DDA3C: Cooperative Distributed Deep Reinforcement Learning in A Group-Agent System

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Abstract

It can largely benefit the reinforcement learning process of each agent if multiple agents perform their separate reinforcement learning tasks cooperatively. These tasks can be not exactly the same but still benefit from the communication behaviour between agents due to task similarities. In fact, this learning scenario is not well understood yet and not well formulated. As the first effort, we provide a detailed discussion of this scenario, and propose group-agent reinforcement learning as a formulation of the reinforcement learning problem under this scenario and a third type of reinforcement learning problem with respect to single-agent and multi-agent reinforcement learning. We propose that it can be solved with the help of modern deep reinforcement learning techniques and provide a distributed deep reinforcement learning algorithm called DDA3C (Decentralised Distributed Asynchronous Advantage Actor-Critic) that is the first framework designed for group-agent reinforcement learning. We show through experiments in the CartPole-v0 game environment that DDA3C achieved desirable performance and has good scalability.

1 Introduction

Applying reinforcement learning methods to realistic application scenarios can be difficult. Challenges arise from many aspects (Dulac-Arnold et al., 2021). High-dimensional state and action spaces, limited computing capability of single process or non-stationary environment in a multi-agent setting can all restrict training. Thus existing reinforcement learning algorithms can have performance issues when applied to real-world applications (Jordan et al., 2020).

Distributed deep reinforcement learning is an approach which tries to address many of these challenges, aiming to improve the performance and speed of training process (Samsami and Alimadad, 2020). Inspired by the breakthroughs resulting from recent advances in deep learning field (Krizhevsky et al., 2012; Sermanet et al., 2013; Mnih et al., 2015) proposed DQN (Deep Q-Network) which tackles the challenge of high-dimensional input with deep reinforcement learning. Further, there appear some work that approach the challenge of single worker limitation with parallelisation achieved through distributed deep reinforcement learning (Mnih et al., 2016; Horgan et al., 2018). Other than parallelisation, distributed reinforcement learning can also mean methods for multi-agent reinforcement learning problems (Lowe et al., 2017). In a multi-agent setting, multiple agents need to learn to cooperate or compete with each other to achieve their goals and their environment becomes non-stationary.

However, there are still some real-life scenario which lacks understanding and cannot be approached by general distributed deep reinforcement learning methods which are either parallelisation or for multi-agent problems. In existing literature, there is an ambiguity between cooperative learning and learning to cooperate. In a typical multi-agent problem, such as robotic soccer playing, all the agents perform learning activities together in a common environment. For each single agent, the other agents...
are part of its environment which becomes non-stationary due to the continually changing behaviour of those agents (Samsami and Alimadad, 2020). In this case, all agents from one team are learning together to cooperate with each other to achieve a common goal. We can see that learning to cooperate largely involves cooperative learning (learning together). But from the other way around, cooperative learning does not necessarily involve learning to cooperate. Agents can be purely communicating knowledge to benefit each other’s learning process without any cooperative or competitive behaviour as a result. The only cooperative behaviour is the communication during learning process, which is native and not learned behaviour. This scenario is different from multi-agent reinforcement learning due to the difference in their ultimate learning goals. The goal of this scenario is to learn faster and better through cooperative learning while the goal of multi-agent case is to learn to cooperate or compete. It cannot be approached by simple parallelisation either since each agent is an autonomous entity which can have different tasks in mind and parallelisation lacks internal flexibility. Besides, most of the recent popular parallelisation methods with good performance are working with a central parameter server, which is not feasible due to the potential difference in parameters of each agent.

We propose group-agent reinforcement learning to describe this kind of scenario, as a third type of reinforcement learning problem formulation with respect to single-agent and multi-agent problems. In this case, multiple agents are performing reinforcement learning activities separately in their own environment while communicating with each other in a group to acquire ready knowledge as well. Their environments are all stationary since no agent will interfere with others’ environment. Then we propose Decentralised Distributed Asynchronous Advantage Actor-Critic (DDA3C), a cooperative distributed deep reinforcement learning algorithm to tackle this scenario. After that we show through experiments that DDA3C achieved good performance. These three efforts constitute our contributions.

2 Background

Reinforcement learning is a process of learning by trial and error. In this process, there is one or several intelligent agents interacting with their surroundings from which they could get feedbacks for the actions they take. This way the agents are able to gain knowledge on how to behave better and gradually improve their performance. Some important components are functional: an environment, a set of environment states, a set of actions, a policy that guides the agents on choosing actions, immediate rewards on the performed actions, and long-term values of states or state-action pairs.

Reinforcement learning process is often formulated as a Markov Decision Process (MDP) which is introduced by Bellman (1957). Specifically, all the states should satisfy the following memoryless state transition property

\[ P[S_{t+1}|S_t] = P[S_{t+1}|S_1, S_2, ..., S_t]. \]  

We can see that the next state is only relevant to the current state without being affected by any previous states, or the current state grabs all necessary information from past states. A state transition probability matrix should be present as follows

\[ P = \begin{bmatrix}
P_{1,1} & P_{1,2} & \cdots & P_{1,n} \\
P_{2,1} & P_{2,2} & \cdots & P_{2,n} \\
\vdots & \vdots & \ddots & \vdots \\
P_{n,1} & P_{n,2} & \cdots & P_{n,n}
\end{bmatrix} \]  

where \( P_{s,s'} \) stands for \( P[S_{t+1} = s'|S_t = s] \). The state transition happens after we take actions. Given the action selection policy \( \pi(a|s) \) which is a probability distribution over all possible actions under state \( s \), we can further have

\[ P[S_{t+1} = s'|S_t = s] = \sum_a P[S_{t+1} = s'|S_t = s, A_t = a] \cdot \pi(a|s). \]
And we have the reward function

\[ R(s, a) = E[R_{t+1}|S_t = s, A_t = a] \] (4)

which is an expectation of the reward for taking action \( a \) under state \( s \). These two pieces of information give us the knowledge on the environment. If a reinforcement learning algorithm requires this knowledge, then it can be categorised as model-based algorithm, otherwise it is model-free.

Reinforcement learning methods can be divided into two broad categories - tabular methods and approximate methods (Sutton and Barto 2018). Introduced by Watkins (1989), Q-learning is a ground-breaking tabular algorithm which later attracted huge amount of attention. Its core mechanism is a Q-table which contains the Q values for all state-action pairs in the current environment. In the beginning of the algorithm, all the Q values are initialised arbitrarily. Actions are selected based on the highest Q value under each state. As the algorithm goes, Q table is updated according to the following rule

\[ Q_{s_t, a_t}^{\text{new}} \leftarrow Q_{s_t, a_t} + \alpha \cdot (R(S_t, A_t) + \gamma \cdot \max_a Q(S_{t+1}, a) - Q(S_t, A_t)) \] (5)

where \( R(S_t, A_t) \) is the immediate reward we get from taking action \( a \) under state \( s \). Note that this is a model-free algorithm since it does not require any environment model knowledge (the reward signal we used in the updating rule is an immediate feedback we get from the environment, not prior knowledge). After enough rounds of training, it will be able to learn an optimal Q table that can acts as the guiding policy for an agent to choose actions in this environment. Presented by Hasselt (2010), double Q-learning maintains two Q tables, which are learned with different sets of experiences while being updated with information from each other. When selecting actions, both tables could be utilised. For the Q value of the next state, it uses the other Q table instead of the same Q table. It is shown that in this way the overestimation of the Q values which happens in Q-learning is avoided.

Deep reinforcement learning is a typical class of approximate methods which use function approximation to generalise the tabular representation when the explored subset of state space is small. In the case of deep reinforcement learning, the tables are replaced with neural networks, called Q networks for Q tables. Another obvious advantage of this method is that it can release the huge memory consumption of the tables when state and action spaces are large.

3 Related Work

Proposed by Mnih et al. (2015), DQN (Deep Q-Network) introduced the first deep neural network model into reinforcement learning which takes raw RGB images as input. The model applies the type of network architecture which takes a state \( s \) as input and outputs the Q values for all possible state-action pairs \((s, a_t)\). It replaces the Q table with this model. One key mechanism of this approach is the usage of a replay memory which stores a number of experiences generated from the reinforcement learning agent’s interaction with environment. Then DQN algorithm will randomly sample minibatches of experiences from the replay memory to update the Q network with stochastic gradient descent. Introduced by Van Hasselt et al. (2016), double DQN combined the ideas of DQN and double Q-learning, which uses two deep Q-networks separately for action selection and action evaluation. Benefiting from this separation, double DQN is able to avoid action value overestimation. Introduced by Schaul et al. (2016), prioritised replay is a method which assigns a priority to each experience in the replay memory so that the Q-network will be trained on the experiences sampled from the priority memory. Wang et al. (2016) proposed dueling DQN, a new Q-network architecture. Same as the original DQN, dueling DQN starts with convolutional layers. But instead of followed by a single sequence of fully connected layers, it has two fully connected layer sequences. One sequence is for estimating the state value function \( V(s) \) and the other is for advantage function \( A(s, a) \). Then the two estimated values are combined to get Q values for each state-action pair \((s, a)\) under state \( s \) as the output. Other than the Q track methods, we also have actor-critic track. A2C is short for Advantage Actor-Critic, which is a typical kind of actor-critic method for reinforcement learning. It has two neural networks for approximating policy function \( \pi_\theta \) and state-value function \( V(s) \). The advantage function \( A(s, a) \) satisfies

\[ A(s_t, a_t) = Q(s_t, a_t) - V(s_t), \] (6)
We propose group-agent reinforcement learning, as a new type of problem formulation between workers will generate experiences at the same time and up to a certain point all stop to communicate with the rest learning process as a learner. A learner has multiple actors working simultaneously where $\hat{A}$ intuitively measures how much better it is to take a specific action $a_t$ under state $s_t$ than generally take actions under this state. The gradient of the loss function for policy network is

$$\nabla_{\theta}\log \pi_{\theta}(a_t|s_t)A(s_t, a_t)$$

We can further have the gradient as follows

$$= \nabla_{\theta} \log \pi_{\theta}(a_t|s_t)(Q(s_t, a_t) - V(s_t))$$

$$= \nabla_{\theta} \log \pi_{\theta}(a_t|s_t)(r + \gamma V(s_{t+1}) - V(s_t)).$$

Hence we can see that the actor-critic setting with these two networks works. Schulman et al. (2017) proposed PPO, short for Proximal Policy Optimisation, which is also an algorithm of the actor-critic style. The major contribution of this work is a new clipped surrogate objective for the policy network $\pi_{\theta}$ shown as below

$$L^{CLIP}(\theta) = \tilde{E}_t[\min(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t)]$$

where $\tilde{E}_t[\ldots]$ is the empirical average over a finite batch of experiences, $\hat{A}_t$ is an estimator of the advantage function at timestep $t$, $r_t(\theta)$ equals $\frac{\pi_k(a_t|s_t)}{\pi_{old}(a_t|s_t)}$, and the term $\text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)$ restricts $r_t(\theta)$ within the range $[1 - \epsilon, 1 + \epsilon]$. Besides, there are some popular distributed variants of the above basic algorithms. Introduced by Mnih et al. (2016), A3C is short for asynchronous advantage actor-critic which is an asynchronous version of distributed A2C. It runs several A2C workers in parallel with multiple CPU threads and maintains a central thread to hold a copy of the policy and value function networks. Periodically, each of the workers sends its gradients to update the central network copy, retrieves the parameters from the central copy back and resets its corresponding network parameters to the retrieved ones. This process is asynchronous among all the workers. Introduced by Espeholt et al. (2018), IMPALA version of distributed A2C. It runs several A2C workers in parallel with multiple CPU threads and restricts gradients. Then they perform the model updates synchronously as well. Introduced by Horgan et al. (2018), Ape-X extended prioritised replay to distributed setting. Similarly, it also has multiple actors generating experiences. Then these experiences are sent to be stored at a replay memory with an initial priority. There a single learner process sampling experiences from replay memory, performing training on them and then updating their priorities in the replay memory. Old experiences are removed periodically.

4 Group-Agent Reinforcement Learning

We propose group-agent reinforcement learning, as a new type of problem formulation between single-agent and multi-agent reinforcement learning. In the classic single-agent setting, there is only one agent performing reinforcement learning tasks in its environment, who is learning simply through interactions with environment. In multi-agent setting, there are multiple learning agents working in a common environment and learning to cooperate or compete with each other. Each agent is part of the others’ environment which becomes non-stationary because of the evolving behaviour policies of the agents. There is inherent difficulty for efforts targeting at multi-agent reinforcement learning problems due to this non-stationarity and high-dimensionality of the joint action space (Wen et al. 2020).
In our case of group-agent reinforcement learning, there are multiple agents learning together in a "study group", which is a very common behaviour in real human intelligence. When we humans study, there are basically two knowledge sources, learning through trial and error in our environment and learning cooperatively through retrieving ready knowledge from other people. Hence we often study together in groups to benefit the latter process. Note that this process happens through explicit communication between the agents. It does not have to happen in a single environment, but can rather work across multiple environments. In the case of group-agent reinforcement learning, multiple agents work separately in their independent environment to learn through trial and error while communicating with each other to gain ready knowledge. Each of these environments is stationary because no one will interfere with others’ environment. To clarify, these agents do not work in a common environment so that they do not learn cooperative or competitive behaviours as in multi-agent setting, and may have different goals in mind so that the problem cannot be solved by simple parallelisation in single-agent setting. We give a better picture of this scenario through Figure 1.

Figure 1: These four agents are separately doing reinforcement learning in their own environment, while communicating with each other through sending messages within the group environment. The group environment is simply a communication network over which messages can be sent, no interactions are performed with it.

We take autonomous driving as an example of real-world scenario. The training of self-driving cars can well take place with reinforcement learning (Sallab et al., 2017). We describe this scenario through three stages.

• Stage 1: Given a certain city environment, one single self-driving car is doing reinforcement learning to gain driving knowledge in one neighbourhood. Its environment, namely this neighbourhood, is stationary. Learning only happens in the form of trial and error in the single-agent setting.

• Stage 2: Still in the previous city environment, there are now multiple self-driving cars all doing reinforcement learning simultaneously, each in a different neighbourhood. Each of their environments, namely the neighbourhoods, is still stationary. The goal of every one of the agents is to learn to drive in its specific neighbourhood environment. We can see that the goals among the agents are slightly different from each other due to the difference between the neighbourhoods. However since these neighbourhoods belong to the same city environment, there is much similarity between them. Therefore, it will largely benefit their learning if we create communication channels between the agents for them to exchange their knowledge acquired through environment exploration. It is very possible that one car is not able to explore its environment thoroughly and leave out many environment states, but some other peer car explores them well, so that sound knowledges can be acquired through communicating with that peer car. In this case, learning happens in a group-agent setting.
Stage 3: With the help of group-agent reinforcement learning method, the multiple self-driving cars all learned to drive in its own environment well and fast. Now some of the cars drive out of their neighbourhoods to meet other peer cars. In one neighbourhood, there are several cars on the road. They need to learn to cooperate with each other to safely co-exist on the road, namely not causing any car crashes. This neighbourhood environment becomes non-stationary since each of these cars becomes a part of the others’ environment and their behaviours are continually evolving. This turns to be a multi-agent reinforcement learning scenario.

Other than the problem formulation based on agents, reinforcement learning problem can also be categorised according to environment type. Two classic environment types are episodic and continuing environment, where the former has a terminal environment state and the latter does not. Silver et al. (2013) proposed concurrent reinforcement learning where a single agent interacts in parallel with multiple instances of one environment. This problem can basically be solved with parallelisation and is obviously different from our problem definition.

Recall that reinforcement learning process can be formulated as MDP. An MDP is basically a tuple

\[
< S, A, P, R, \gamma >
\] (11)

where \( S \) is a finite set of environment states, \( A \) is a finite set of actions, \( P \) is the state transition probability matrix, \( R \) is reward function, and \( \gamma \) is the discount factor used in the Bellman equation formulation of value functions. For example, the state value function \( V(s) \) can be stated as follows

\[
V(s) = E[R_{t+1} + \gamma V(S_{t+1})|S_t = s].
\] (12)

To be more specific, this MDP formulation expresses a single-agent setting. Here we propose group MDP to formulate the group-agent reinforcement learning process. Three elements are added to the MDP tuple

\[
< S, A, P, R, \gamma, n, N, K >
\] (13)

where \( n \) is an identification number that uniquely identifies this agent in the group, \( N \) is a set of identification numbers of all the agents in the group and \( K \) is a storage queue that stores the knowledge coming from other agents. Each agent can send its knowledge to any other agents arbitrarily and store its received knowledge in local memory for training (namely updating policy \( \pi \) and further updating \( P \)). One group MDP formulates one agent process in group-agent reinforcement learning.

5 DDA3C

Group-agent reinforcement learning problem is better to be solved by decentralised methods due to its nature of multiple agents. If we could solve it in a decentralised way, it will be redundant to have a central controller which can be very expensive.

We propose DDA3C as in Algorithm 1, an algorithm designed for the case of group-agent reinforcement learning. It is a completely decentralised distributed algorithm in which multiple A2C reinforcement learning agents both study in separate environments and communicate with each other to exchange knowledge. In our implementation of DDA3C, we utilise torch multiprocessing and Salina (Denoyer et al. 2021) which is a lightweight library extending PyTorch modules for developing sequential decision models. Salina is used for the development of every A2C reinforcement learning agent in the learning group, while torch multiprocessing is used for the communication between different agent processes. To be specific, the communication happens through multiprocessing queues. Every agent has its own queue to hold the knowledge received from other agents, and these queues are shared among all agents so that each agent is free to send its knowledge to any other agent’s queue. This communication is asynchronous, as there is no dedicated synchronous communication rounds and each agent can send knowledge to others’ queues or retrieve knowledge from its own queue at any convenient time.

We design to have the agents start knowledge sharing after a number of training epochs, namely to let them learn separately during the first few epochs. To explain this from intuition, we are probably not
able to acquire very accurate knowledge at the beginning stage of our learning and sharing of the mistakes of beginners would have negative effect on others’ learning experiences, hence it is good practice to start group communication after everyone has reached a relatively stable learning status.

Besides, we also have an average mechanism to further stabilise the group learning behaviour. After the sharing begins, we start to do model updates every few epochs with an average of a number of the gradients (knowledge) received and locally generated. This way we are able to mitigate the influence introduced by poor experiences.

6 Experiments

We test DDA3C on the task of CartPole-v0 game in OpenAI Gym. Note that the framework that DDA3C follows should not be restricted to any specific kind of reinforcement learning agents or tasks, but we focus on A2C agents in this work and take CartPole-v0 as an example since tuning parameters for different games is not the attention of this work. We want to focus on the behaviour of the group learning system. In each epoch, we run one episode of CartPole-v0 with a limitation of maximum 100 steps. CartPole-v0 environment will give a reward of +1 for every timestep that the pole remains upright and end when terminal states reached. Hence a total reward of 100 means an optimal policy for a 100-step episode. The epoch minibatch size is set to 100.
Figure 3: Group-agent (4 agents)

Figure 4: Group-agent (6 agents)
Algorithm 1 DDA3C at each agent

Require: \( m \) queues for all \( m \) A2C reinforcement learning agents where the \( k \) – \( th \) queue is my own

1: for each epoch do
2: Generate \( n \) experiences
3: Compute gradient
4: if \( epoch < \text{threshold} \) then
5: Update model with gradient
6: else
7: Store a copy of the gradient to each one of the \( m \) queues
8: if \( epoch \% \text{minibatch} == 0 \) then
9: Get a number of gradients from the \( n \) – \( th \) queue
10: Compute the average of these gradients
11: Update model with the averaged gradient
12: end if
13: end if
14: end for

In Figure 2, we do the training for totally 50k epochs and start the knowledge sharing at 20k-th epoch for group-agent learning case. Figure 2a is the single-agent baseline, in which we can see that the total reward keeps having big fluctuations over the entire training process. This means the agent hasn’t been able to learn an optimal policy so that it is not able to always choose the right action under every state. In contrast, Figure 2b and Figure 2c keep very stable at 100 after knowledge sharing starts at 20k-th epoch, showing that two-agent group learning quickly learned optimal policy.

For the game of CartPole-v0, group learning with two agents already has very good performance. We perform more experiments to test DDA3C’s ability to scale to more agents. With more agents, we made attempts to start knowledge sharing earlier. For 4 agent case in Figure 3, we train for totally 20k epochs and start sharing at 10k-th epoch, and for 6 agent case in Figure 4, we train for totally 10k epochs and sharing starts at 5k-th epoch. They show that we still reached good results. Agent 4 in the 4-agent group has some very small fluctuations after 10k-th epoch as shown in Figure 3d, meaning that the learned policy is near-optimal. All other three agents have learned stable optimal policy with group learning. As shown in Figure 4c, agent 3 in the 6-agent group was trapped in a bad state before knowledge sharing starts and not able to get over it in following studies. It happens sometimes that certain individuals are not doing well, and the probability to see this case can rise when the number of agents in the group goes up. What’s interesting is that even in the presence of outliers, others are not affected which shows the robustness of the group learning system. The majority of agents in this 6-agent group works well (5 out of 6) – stable optimal policy learned after knowledge sharing starts at 5k-th epoch.

7 Conclusion

We introduce a third type of reinforcement learning problem formulated as group-agent reinforcement learning in which multiple agents study cooperatively in a group, sharing knowledge with each other. To give a clearer picture of this learning scenario, we describe a three-stage autonomous driving training process which can be a key application of our proposed algorithm DDA3C. We tested DDA3C in the CartPole-v0 game environment. The result shows that with just two agents DDA3C is able to learn stable optimal policy. With more agents there is a better probability for some outliers to show up but the group learning system is robust since the normal agents that work well are still the majority.

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