add many related notes in this paper)!!!

Conclusion

In this paper, we propose a general model capable of learning communication protocols from scratch for fully cooperative, partially observable MARL problems, no matter the action space is continuous or discrete. In contrast to previous multi-agent “learning-to-communicate” studies that rely on un-generalized assumptions (predefined protocols) and technologies (tabular RL or evolutionary algorithm), the proposed ACCNet, born with the combined abilities of deep models and actor-critic reinforce models, is able to learn the communication protocols automatically even under limited bandwidth channel. Experiments on various environments demonstrate the superior performance of ACCNet and especially A-CCNet, which does not need communication during execution but still has a good generalization ability. Besides, we also give a detailed analysis
for the learned communication protocols and design considerations.

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