CESMA: Centralized Expert Supervises Multi-Agents

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Abstract

We consider the reinforcement learning problem of training multiple agents in order to maximize a shared reward. In this multi-agent system, each agent seeks to maximize the reward while interacting with other agents, and they may or may not be able to communicate. Typically the agents do not have access to other agent policies and thus each agent observes a non-stationary and partially-observable environment. In order to resolve this issue, we demonstrate a novel multi-agent training framework that first turns a multi-agent problem into a single-agent problem to obtain a centralized expert that is then used to guide supervised learning for multiple independent agents with the goal of decentralizing the policy. We additionally demonstrate a way to turn the exponential growth in the joint action space into a linear growth for the centralized policy. Overall, the problem is twofold: the problem of obtaining a centralized expert, and then the problem of supervised learning to train the multi-agents. We demonstrate our solutions to both of these tasks, and show that supervised learning can be used to decentralize a multi-agent policy.

1. Introduction

Reinforcement Learning (RL) is the problem of finding an action policy that maximizes reward for an agent embedded in an environment (Sutton & Barto, 2018). Recently, reinforcement learning has seen an explosion in popularity due to its many achievements in various fields such as, robotics (Levine et al., 2016), industrial applications (Evans & Gao), game-playing (Mnih et al., 2015; Silver et al., 2017; 2016), and the list continues. However, most of these achievements have taken place in the single-agent realm, where one does not have to consider the dynamic environment provided by interacting agents that learn and affect one another.

This is the problem of Multi-agent Reinforcement Learning (MARL) where we seek to find the best action policy for each agent in order to maximize their reward. The settings may be cooperative, and thus they might have a shared reward, or the setting may be competitive, where one agent’s gain is another’s loss. Some examples of a multi-agent reinforcement learning problem are: decentralized coordination of vehicles to their respective destinations while avoiding collision, or the game of pursuit and evasion where the pursuer seeks to minimize the distance between itself and the evader while the evader seeks the opposite. Other examples of multi-agent tasks can be found in (Panait & Luke, 2005a) and (Lowe et al., 2017).

The key difference between MARL and single-agent RL (SARL) is that of interacting agents, which is why the achievements of SARL cannot be absentmindedly transferred to find success in MARL. Specifically, the state transition probabilities in a MARL setting are inherently non-stationary from the perspective of any individual agent. This is due to the fact that the other agents in the environment are also updating their policies, and so the Markov assumptions typically needed for SARL algorithm convergence are violated. This aspect of MARL gives rise to instability during training, where each agent is essentially trying to learn “a moving target.”

In this work, we present a novel method for MARL in the cooperative setting (with shared reward). Our method first trains a centralized expert with full observability, and then uses this expert as a supervisor for independently learning agents with partial observability. After the supervised learning stage, the agents are able to successfully act in a decentralized manner. We call this algorithm Centralized Expert Supervises Multi-Agents (CESMA). CESMA adopts the framework of centralized training, but decentralized execution. As explained in (Kraemer & Banerjee, 2016), one can interpret the centralized learning phase as a rehearsal of a performance where each agent receives instruction from

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the (centralized) instructor, and the decentralized execution phase as performing the final state performance (where the instructor is absent).

In training the centralized expert, we use the idea of *treating a multi-agent problem as a single-agent problem*. This amounts to training the expert with the concatenated observation spaces of all agents in order to output individual actions for each agent. Using this scheme, we *are able to utilize the advances and algorithms in single-agent RL* in order to train our centralized expert. We additionally demonstrate a way to avoid the exponential growth of actions in the number of agents, to a linear growth in the number of agents.

After we obtain a centralized expert, we then train the multi-agents by labeling each agent’s observation with an action from the expert. We provide a procedure for both situations in which agents can or cannot communicate. After this, we show that the multi-agents can act in a decentralized fashion.

In training the expert, we choose to use DQNs (Mnih et al., 2013) for its simplicity, although the proposed framework can support other SARL algorithms (e.g. DDPG (Lillicrap et al., 2015), A3C and A2C (Mnih et al., 2016), Dueling DQN (Wang et al., 2015), and more). For training the decentralized agents, we also use DQNs, but again other algorithms could be used in this framework.

## 2. Related Works

The most straight-forward way of adapting single-agent RL algorithms to the multi-agent setting is by having agents be independent learners. This was applied in (Tan, 1998), but this training method gives stability issues, as the environment is non-stationary from the perspective of each agent (Matignon et al., 2012; Busoniu et al., 2010; Claus & Boutilier, 1998). This non-stationarity was examined in (Omidshafiei et al., 2017), and stabilizing experience replay was studied in (Foerster et al., 2017a).

Another common approach to stabilizing the environment is to allow the multi-agents to communicate. In (Sukhbaatar et al., 2016b), they examine using continuous communications so one may backpropagate to learn to communicate. And in (Foerster et al., 2016a), they give an in-depth study of communicating multi-agents, and also provide training methods for discrete communication. In (Paulos et al., 2018), they decentralize a policy by examining what to communicate and they also utilize supervised learning, although they mathematically solve for a centralized policy and their assumptions require homogeneous communicating agents.

Others approach the non-stationarity issue by having the agents take turns updating their weights while freezing other agents for a time, although non-stationarity is still present (Egorov, 2016). Other attempts adapt $Q$-learning to the multi-agent setting: Distributed $Q$-Learning (Lauer & Redmiller, 2000) updates $Q$-values only when they increase, and updates the policy only for actions that are not greedy with respect to the $Q$-values, and Hysteretic $Q$-Learning (Matignon et al., 2007) provides a modification. Other approaches examine the use of parameter sharing (Gupta et al., 2017) between agents, but this requires a degree of homogeneity of the agents. And in (Tesauro, 2004b), their approach to non-stationarity was to input other agents’ parameters into the Q function. Other approaches to stabilize the training of multi-agents are in (Sukhbaatar et al., 2016a), where the agents share information before selecting their actions.

From a more centralized view point, (Oliehoek et al., 2008; Rashid et al., 2018; Sunehag et al., 2017) derived a centralized $Q$-value function for MARL, and in (Usunier et al., 2016), they train a centralized controller and then sequentially select actions for each agent.

Works that follow the framework of centralized training, but decentralized execution come from: (Kraemer & Banerjee, 2016), where they introduce RLaR (Reinforcement Learning as Rehearsal), and also in (Foerster et al., 2018b) – where they introduce COMA (Counterfactual Multi-Agent) – and (Lowe et al., 2017) – where they introduce MADDPG (Multi-Agent Deep Deterministic Policy Gradient) – where they train agents in an actor-critic framework, and the critic is centralized but the actors are not. After training completes, the agents are able to be separated from the critics and execute independently. In (Dobbe et al., 2017), they examine decentralization of policies from an information-theoretic perspective.

The idea of knowledge-reuse is examined in (Silva et al., 2018; Foerster et al., 2018a)

For some surveys of MARL, see articles in (Bu et al., 2008; Panait & Luke, 2005b).

## 3. Background

In this section we briefly review the requisite material needed to define MARL problems. Additionally we summarize some of the standard approaches in general reinforcement learning and discuss their use in MARL.

**Markov Games:** We mathematically formulate the MARL problem as a partially observable Markov game (Littman, 1994). A Markov game is defined by $N$ agents with a set of states $S$ giving all configurations of all agents, a set of action spaces for each agent: $A_1, \ldots, A_N$, and a set of observation spaces for each agent: $O_1, \ldots, O_N$. Each agent
has a (stochastic) policy \( \pi_i : \mathcal{O}_i \times \mathcal{A}_i \rightarrow [0, 1] \), and the next state is given by the state transition function \( \mathcal{T} : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S} \). The reward for each agent is a function of the state and each agent’s actions \( r_i : \mathcal{S} \times \mathcal{A}_i \rightarrow \mathbb{R} \), and each agent will receive a private observation \( o_i : \mathcal{S} \rightarrow \mathcal{O}_i \). To initialize the game, the initial states are given by an initial distribution \( \rho : \mathcal{S} \rightarrow [0,1] \). The goal for each agent is to maximize its total expected reward: \( R_i = \sum_{t=0}^{T} \gamma^t r_i^t \), where \( \gamma \) is the discount factor and \( T \) is the final timestep (note \( T = \text{finite or } \infty \)).

**Deep Q-Networks (DQN):** Deep Q-Networks (Mnih et al., 2013) is a deep-learning extension of Q-Learning (Watkins & Dayan, 1992; Sutton & Barto, 2018). In Q-Learning, for each policy \( \pi \), we try to estimate the state-action pairs \( Q^\pi(s,a) \), which we call “Q-values”, and they give the value of taking action \( a \) when in state \( s \) (at time \( t \)). The Q-values are precisely the expected return:

\[
Q^\pi(s,a) = \mathbb{E} \left[ \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} | s_t = s, a_t = a \right],
\]

which can be recursively written as

\[
Q^\pi(s,a) = \mathbb{E}_{s'} [R(s,a) + \gamma \mathbb{E}_{a' \sim \pi} [Q^\pi(s',a')]]
\]

For DQNs, the optimal \( Q^* \) function is represented as a neural network, and the loss function is

\[
L(\theta) = \mathbb{E}_{(s,a,r,s')} [(y - Q^\pi(s,a|\theta))^2],
\]

where \( y = r + \gamma \max_{a'} \bar{Q}^\pi(s',a') \)

where \( \theta \) are the neural network parameters, and \( \bar{Q} \) is called the “target Q-Function” whose parameters are periodically updated with the parameters \( \theta \). We will be mainly using DQNs in training our expert, but any other single-agent RL algorithm will work.

DQNs have been previously applied to MARL problems (Foerster et al., 2016b; Tesauro, 2004a), but due to the non-stationary environment, i.e. the breaking of the Markovian assumption in MDPs, the training suffers from instability. Another issue observed in (Foerster et al., 2017c) is that experience replay cannot be effectively applied because of the violation \( P(s'|s,a,\pi_1,\ldots,\pi_N) \neq (s'|s,a,\pi'_1,\ldots,\pi'_N) \) if any \( \pi_i \neq \pi'_i \).

**Policy Gradients (PG):** Another approach to RL problems are policy gradient methods (Sutton et al., 2000): instead of learning state-action values, we instead adjust the parameters \( \theta \) of the policy \( \pi_\theta \), so as to maximize the objective,

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

where \( p^\pi \) is the state distribution from following policy \( \pi \). The gradient of the above expression can written (Sutton et al., 2000; Sutton & Barto, 2018):

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

Many policy gradient methods seek to reduce the variance of the above gradient estimate, and thus many study how one estimates \( Q^\pi(s,a) \) above (Schulman et al., 2015). For example, if we let \( Q^\pi(s,a) \) be the sample return \( R^t = \sum_{i=1}^{T} \gamma^{i-1} r_i \), then we get the REINFORCE algorithm (J. Williams, 1998). Or one can choose to learn \( Q^\pi(s,a) \) using temporal-difference learning (Sutton, 1988; Sutton & Barto, 2018), and would obtain the Actor-Critic algorithms (Sutton & Barto, 2018). Other policy gradients algorithms are: DPG (Silver et al., 2014), DDPG (Lillicrap et al., 2015), A2C and A3C (Mnih et al., 2016), to name a few.

Policy Gradients have been applied to multi-agent problems; in particular the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) (Lowe et al., 2017) uses an actor-critic approach to MARL. Another policy gradient method is by (Foerster et al., 2017b) called Counterfactual Multi-Agent (COMA), who also uses an actor-critic approach.

### 4. Methods

In this section, we explain the motivation and method of our approach: Centralized Experts Supervising MultiAgents (CESMA).

**Treating a multi-agent problem as a single agent problem**

Intuitively, the optimal strategy of a multi-agent problem should be one found by a centralized expert. This is because not only does a central controller have all information available to all individual agents, but it can also combine that information for more powerful analysis. Thus, in order to find the most optimal strategy for a multi-agent problem, we first try to find a centralized expert (and then have this expert supervise the multi-agents).

To find this centralized expert, we take the key idea of *treating a multi-agent problem as a single agent problem*. This is done by by concatenating the observations of all agents into one observation vector, and this will be the observation of the expert. Using this observation the expert outputs a stacked(concatenated) action vector containing the actions for each agent. More precisely, if we have \( N \) agents with observations \( o_1,\ldots,o_N \), then we stack this to obtain \( o_1,\ldots,o_N \). This is the input into the centralized expert. The expert will output actions \( a_1,\ldots,a_N \), where each \( a_i \) is an action for agent \( i \).

In this way, we have turned an MARL problem into a single-agent RL problem, and we now have all tools available to us from single-agent RL. Here we will utilize a simple DQN, although in principle one can use any of the plethora
of RL algorithms available.

Reducing exponential growth of joint actions to linear growth

A straight-forward way for the expert to output actions is to have it evaluate every possible action in the joint space of all agents. This leads to an action vector that is exponential in the number of agents which can complicate training. In this section we demonstrate a method to reduce this exponential growth to linear growth. Namely, if agent $i$ has action space $A_i$ of size $|A_i|$, then after turning the multi-agent problem into a single-agent problem, the action space of the expert will be $A_1 \times A_2 \times \ldots \times A_N$, which means the action space will have size $\prod_{i=1}^N |A_i|$, i.e. exponential growth. We resolve this issue in the DQN setting, whose solution can be easily extended in the DDPG setting (with continuous action spaces). Also see section 4.1 of (Gupta et al., 2017) for DDPG.

In most applications of a DQN, the input of the DQN will be the observation, and the output will be the $Q$-values for the expert to be

$$Q(s, a_1, \ldots, a_N) = \sum_{i=1}^N \hat{Q}_i((a_1, \ldots, a_N), a_i)$$

and so the relationship between the $Q$-value and the expert will be,

$$Q((o_1, \ldots, o_N), (a_1, \ldots, a_N)) = \sum_{i=1}^N \text{Expert}(o_1, \ldots, o_N), (a_1, \ldots, a_N)\]$$

And thus, we want our expert neural network to learn the $Q$-values in $\mathcal{O}(N)$ time, which is much faster than outputting every possible action. This means we need $2^N$ $Q$-values of the expert, and let the output of the expert be

$$Q((o_1, \ldots, o_N), (a_1, \ldots, a_N)) = \sum_{i=1}^N \hat{Q}_i((o_1, \ldots, o_N), a_i)$$

where $\hat{Q}_i$ can be thought as a pseudo-$Q$-value for agent $i$ taking action $a_i$. For our expert, we make each $\hat{Q}_i((o_1, \ldots, o_N), a_i)$ correspond to a block of output nodes, that have $|A_i|$ number of nodes, so we now have $\sum_{i=1}^N |A_i|$ number of output nodes for our expert, i.e. linear growth.

From this, we then let our expert input-output be,

$$\text{Expert}(o_1, \ldots, o_N)$$

and so the relationship between the $Q$-value and the expert input-output be,

$$Q((o_1, \ldots, o_N), (a_1, \ldots, a_N)) = \hat{Q}(o_1, \ldots, o_N)$$

Implementation of the Centralized Expert

In our implementation, the DQN expert is represented by a simple 2 hidden layer MLP. The input is the stacked observations of all agents, $(o_1, \ldots, o_N)$, and the output will have $\sum_{i=1}^N |A_i|$ number of output nodes, where each block of $|A_i|$ nodes consists of the $\hat{Q}$-values for the actions of agent $i$. The action selection proceeds by taking the argmax output of each of these blocks. See Figure 4 for a diagram of the expert network.

The rest of the implementation follows standard DQN execution with the usual loss function,

$$L(\theta) = \mathbb{E}_{(s,a,r,s') \sim \text{ER}} \left[ y(s,a,r,s') - Q_\theta(s,a) \right]$$

where $y(s,a,r,s') = r + \gamma \max_{a'} Q_\theta-(s', a')$ and $\gamma$ is the discount rate. We
Additionally have that $s = (o_1, \ldots, o_N)$, the stacked observations of the agents, and $a = (a_1, \ldots, a_N)$ (and similarly with $a'$).

Note that in our implementation,

$$\max_{a'} Q_{\theta'}(s', a') = \max_{a'_1} \hat{Q}(s', a'_1) + \cdots + \max_{a'_N} \hat{Q}(s', a'_N)$$

where $a'$ is the stacked actions of all agents, and $a'_i$ is the individual action of agent $i$.

### Supervising Multi-agents

After training the centralized expert, we proceed to do supervised learning to train the decentralized agents. In order to obtain a dataset matching the distribution of states encountered by the multi-agents, we run through the environment, and at each timestep we store the state $s = (o_1, \ldots, o_N)$, similar to an experience replay buffer, and we call this aggregated dataset an observation buffer (as we also impose a storage limit). After a sufficient amount of states have been collected, we sample a batch from the observation buffer and have the expert label each state with an action. This procedure is very similar to DAgger (Ross et al., 2010), where they label actions for single-agent problems. The problem then simplifies to a supervised learning problem on the correct action to take, where the inputs for each agent are its local observations and the labels are actions computed by the centralized expert. See Figure 2 for a diagram of the procedure, and Algorithm 1 for the algorithm.

### Supervising Multi-agents that Communicate

In order to train multi-agents that communicate, especially in an environment where communication is necessary (see Section 5 for such a case), we have to slightly modify the above procedure, specifically the supervised learning of multi-agents portion. Training the centralized expert in a communication scenario follows the same procedure as before, although one may be able to perform dimensionality

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**Algorithm 1 CESMA: Centralized Expert Supervises Multi-Agents**

**Require:** A centralized policy $E$ obtained by first treating the multi-agent problem as a single-agent problem (as described in 4), and then using any single-agent RL algorithm.

**Require:** $N$ agents $\pi_{\theta_1}, \ldots, \pi_{\theta_N}$, observation buffer $D$ for multi-agent observations, batch size $B$

1: while $\pi_{\theta_1}, \ldots, \pi_{\theta_N}$ not converged do  
2: Obtain observation $o_1, \ldots, o_N$ from the environment  
3: Obtain agents’ actions, $a_1 = \pi_{\theta_1}(o_1), \ldots, a_N = \pi_{\theta_N}(o_N)$  
4: Store the observations together, i.e. put $(o_1, \ldots, o_N)$ in $D$  
5: if $|D| > B$ then  
6: Sample a batch of $B$ multi-agent observations $\{(o_1^b, \ldots, o_N^b)\}_{b=1}^P$  
7: Let the centralized expert $E$ label each observation to obtain an action: $\hat{a}_i^b = E(o_1^b, \ldots, o_N^b)$, for $i = 1, \ldots, N$ and $b = 1, \ldots, B$.  
8: Form the input-label pairs $\{(o_1^b, \hat{a}_1^b), \ldots, (o_N^b, \hat{a}_N^b)\}_{b=1}^P$.  
9: Perform supervised learning for $\pi_{\theta_i}$, where the inputs are $\{o_i^b\}$ and the labels are $\{\hat{a}_i^b\}$, for $i = 1, \ldots, N$.  
10: end if  
11: Obtain new observations from agents’ actions, $(o_1', \ldots, o_N')$, and set $o_1 = o_1', \ldots, o_N = o_N'$.  
12: end while
reduction by removing the communication observations and communication actions, as the expert has no incentive to communicate with itself. Thus using the expert communication actions as labels for the multi-agents would not help (which we also experimentally verify). Thus in the next phase, the agents must learn the communication themselves.

Before going into the details of the method, we give an overview: Firstly, we consider observations at timestep \( t - 1 \) and \( t \). The idea is to separate the losses of the agent actions, and the losses of the agent output communications. In order to obtain the action loss, we do as before and use supervised learning on the observation at time \( t \) where the input is the observation and the label is the centralized expert (physical) action label; so we extract the physical action portion of the agent to obtain the action loss. The communication loss for agent \( i \) is computed by first obtaining agent \( i \)'s output communication action based off the observation at \( t - 1 \), this is then combined with the observations of all other agents at time \( t \). After, we obtain a physical action from these agents, and then do supervised learning on these actions, with the expert action label.

In order to best describe the method, we simplify to the case of two agents. It is useful to provide notation which differentiates the physical observations (the observations that do not come from the output of an agent action), and the communication observations (the observations that come from agent outputs). We denote \( o_i = (p_i, c^{in}_i) \), where \( o_i \) is the whole observation for agent \( i \), and \( p_i \) is the physical observation while \( c^{in}_i \) is the (incoming) communication observation. We also break up the actions similarly, so \( a_i = (q_i, c^{out}_i) \), where \( a_i \) is the whole action for agent \( i \), and \( q_i \) is the physical action (e.g. movement) while \( c^{out}_i \) is the (output) communication action.

Our communication protocol is such that each agent outputs a communication that is available to others in the subsequent timestep. Each agent first locally observes the environment, including incoming communications from the prior timestep, and then outputs both a physical action and an output communication action. Under this protocol, the incoming communications are based on agent observations in the prior timestep.

Continuing with our procedure, we must also modify our observation buffer so that it now holds observations of the form \( (o_{1,t-1}, o_{1,t}), (o_{2,t-1}, o_{2,t}) \), where \( o_{1,t-1} \) is the observation for agent 1 at time \( t - 1 \), and similarly for the others. Now in order to train each agent, we break up the loss function into two: an action loss and a communication loss. The total loss used for training is the sum of these losses.

The action loss is obtain by doing supervised learning as before on the agents where the input is \( o_{1,t} \) and the label is the expert action \( \tilde{a}_1 \).

The communication loss is easier to describe from the perspective of a pair of agents. Consider the computation of agent 1’s communication loss. We feed agent 1 the observation \( (p_{1,t-1}, c^{in}_{1,t-1}) \) to obtain the actions \( (a_{1,t}, c^{out}_{1,t-1}) \). We then replace the observation \( (o_{2,t}, c^{in}_{2,t}) \) for agent 2 obtained from the buffer, with the modified observation \( (o_{2,t}, c^{out}_{1,t-1}) \), and then have agent 2 compute the action \( a_2 \). Supervised learning is then used with the centralized expert label \( \tilde{a}_2 \), to compute the communication loss. This loss is then used to update agent 1’s weights (and not agent 2’s). To update agent 2, the same procedure is used, but it is important to note that we use the pre-updated weights for agent 1 (so that the updates for both agents occur simultaneously). This procedure can be extended for an arbitrary number of agents. See Figure 3 for a diagram.
Figure 3. A diagram showing the training procedure for supervising multi-agents that communicate, specifically for agent 1 in the case of two agents. Here the observation vector is broken up into two parts: an observation of the physical environment $p^1_t$ (which is agent 1’s physical observation at time $t$) and the incoming communication observation $c^{in}_{n,t-1}$ (which is agent 1’s communication observation at time $t$). And $q^1_t$ is the agent’s physical action at time $t$, whereas $c^{out}_{n,t-1}$ is the agent’s output communication action. The above diagram showcases how to train agent 1 when there are two communicating agents. This procedure can be easily extended to the case of $N$ agents.

5. Experiments

Our experiments are conducted in the Multi-Agent Particle Environment (Mordatch & Abbeel, 2017; Lowe et al., 2017) provided by OpenAI, which has basic simulated physics (e.g. Newton’s law) and multiple multi-agent scenarios.

Cooperative Navigation – Homogeneous and Nonhomogenous Agents

In this experiment, we examine the situation of 3 agents occupying 3 landmarks in a 2D plane, and the agents are either homogeneous or heterogeneous. The environment consists of:

- Observations: The (continuous) observations of each agent are the relative positions of other agents, the relative positions of each landmark, and its own velocity. So agents do not have access to other’s velocities, and thus each agent only partially observes the environment (aside from not knowing other agents’ policies).
- Reward: At each timestep, if $A_i$ is the $i$th agent, and $L_j$ the $j$th landmark, then the reward $r_t$ at time $t$ is:

$$r_t = -\sum_{j=1}^{N} \min \{ ||A_i - L_j|| : i = 1, \ldots, N \}$$

So it’s the sum over each landmark of the minimum agent distance to the landmark. Agents also receive a reward of $-1$ at each timestep that there is a collision.
- Actions: Each agents’ actions are discrete and consist of: up, down, left, right, and do nothing. These actions are acceleration vectors (except do nothing), which the environment will take and simulate the agents’ movements using basic physics (i.e. Newton’s law).

We transform this multi-agent problem into a single-agent problem as described in Section 4, and we use a simple DQN algorithm for our centralized expert, which is a fully-connected neural network (with two hidden layers).

We first show that our centralized expert with the action-selection described in Section 4 is able take advantage of the nonhomogeneity of the agents. Namely, in Figure 4, we see that for homogeneous agents, the optimal path for each agent is as expected: all agents shift uniformly together to their respective landmarks. But for nonhomogeneous agents, we see that the optimal path for each agent depends on who is faster: in Figure 5 we have three agents, small and fast, medium-sized and medium-speed, and big and slow, and we see that even though small and fast is furthest from the right-most landmark, the centralized expert decides to take advantage of its speed and size to assign this landmark to it. In training the multi-agents, we observe similar behavior with the expert.

Cooperative Communication

Here we we adapt CESMA to a task that involves communication. In this scenario, communication is defined as having the output of one agent become the input of another agent, i.e. in the context of neural networks this means some of the output nodes of an agent is directly connected to some of the input nodes of another agent. Practically,
this means that when one does backpropagation, then one can backpropagate from one agent to another. So the agent that communicates can update its weights according to the action chosen by the agent being communicated to. Note we have also defined a communication action as one that does not affect the (physical) environment. This is in contrast to a communication action that does indeed affect the environment, e.g. perhaps the agents do certain dances (and thus change their position and velocities) to communicate. It is fair to say both types of communication are seen in nature.

In this particular scenario, we have 2 agents and 3 landmarks, and each agent has a goal landmark that is only known by the other agent. Thus the each agent must communicate to the other agents its goal. The environment consists of:

- Observations: The observations of each agent consist of the agent’s personal velocity, the relative position of each landmark, the goal landmark for the other agent (an 3-dimensional RGB color value), and a communication observation from the other agent.

- Reward: At each timestep, the reward is the sum of the distances between and agent and its goal landmark.

- Actions: This time, agents have a movement action and a communication action. The movement action consists of either not doing anything, or outputting an acceleration vector of magnitude one in the direction of up, down, left, or right; so do nothing, up, down, left right. The communication action is a one-hot vector;

In our experiments, under the above procedures, we are able to train the multi-agents effectively and they achieve the same reward as the centralized expert.

6. Conclusion

We have proposed a MARL algorithm, called Centralized Expert Supervises Multiagents (CESMA), which takes the training paradigm of centralized training, but decentralized execution. The approach consists of two parts: (1) treating a multi-agent problem as a single-agent problem to obtain a centralized (expert) policy, and then (2) using the centralized expert to guide supervised learning for multiple independent agents (that may or may not communicate), which decentralizes the policy. On the implementation side, we also demonstrate a way to reduce the exponential growth of the joint action space of the expert, to one that will grow linearly. And we also provide experimental evidence for the effectiveness of the CESMA training paradigm.

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