Learning Efficient Coordination Strategy for Multi-step Tasks in Multi-agent Systems using Deep Reinforcement Learning

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Abstract: We investigated whether a group of agents could learn the strategic policy with different sizes of input by deep Q-learning in a simulated takeout platform environment. Agents are often required to cooperate and/or coordinate with each other to achieve their goals, but making appropriate sequential decisions for coordinated behaviors based on dynamic and complex states is one of the challenging issues for the study of multi-agent systems. Although it is already investigated that intelligent agents could learn the coordinated strategies using deep Q-learning to efficiently execute simple one-step tasks, they are also expected to generate a certain coordination regime for more complex tasks, such as multi-step coordinated ones, in dynamic environments. To solve this problem, we introduced the deep reinforcement learning framework with two kinds of distributions of the neural networks, centralized and decentralized deep Q-networks (DQNs). We examined and compared the performances using these two DQN network distributions with various sizes of the agents' views. The experimental results showed that these networks could learn coordinated policies to manage agents by using local view inputs, and thus, could improve their entire performance. However, we also showed that their behaviors of multiple agents seemed quite different depending on the network distributions.

1 INTRODUCTION

Learning efficient coordination and cooperation strategy in solving the problems in a complex environment is a central issue in a multi-agent system. To achieve this sort of learning, agents are expected to observe the surrounding environment combined with their internal states to make appropriate decisions. Although a number of studies such as (Miyashita and Sugawara, 2019) showed that agents could learn coordinated policy well for the execution of a simple one-step task in the environment using the *deep Q-learning*, intelligent agents need to learn to execute tasks consisting of a few steps in a cooperative manner. For example, in a takeout platform environment, such as Uber Eats and Talabat, delivery agents have to locate restaurants to pick up ordered dishes firstly and then deliver them to the destinations where customers wait. Besides, being aware of their current state is very important because they will be unable to take any other future order for a while if they get a contract of the current order. To achieve desirable cooperative behavior, all agents should know what they need to do in the current situation; otherwise, agents might be affected by other agents that have inappropriate behaviors.

The *deep reinforcement learning* (DRL) has been proved working in many fields such as video games (Mnih et al., 2013) and traffic control (Li et al., 2016). Because it is impractical to learn appropriate actions in the environment in which a vast number of observable states exist with traditional algorithms like Q-learning, we also attempt to apply the DRL to the multi-agent system in our experiments to solve the coordination/cooperation problems in the dynamic environment. In addition, Markov game model (Littman, 1994) has been widely used as a universal model in the *multi-agent deep reinforcement learning* (MADRL) (Egorov, 2016). Training a model for the multi-agent system is still challenging because the states of agents and their appropriate actions are mutually and dynamically affected with each other.

Therefore, we examine whether the DRL can generate a coordination regime for multi-step tasks, like takeout problems, without conflicting their behaviors. The function of MADRL used to tackle these prob-

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lems in this paper is to learn to generate appropriate actions for specific states to maximize the numerical rewards for all or individual agents depending on the deployment of the *deep Q-networks* (DQNs) for the DRL. To examine from these perspectives, we introduce two types of training in MADRL; centralized training, in which a manager has a DQN to be trained to generate actions for all agents, and decentralized training, in which individual agents are trained to generate better actions for themselves. Our contribution is to examine the performance of these two training methods and compare the agents' behavior for multi-step tasks (i.e., orders) constantly occurring in the environment.

Furthermore, we also changed the observable views of each agent for training to see the differences in the emerging collective behaviors. We developed a takeout platform simulator in which multi-step tasks are generated continuously and investigated the effect of the DQN distribution on the entire performance. Note that although the size of our simulation environment is not so large, the number of states for learning is enormous and the rules in the environment are complex. Nevertheless, our experimental results indicate that learning by MADRL converged to efficient behaviors of multiple agents but their behaviors were quite different depending on the distribution of the DQNs.

2 RELATED WORKS

In general, *multi-agent reinforcement learning* (MARL) is used so that multiple agents appropriately cooperate, coordinate or compete with each other through taking joint actions with the associated rewards in the given environment. We focus on the most related and recent work for multi-agent systems, especially cooperation and coordination, to accomplish sophisticated coordinated tasks. The Q-learning algorithm explained in (Watkins and Dayan, 1992) is the most fundamental method for MARL problems. (Tan, 1993) showed that the agents could learn cooperative behaviors independently with Q-learning in a simulated social environment in which independent agents did not perform well with Q-learning in (Matignon et al., 2012). Unfortunately, traditional learning approaches such as Q-learning or policy gradient (Silver et al., 2014) result in poor performance in our study due to the large size of observable states of our environment.

Meanwhile, (Mnih et al., 2013) indicated that the online Q-learning method based on deep learning models could be used to overcome the problems

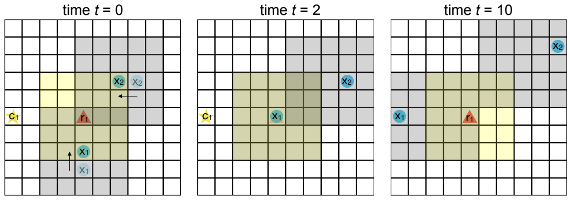


Figure 1: Example Environment with an execution of an Order.

caused by dynamic environments. Furthermore, several ideas have been introduced to make the DQNs more stable during training procedures. For example, the experience replay shown in (Mnih et al., 2015) lets multiple agents remember and reuse experiences from the past and is the practical method to reduce the number of transitions required to learn strategies. The learning algorithms such as DQN and *double DQN* (DDQN) (Van Hasselt et al., 2016) architectures are also used to improve the learning abilities, for example, a distributed DDQN framework was applied to train agents cooperatively move, attack and defend in various geometric formations (Diallo and Sugawara, 2018).

Moreover, (Lin et al., 2018) used centralized neural networks to solve the relocation problem in the large-scale online ride-sharing platform. They proposed a contextual MARL framework in which the neural network was given additional environment information when making decisions. However, we have to mention that the goal of their study was to predict where agents could take more tasks and agents would be relocated to destinations instead of exploring destinations by themselves. (Miyashita and Sugawara, 2019) compared the coordination regimes as well as the learning performance with different view sizes for independent agents. They claim that agents could learn coordination structures without conflicts with a partial view of the environment, although the tasks they introduced were the simple one-step tasks, unlike ours.

3 PROBLEM

We consider a multi-agent problem in which a group of agents learn the coordinated behavior for delivering ordered dishes in an online takeout platform. Delivering tasks are continuously generated by restaurants according to customers' requests. When one of the agents picks up an order from the restaurant and delivers the ordered dishes to the customer's location, the order is completed. The goal of this problem is to maximize the order completion rate by agents' coordinated behaviors learned with deep neural networks. Note that a task in our problem consists of two-step and ordered subtasks; *pickup* and *delivery*. An example of our problem environment is shown in Fig. 1, in which the environment is a grid world, red triangles are restaurants, yellow stars are customers, and blue circles are delivery agents. The possible actions of agents are one of $A = \{\text{up, right, down, left}\}$. We assume that each grid cell has a certain size in which there can be up to five agents in it.

When the ordered dishes are almost ready, the restaurant broadcasts order information to nearby agents in the *broadcast area*, which is expressed by a yellow area in Fig. 1. The restaurant selects and makes a contract with one of the delivery agents in this area according to a particular rule, and the selected agent would be guided to this restaurant to pick up the order. Then, the order will be marked as the *finished state* when the agent arrives at the customer's cell. The agent is expected to learn policy π that decides where it should wait for future orders from restaurants, and its actions to deliver the ordered dishes along with the appropriate path.

We model this problem as a Markov game $\langle N, K, S, A, R \rangle$, where N, K, S, A, R are the set of n agents, the set of restaurants, the set of all local states, the joint action space, and the reward functions, respectively. The details are given as follows:

- **Agent** $i \in N = \{1, ..., n\}$**:** Agent i is an robot or delivery person for delivering orders in the take-out platform.
- **Restaurant** $j \in K$**:** Restaurant j will broadcast orders information to agents in the $M \times M$ area whose center is itself when j has an order to deliver. Parameter M is called the *broadcast area size*.
- **State** $s_t \in S$**:** Each state is expressed by $s_t = s_t^1 \times \cdots \times s_t^n$, where s_t^i is the local state observed by agent i at time t and contains the information about the position of itself, the local restaurants and customers at time t.
- **Action** $a_t \in A$**:** Joint action $a_t \in A$ at time t can be denoted by the product of all actions $a_t = (a_t^1 \times \cdots \times a_t^n) \in A_1 \times \cdots \times A_n$, where A_i is the action space of agent i.
- **Reward Function** R **:** R is the function $R : S \times A \longrightarrow \mathbb{R}$, which expresses the reward for joint action $a_t \in$ at state $s_t \in S_t$ and whose value $R(s_t, a_t)$ may be a positive or negative real number.

Fig. 1 shows an example process of delivering an order. At time $t = 0$, *agent*1 (which is denoted by x_1 in this figure) takes the action to go up and *agent*2 (x_2) takes action to go left. Then *restaurant*1 (which is denoted by r_1) broadcasts the request signal about *order*1 to nearby agents in the yellow area. Both x_1 and x_2 report their positions to r_1. Then, r_1 selects x_1 to deliver this order because the distance between x_1 and r_1 is the shortest. From time t = 1 to 2, x_1 will be navigated by r_1 to the r_1's cell and given a certain reward (this reward is +5 in an experiment below) for picking the order up at $t = 2$. From time t = 3, x_1 starts to locate *customer*1 (which is denoted by c_1 in this figure) with actions from the deep networks (or random actions because we will use the ε-greedy learning strategy) until it arrives at c_1's cell. Note that x_1 cannot pick up any other order before it completes the current order. At time t = 10 in this example, x_1 reaches c_1 and receives a certain reward (which is +10 in our experiment below).

4 PROPOSED METHOD

This section describes the methods that were taken in our experiments to analyze the performance and the emerging coordinated behaviors by the DQNs. We applied the centralized DQN and the decentralized DQNs for learning the agents' behaviors in a multi-agent system.

4.1 Decentralized DQNs

The decentralized DQNs mean that agents have their own deep neural networks whose structures are the DDQN to generate actions for themselves on the basis of the local information, in order to achieve their goals independently. We think that agent $i \in N$ will learn a coordinated strategy through this learning process because the appropriate coordination allows it to maximize its cumulative discounted future reward R_t^i at time t. Note that R_t^i is calculated by

$$R_t^i = \sum_{t'=t}^{T} \gamma^{t'-t} \cdot r_{t'}^i, \tag{1}$$

where T is the time step at which the simulation environment terminates and $\gamma \in [0, 1]$ is the discount factor that weights the importance of rewards.

Then, the action value of Q for agent i with policy π^i is defined as

$$Q_{\pi^i}(s^i, a^i) = \mathbb{E}[R_{t+1}^i | s = s_t^i, a = a_t^i], \tag{2}$$

and the optimal Q_* is defined as

$$Q_*(s^i, a^i) = \max_{\pi^i} \mathbb{E}[R_{t+1}^i | s = s_t^i, a = a_t^i]. \tag{3}$$

The action-value function for agent i is defined as

$$Q_*(s^i, a^i) = \mathbb{E}[R_{t+1}^i + \gamma \max_{a^i} Q_*(s_{t+1}^i, a^i) | s, a]. \tag{4}$$

Moreover, the optimal policy of an agent depends not only on its own states but also on the policies of other agents. To be more concrete, agents should observe other agents' locations and restaurants in their views to avoid the conflicts and redundant activities, such as gathering in one restaurant, so that they could cooperate to finish more orders from various restaurants.

At time t, the neural network weight θ_t^i is updated to minimize the loss function $L_t(\theta_t^i)$ for agent i, which is defined as:

$$L_t(\theta_t^i) = \mathbb{E}_{(s^i,a^i,r^i,s_{t+1}^i)}\left[\left(y_t^i - Q^i(s^i,a^i;\theta_t^i)\right)^2\right], \quad (5)$$

where y_t^i is the target Q-value of agent i from target network (Mnih et al., 2015) with parameters $\theta_t^{i,-}$:

$$y_t^i = R_{t+1}^i + \gamma Q\left(s_{t+1}^i, \underset{a^i}{argmax}\, Q(s_{t+1}^i, a^i; \theta_t^{i,-})\right) \quad (6)$$

The Q-value for each agent is independent in this method, and therefore, agents can modify their own behaviors on the basis of the individual observations. The state of agent i at time t, s_t^i, is concatenated with the observations and the distance information. Note that we use the target Q-network with parameters $\theta^{i,-}$ updated every P steps to improve the stability of DQN. P is called the *update rate*, after this.

4.2 Centralized DQN

The centralized DQN means that there is only one deep neural network generating actions for all agents in the environment. In this paper, we consider the case in which a manager is trained by a neural network with DDQN structure whose inputs are the collection (or tensor) of the local states observed by all agents.

Then, the manager attempts to maximize the sum of the discounted future rewards earned by all agents R_t at time t, which is defined as

$$R_t = \sum_{i=1}^{n}\sum_{t'=t}^{T} \gamma^{t'-t} \cdot r_{t'}^i, \quad (7)$$

where T and γ are identical to those in Section 4.1. The action value of Q for all agents with policy π is calculated by

$$Q_\pi(s,a) = \mathbb{E}[R_{t+1} | s = s_t, a = a_t], \quad (8)$$

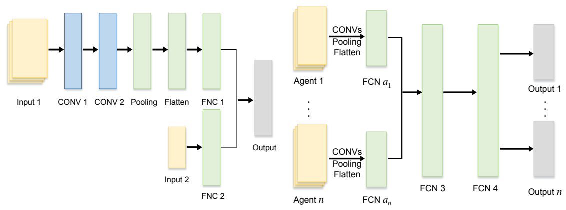
and the optimal Q_* for all agents is defined as

$$Q_*(s,a) = \max_\pi \mathbb{E}[R_{t+1} | s = s_t, a = a_t]. \quad (9)$$

The action-value function for all agents is defined as

$$Q_*(s,a) = \mathbb{E}[R_{t+1} + \gamma \max_a Q_*(s_{t+1},a) | s,a]. \quad (10)$$

When optimizing the policy, it should observe the actions, rewards, and states of all agents. The challenge



(a) Decentralized DQN. (b) Centralized DQN.

Figure 2: Neural network architecture.

is to consider and select useful information as input for training to make all agents work efficiently without predefined precise control.

The Q-function is estimated by the network function approximator with the collection of weights θ of the network. The network parameters can be updated by minimizing the loss function $L_t(\theta_t)$ at time t for all agents:

$$L_t(\theta_t) = \mathbb{E}_{(s,a,r,s_{t+1})}\left[\left(y_t - \sum_{i=0}^{n} Q^i(s^i,a^i;\theta_t)\right)^2\right], \quad (11)$$

where y_t is the target Q-value of all agents which is generated from the target network with parameters θ^-:

$$y_t = R_{t+1} + \gamma \sum_{i=0}^{n} Q\left(s_{t+1}^i, \underset{a^i}{argmax}\, Q(s_{t+1}^i, a^i; \theta_t^-)\right) \quad (12)$$

The target network whose parameters θ^- are updated from the online target network only every P steps to improve the stability of the output from the DQN. Two kinds of states, which includes the agent observations and distance information, are stored together in the memory pool. In this method, the Q value is the sum of rewards from all agents to make sure that all agents can receive appropriate actions from the manager. When one or a few agents do not work correctly, the total value of rewards will decrease; thus, the deep neural network should be adjusted in time.

4.3 Structure of Deep Q Networks

The architecture of the decentralized DQNs used in our experiments is shown in Fig. 2a. It is composed of convolution network layers, max-pooling layer, flatten layer, and fully connected network (FCN) layers. *Input*1 includes the local view observation by the individual agents, the order distribution, and the customer locations, while *Input*2 includes the associated information, such as the distance from the agent to the customer. The output is four values of actions, i.e., up, right, down, or left, and the action with the maximum value is selected (with possibility $1-\varepsilon$).

Fig. 2b shows the centralized DQN architecture used in our experiments. The convolution layers are used to maintain spatial relationships between the states of all agents. The observations from all agents are collected and processed with the same network structure shown in Fig. 2a. Then, all of them will be concatenated into FCN layers (FCNs 3 and 4). Finally, n outputs which include the values of actions for all agents, will be generated for the corresponding agents.

4.4 Reward Structure

We design a reward scheme to encourage agents to behave reasonably as well as to accelerate the learning process. Each time when agents move one step, they receive a small negative reward -0.01. If they get stuck in the border of the grid world, which means they try to get out of the environment, they receive a negative reward -0.1. When they pick up an order from the restaurant, they receive a positive reward $+5.0$. Because it is more difficult for them to deliver the dishes to the customers' positions, they will be given a bigger positive reward $+10.0$ when they succeed in arriving in customers' cells.

4.5 Exploration and Exploitation

Exploration means that agents explore new states by random actions to improve the policy. On the other hand, with exploitation, agents select the most optimal action based on past memory. We use ε-greedy $(0 \leq \varepsilon \leq 1)$ to make a balance between exploration and exploitation. At the time t, agents take a random action with the possibility ε_t and take an optimal action according to current policy with the possibility $1 - \varepsilon_t$. ε_t can be calculated by

$$\varepsilon_t = \max(\varepsilon_{init} \cdot \phi^t, \varepsilon_{min}),$$

where ε_{init} is the initial value at time $t = 0$ and ε_{min} is the lower bound.

5 EXPERIMENTS

5.1 Experimental Settings

We conducted a number of experiments to compare the performances of the learned behaviors by using both the centralized DQN and the decentralized DQNs with different view sizes of inputs for the neural networks. The parameters used in our experiments are listed in Table 1. We set the local view size to

Table 1: Experimental parameters.

Parameter	Value
Size of environment	20×20
Number of agents (n)	12
Number of restaurants ($\lvert K \rvert$)	10
Broadcast area size (M)	5
Time steps in one episode	720 time steps
Total number of orders	344 per episode
Initial value of ε (ε_{init})	1.0
Lower bound of ε (ε_{min})	0.1
Decay rate (ϕ)	0.9999995
Update rate (P)	7200 time steps
Discount factor (γ)	0.95

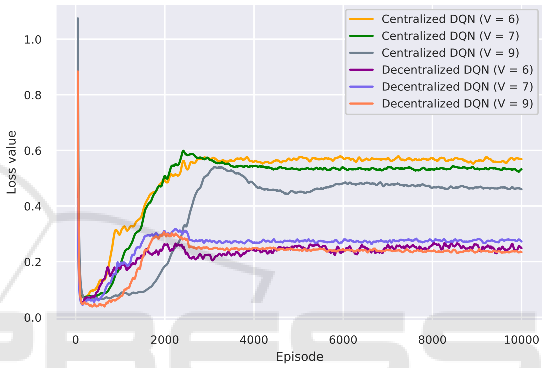


Figure 3: Training loss value.

$(2 \times V + 1, 2 \times V + 1)$ and changed V in the experiments. The takeout simulation environment was terminated when the time step increased to 720, even if there were remaining orders in the restaurants. The positions of the agent were scattered in the environment randomly at the beginning of each episode while the positions of restaurants were fixed in all episodes. Customers whose positions were randomly determined in the grid world were generated together with their orders. The positions of customers were only shown to the agents that have picked up the corresponding ordered dishes at the restaurants. Then, the customers disappeared right after agents arrived at the customers' positions. The number of orders in each episode was 344 because we expect each agent could complete one order within 25 time steps after sufficient training. All orders in the experiment had no time limitation and restaurants would broadcast orders information when the orders were generated. All experimental results of the learning methods presented here are averaged over three runs.

Table 2: Order completion rate in percentage (%) with all methods for each restaurant.

Restaurant ID	Centralized DQN			Decentralized DQN		
	V = 6	V = 7	V = 9	V = 6	V = 7	V = 9
1	48.16	73.52	86.38	11.81	37.91	54.60
2	98.49	98.12	98.99	75.30	95.48	96.56
3	97.69	97.80	100.00	69.39	98.24	99.26
4	72.83	89.69	97.61	22.78	65.82	76.95
5	98.56	98.62	97.23	78.17	96.70	97.10
6	85.54	95.78	99.38	38.50	86.78	95.63
7	97.89	95.48	97.33	73.14	96.62	98.70
8	93.47	98.48	95.83	78.46	95.90	98.82
9	97.47	95.91	97.27	47.54	88.07	96.01
10	97.76	99.49	98.23	61.30	96.36	97.12
Average	88.79	94.29	96.82	55.64	85.79	91.08

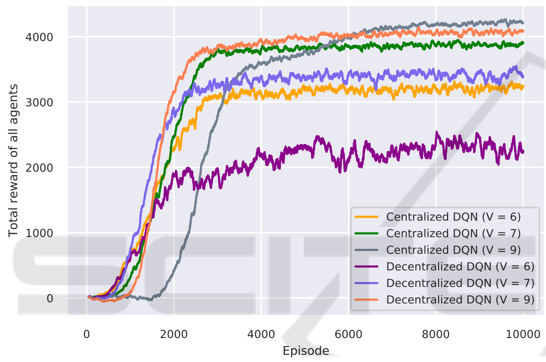


Figure 4: Reward.

5.2 Learning Convergence and Loss Values

The loss values obtained in our experiments is shown in Fig. 3. This figure clearly shows that the learning process by centralized DQN and decentralized DQNs with various local view sizes (where $V = 6$, 7, and 9) could converge around 2,500 to 4,000 episodes. The centralized DQN required more time to learn the policy π probably because the input contains the observations from all agents, but the loss values of the centralized DQN became much smaller than those of the decentralized DQNs. As the value of V increased, the loss values converged to lower values in both DQNs. Note that when $V = 9$, the local view size was 19×19, which means they could almost see the whole environment.

5.3 Rewards

The rewards reflecting the results of doing tasks is an essential factor to investigate the performance of all agents. Fig. 4 shows the total rewards that all agents received. As the results of the loss functions in the previous section, agents with centralized DQN performed better than agents with decentralized DQNs when V was identical. It is evident that when $V = 6$, the performance of agents with decentralized DQNs was the lowest. Each agent believed that their actions were appropriate, but the total rewards were lower than those with the centralized DQN. Besides, they were more likely to gather in the same area as shown in Table 2 which is listed the completion rates of order deliveries requested by restaurants; this is probably due to the limited observations ($V = 6$).

When the agents' view size was large ($V = 9$), although the learning using the centralized DQN took longer time to converge, the centralized DQN learned a better policy π to make most agents cooperate to achieve more rewards in the environment after 6,000 episodes (Fig. 4). Note that the manager with centralized DQN could not always learn a good policy to generate appropriate actions for all agents, while agents with the decentralized DQNs could always learn the individual policies, which might not be better than those with the centralized DQN, to generate actions for our problems.

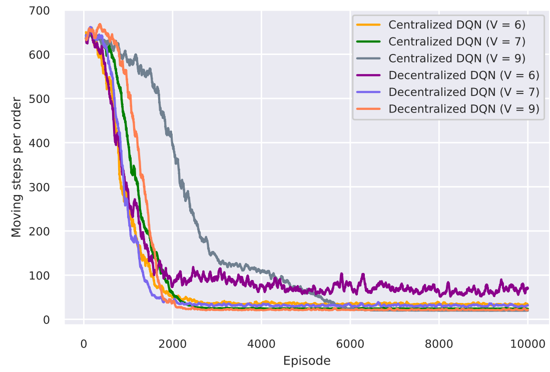


Figure 5: Average steps to finish one order.

5.4 Behaviors of Agents

Fig. 5 plots the steps to finish one order during the training process. At first, all of them needed around 650 time steps, which was almost one episode, to finish an order. Then, most DQNs could generate better actions to execute orders, resulting in less than 100 time steps per order after around 2000 episodes. Note that $\varepsilon \approx 0.15$ around 2000 episodes. As we mentioned in Section 5.3, agents controlled by the centralized DQN ($V = 9$) took more time steps (approximate 5800 episodes) for learning to pick up and deliver ordered dishes. The agents with centralized DQN required fewer time steps to complete the orders than those by

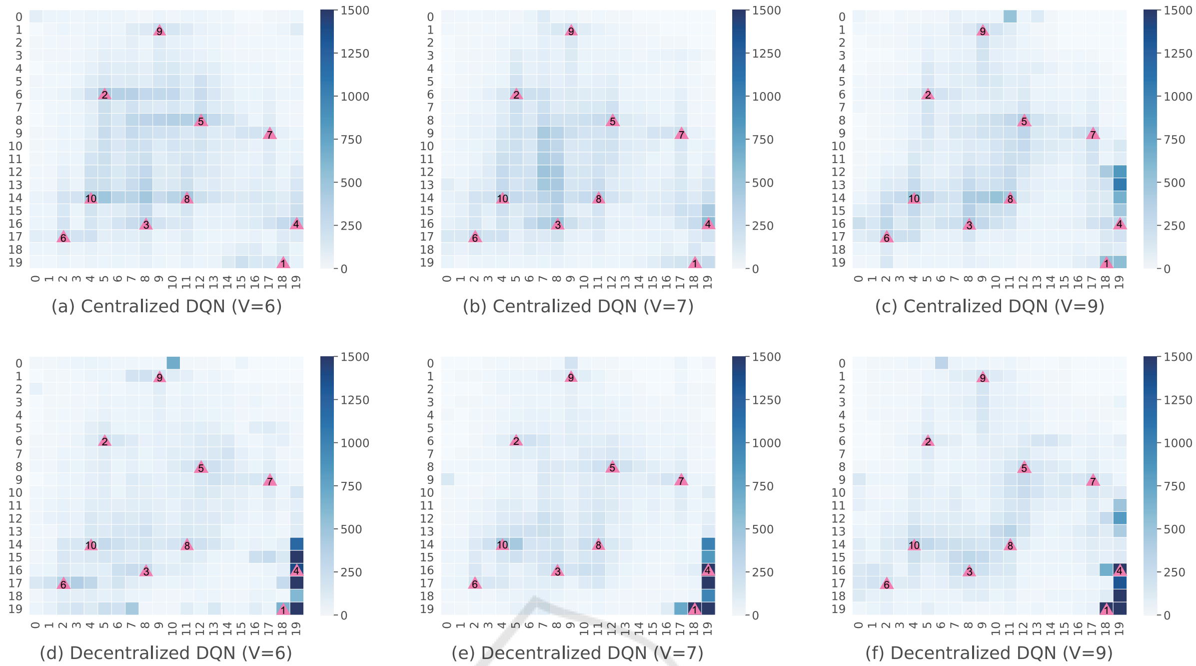


Figure 6: Locations of agents movement from the evaluation experiment.

the decentralized DQNs when their local view sizes are identical.

After training, we conducted the three experimental runs using the trained DQNs to observe the emerging behaviors of all agents. The parameter ε was set to 0.1 in these experiments. Each experimental run consisted of five episodes, and actions taken by these agents were generated by the resulting neural networks or the random method. Fig. 6 shows the location heat maps of all agents' movements, meaning that how many times agents were at each cell. The color of the cell becomes darker if agents moved to the cell more times. The red triangles with integers indicate the restaurants with their IDs. We can see that the right-bottom corner in Fig. 6d, Fig. 6e and Fig. 6f are much darker than other cells in the environment when agents used the decentralized DQNs.

We found that a few agents were wandering in this corner and waiting for requesting signals from two restaurants nearby. The agents that wait around this corner for a long time were different in each episode. This means that all policies learned from the decentralized DQNs could not perform well if agents found restaurants in the corner. However, this phenomenon did not appear in the heat maps of the centralized DQN experiments; agents were trained well and not suffering from getting stuck in corners. We can also observe that the agents with both methods learned strategies to avoid passing through the areas where there were no restaurants.

The average order completion rate (in percentage) with all methods for each restaurant are listed in Table 2. Because *restaurant*1 and *restaurant*4 were located near a corner and therefore, it has slightly lower chances to receive the order from them and the average length from them to customers were likely to be longer; thus, their order completion rates were relatively low. On the other hand, other restaurants, such as *restaurants*5 and 8, which are located in the center of the environment, have higher order completion rates. The order completion rates always increased if the local view size V increased in both centralized and decentralized DQNs.

5.5 Discussion

We can find a few interesting phenomena from our experimental results. First, both the centralized DQN and decentralized DQNs with partial observations could be trained well to learn strategies to complete the established two-step tasks. It is known that the small size of inputs could accelerate the convergence speed for DRL but their solution qualities were lower. When $V = 7$, the local view size covers around 56% of the whole environment, the manager with the centralized DQN still could learn a good policy π to manage all agents well.

Second, the quality of learned behaviors by the centralized DQN was better than that of the decentralized DQNs in terms of total rewards and the resulting coordinated strategy. One reason is that states of all agents were observed and aggregated as the inputs to the central neural network. Thus, it tries to learn the policy π to help all agents by avoiding to gather in one place. Agents using the centralized DQN could cooperate efficiently because they could find nearby restaurants and pick up orders immediately after delivering orders to customers by helping and receiving orders from any restaurants. In contrast, although agents with decentralized DQNs still can learn policies for executing the tasks, it is hard for them to learn such coordinated strategy by mutual cooperation, especially when they only have a small size of observations. Instead, they focused on a few restaurants to receive the orders shown and this is the main difference in their coordinated behaviors by the centralized and decentralized DQNs.

6 CONCLUSION

We investigated that a certain coordination strategy could be learned by multi-agent in a dynamic takeout platform problem. Our experiment results show that agents with both DQN methods can learn the cooperation strategy efficiently, especially for the centralized DQN method. With the centralized DQN method, agents controlled by a manager that could get the states of all agents could have cooperative behaviors by receiving the orders from any restaurant flexibly. On the other hand, agents with decentralized DQNs could also learn strategies for picking up and delivering orders, but their behaviors were quite different; they focused on a few specific restaurants to receive orders. However, there was an obvious problem that agents could not learn well with too small observation area. This is a pivotal issue which we want to focus on and solve in the future.

We want to extend the size of the simulation environment and the number of agents for our future work. For example, agents are divided into a few teams in a large environment, and agents are controlled by various team leaders. Different teams are expected to be responsible for an inevitable part of the region with coordinated strategies.

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