Evolution of Cooperative Hunting in Artificial Multi-layered Societies *

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Abstract

The complexity of cooperative behavior is a crucial issue in multiagent-based social simulation. In this paper, an agent-based model is proposed to study the evolution of cooperative hunting behaviors in an artificial society. In this model, the standard hunting game of stag is modified into a new situation with social hierarchy and penalty. The agent society is divided into multiple layers with supervisors and subordinates. In each layer, the society is divided into multiple clusters. A supervisor controls all subordinates in a cluster locally. Subordinates interact with rivals through reinforcement learning, and report learning information to their corresponding supervisor. Supervisors process the reported information through repeated affiliation-based aggregation and by information exchange with other supervisors, then pass down the reprocessed information to subordinates as guidance. Subordinates, in turn, update learning information according to guidance, following the “win stay, lose shift” strategy. Experiments are carried out to test the evolution of cooperation in this closed-loop semi-supervised emergent system with different parameters. We also study the variations and phase transitions in this game setting.

Keywords: Agent-based Models, Social Rank, Learning, Semi-supervision,

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1. Introduction

Multi-agent system is a distributed system that consists of multiple autonomous, reactive, sociable, adaptive, movable, changeable, and (bounded) rational human-like agents. It is widely recognized as an efficient tool for social simulation and modeling, since the individuals in the society can be modeled as agents, and a series of communication protocols, e.g., game-theoretical interactions, reinforcement learning-based interactions, behavioral science-inspired interactions can be defined to represent individual interactions. Many crucial issues have been widely studied based on multi-agent or agent-based paradigm, including digital evolution, social dynamics, cooperation and coordination, and emergence of language, sex, and intelligence.

Cooperation is a widely-studied behavior among social individuals. A common form of cooperation in animal society is cooperative hunting. Many previous works showed that cooperation could increase hunters’ return through increasing prey capture success than hunting alone. Understanding the mechanisms forming cooperative hunting behaviors has been an issue of much interests among evolutionary biologists and behavioral zoologists. Many theoretical or empirical biology models have been proposed on this topic.

Since the classic human-behavioral game-theoretical experiments proposed by Axelrod, the evolution of cooperation among selfish and rational agents is a cutting-edge topic in social sciences, psychology, and behavioral sciences. Many works in the multi-agent system community focus on facilitating the evolution of cooperation and understanding the mechanisms behind the cooperation, particularly cooperative hunting among selfish agents. Some approaches are constructed on a co-evolutionary framework to study adaption. Some works designed different mechanisms to facilitate the emergence of cooperative hunting, such as learning-based approaches, evolutionary algorithmic approaches, neural network-based approaches, and behavioral rules.
e.g., imitation [17], penalty [18, 19], and opinion diffusion [20]. Some works which lie in the intersections of multi-agent systems and multi-robot systems focus on constructing and evaluating theoretical analysis on robot team settings [21, 22].

These works both from empirical biology research and simulation analysis provide insightful basics for us. In this paper, based on an evolutionary game theoretical framework, we extend it with multi-agent reinforcement learning to investigate the mechanisms behind the cooperative hunting phenomena in social animals. Besides that, inspired by the division of labor in many natural or artificial societies [23], we introduce social hierarchy to make the model more realistic, combine up-level semi-supervision with bottom-level individual learning [24], and synthetically investigate multiple related factors, such as division of reward, penalty, and social learning. Our work aims to test the influence factors of cooperative hunting in complex society or nature, and introduce them to design a more insightful model, rather than the most straightforward mechanism or a stronger emergence. This model provides perspectives on understanding mechanisms behind cooperative hunting behaviors, and gives insights into decentralized control of large-scale heterogeneous distributed systems.

The rest of this paper is organized as follows: game-theoretical interaction is described in Section 2. In Section 3, the entire algorithmic framework is described in detail. In Section 4, we give experimental results and analysis. In Section 5, we give a comprehensive literature review. In Section 6, we conclude this paper and point out future directions.

2. Modified Game Theoretical Interaction

In this section, a modified hunting-game based interactions with dominant social rank and penalty will be described. We first introduce the standard stag hunting game, then bring in social rank and penalty.
Table 1: Payoff matrix of standard stag-hunting game.

|        | stag   | hare   |
|--------|--------|--------|
| stag   | a,a    | c,b    |
| hare   | b,c    | d,d    |

2.1. Standard Stag Hunting Game

In standard game theory, the stag hunting game is used to model conflict and cooperation in human societies. The classic stag hunting game describes a situation where multiple hunters go for hunting multiple preys. Hunters can use different strategies, but they do not know which behavior other hunters adopt. They can only guess their rival’s strategy and respond accordingly. The main rational goal of each individual is to maximize the cumulative payoff to themselves.

Here we simplify this situation to a game of two hunters and two kinds of prey. A hunter can individually hunt a small prey (e.g., hare), and receive a corresponding payoff $d$. Or, hunters can cooperate to hunt a big prey (e.g., stag) and receive a larger payoff $a$, since a stag is worth more than a hare and more difficult to hunt. If one hunter chooses to cooperate for hunting a stag, while the other chooses to defect by hunting a hare, rewards are different: The hunter who chooses a stag will receive a sucker’s payoff $c$, while the hunter who chooses a hare will receive a temptation payoff to defect $b$. The payoff matrix of the classic stag-hunting game can be formalized as in Table 1, satisfying $a > b ≥ d > c > 0$ [25].

The primary purpose of this paper is to investigate the evolution of cooperative hunting behavior in animal societies. We modify this game-theoretical interaction and make it more realistic to model animal societies. To that end, we introduce some new parameters as variables, including social rank, unequal food sharing, and penalty.
2.2. Social Rank

The dominant social hierarchical structure (multi-layered dominance hierarchy or linear dominance hierarchy) can be found in many social animals, such as African elephants *Loxodonta Africana* [26], wolves, spotted hyaena [27], baboons, and birds especially chicken [28]. A widely studied example is the African elephant society. An experimental illustration of social hierarchy in African elephant society is shown in Fig.1. There are multiple regularly associating mother-calf units sharpening the hierarchical dominance structure in *Loxodonta Africana* society. In such a structure, the mother-calf units can be regarded as the first tier merging into the next tiers, which are called “familial” units. The second tier gathering familial units coalesces into “bond groups”. Bond groups can be viewed as extensions of familial units. Multiple bond groups then coalesce into the fourth tier, “episocial units” or “clan units” [26, 29]. In this paper, we borrow this structure to build our artificial agent-based animal society.

![Figure 1: The multi-layered dominance hierarchy in nature](image29)

Consider a multi-layered social animal structure in which a supervisor manages multiple subordinates. The subordinates, in turn, manage lower-level subordinates, and so on. Here, “managing” has many meanings in both social animals and human beings, such as 1), accessing a higher fraction of food (such as prey); 2), collecting information from their subordinates; 3), synthesizing rational responses according to reported information; and 4), giving guidance to educate subordinates adaptively. These four aspects can be viewed as the
duties of supervisors. From a multi-agent perspective, the social animal in such a structure is modeled as “agent” nodes, and the interaction between social animals are modeled as the edges connecting these nodes. A series of same-layered communication protocols and cross-layered guidance rules are also defined to represent interactions.

The formalized social structure is a multi-layered networked structure with dominance between higher and lower layers. This networked structure is divided into multiple small groups $G_x, x \in (1, ..., X)$, where $X$ indicates the number of small groups in the society, and $x$ indicates the supervisor of a particular group. Supervisors of lower-level subordinates can also be subordinates of higher-level supervisors. Finally, we can build a multi-layered complex interconnected network structure recursively. The terminal condition is that the highest-level agent group is small but powerful enough to make a decision accurately and quickly without guidance. It can be achieved by adjusting parameter settings. Notice these agents are not global controllers. They also make decisions based on local information reported by subordinates. According to the biological literature, social rank is public information of the entire society. In other words, agents know their ranks, and they can also sense the ranks of other individuals using chemical signals (such as pheromones), visual, auditory or sound-based signals, and tactile or touch-based signals [30].

2.3. Unequal Payoff Sharing

In nature, unequal social order based food sharing is a typical social dominance phenomenon. Many behavioral biologists study how food items being shared among social animals. Smith and Holekamp studied ecological and social determinants of fission-fusion dynamics in a group of the well-studied social animals, spotted hyaena [27]. In general, the sharing principles of their society can be explained simply by the fact that higher rank individuals access the majority of the food.

After playing the hunting game with its rivals, we assume that agents receive a payoff with an adjustment parameter $\eta_l$. $l$ indicates the specific layered rank.
of a focal agent. Agents in higher ranks (e.g., supervisors) keep the majority of the original payoff in Table 1. Lower ranked agents receive less payoff by adjusting parameter $\eta_l$ accordingly. According to the biological literature [27], $\eta_l$ should satisfy some function-based relationships, e.g., it should be a linear or a non-linear function.

In this paper, we borrow a basic example of the converging geometric series to represent food sharing. We assume that the highest-ranked supervisor has access to 50% of the entire food, and the $l^{th}$ layer of agents share part of the food with a fraction of $1/2^l$. When $l \to +\infty$, the sum of food in the entire society will converge to 100%.

2.4. Penalty

Penalty is an efficient way of facilitating cooperation in human behavioral experiments [11]. Some experimental studies have also shown that animals use penalty mechanisms to facilitate the evolution of cooperation [31, 32]. We use two kinds of penalty for defectors, food stealing and withdrawal.

2.4.1. Food Stealing

Biological literature suggested that one of the benefits of cooperative hunting is increasing success of defending kleptoparasites that steal food or prey from other animals [7, 8]. In our model, defectors hunting alone cannot protect food by themselves because of kleptoparasites or competitive theft. Only cooperative hunting in a group can protect food completely. We assume there is a probability $S$ of getting food lost when hunting alone. In this modified hunting game, we assume defectors have only access to the part of food with a fraction of $1 - S$, since original food has been stolen at a fraction of $S$ by kleptoparasites or competitive theft.

2.4.2. Withdrawal

In a particular round of our model, the focal agent has a choice to do nothing to refuse to play the hunting game with a previous defector. We introduce $P_d$
Table 2: Payoff matrix of the modified stag-hunting game. One player is at layer $l$, the other is at layer $w$. To represent this disconnecting probability, which is another penalty mechanism [19].

To summarize, the modified hunting game payoff matrix with social-rank based payoff sharing and penalty mechanism is illustrated in Table 2, satisfying $a > b \geq d > c > 0$, $0 < S < 1$, $0 < P_d < 1$, $0 < \eta_l, \eta_w \leq 1/2$, and $l = w$ or $l = w \pm 1$.

3. Overall Framework

An agent-based model is proposed in this paper to facilitate the evolution of cooperative hunting. Back to the multi-layered artificial society, which is shown in Fig.1. An agent $i$ interacts with its rivals who connect with it directly, and uses Q-learning with an exploration algorithm to choose a best-response action $a_i$. Then agent $i$ receives corresponding payoff $r_i$ according to Table 2. After action-selection, focal agent $i$ stores action $a_i$, cumulative payoff $R_i$ (calculated by the sum of corresponding payoffs of all rivals), and learning parameters in a table, reports all of them to agent $i$’s supervisor $x$, and recognizes the rivals’ actions to determine whether to withdraw. Supervisor $x$ combines all reported best-response actions of its subordinate agents into an overall action $a_x$. Supervisor $x$ then interacts with a randomly selected rival in the same cluster of the supervisor layer, and imitates to update $a_x$ into $a'_x$ according to the performance difference between the overall actions of supervisor $x$ and this rival (e.g., average cumulative payoff). After aggregating the subordinates’ actions and imitation, supervisor $x$ has a final action $a'_x$ which will be used as guidance to teach its subordinate agents to act better. Two basic parameters
of the learning process, i.e., learning rate $\alpha$ and exploration probability $\mu_t$, will be adjusted based on supervisor $x$'s steering information among subordinate agent $i$ and the peers within the same subordinate cluster. Finally, all agents update their learning information using the new learning rate and exploration rate. Details of the reinforcement learning interaction protocol, action aggregation, imitation method, and semi-supervised adjusting will be described in the next subsections. This closed-loop semi-supervised process is iterated for $T$ time steps. The entire picture of the overall algorithmic framework (Algorithm 1) is shown in Figure 2.

Figure 2: The overview of multi-layered artificial social structure. The focal agent $i$ selects a best response action $a_i$ according to rivals’ reactions (environments), and then reports $a_i$ and cumulative payoff $R_i$ to its supervisor $x$. At the same time, agent $i$ decides whether to withdraw on the rivals. Supervisor $x$ aggregates all the best response actions into an overall action $a_x$, exchanges information with other supervisors in the same cluster, and converges $a_x$ into $a'_x$. Then passes down $a'_x$ to subordinates as guidance. Subordinates in turn update all learning information.
Algorithm 1: The overall framework

1. Initializing all parameters;
2. for each time step $t(t = 1, \cdots, T)$ do
3.    for each agent $i(i = 1, \cdots, n)$ do
4.       Interacts and chooses a best response action $a_i$ using Q-learning with the simulated annealing exploration;
5.       Holds $a_i$ to play the hunting game with all rivals, and receives corresponding payoff $r_i$ from the rivals;
6.       Calculates cumulative payoff $R_i$;
7.       Recognizes the rivals' actions to determine whether to withdraw;
8.       Reports $a_i$ and $R_i$ to its supervisors if applicable;
9.    end
10.   for each supervisor agent $x(x = 1, \cdots, m)$ do
11.      Combines all reported best response actions of subordinate agents into $a_x$;
12.      Communicates with a random peer $y$ within the same group, and imitates to convert $a_x$ into $a_x'$ with a probability $E$;
13.      Passes down $a_x'$ as guidance to its subordinate agents;
14.    end
15.   for each agent $i(i = 1, \cdots, n)$ do
16.      Adjusts learning rate and exploration rate according to the guidance from supervisors $x$ if applicable;
17.      Updates all learning information;
18.    end
19. //Notice agent $i(i = 1, \cdots, n)$ means the agent population in the entire society, agent $x(x = 1, \cdots, m)$ represents the corresponding supervisors;
20. //For the agents at the top level of the society, it is not applicable for line 8 and 16;
21. end

3.1. Interaction Protocol

In this paper, Q-learning, a widely used reinforcement learning technique is adopted as interaction protocol. Every single step in Q-learning is updated as in Equation 1 [33].

$$Q(s, a) = Q(s, a) + \alpha[r(s, a) + \lambda \max_{a'} Q(s', a') - Q(s, a)]$$  (1)

where $\alpha \in (0, 1]$ is a learning rate of agent $i$, $\lambda \in [0, 1)$ is a discount factor to trade off future and current reward, $Q(s, a)$ and $r(s, a)$ are the expected and immediate reward of choosing action $a$ in state $s$ at time step $t$, respectively, and $Q(s', a')$ is the expected (discounted) reward of choosing action $a'$ in state $s'$ at time step $t + 1$. 


Getting stuck at sub-optima is one of the inherent limitations of Q-learning [33]. To overcome this limitation and facilitate the convergence, simulated annealing exploration is used to trade-off the exploitation of learned knowledge and the exploration of unknown environments. One step of the simulated annealing exploration is given by Equation 2.

\[ \mu_t = \mu_0 / \log(1 + t) \]  

where \( \log \) is decimal logarithmic function, \( \mu_t \) is the real time exploration rate, \( t \) is the \( t^{th} \) round of simulation, and \( \mu_0 \) is initial exploration rate, a hyper-parameter in our model [34].

Agent \( i \) learns through interaction with the local environment with learning rate \( \alpha \). In time step \( t \), agent \( i \) chooses the best response action with the highest Q-value with exploitation rate \( 1 - \mu_t \), and randomly chooses another action with exploration rate \( \mu_t \). The exploration rate decreases with time while the exploitation rate increases, which means the focal agent \( i \) not only has a chance to escape from a sub-optimum, but also can exploit learned “correct” knowledge better than traditional \( \epsilon \)-greedy exploration [34].

### 3.2. Aggregation of Reported Actions

In both human and animal societies, individuals have a preference to select rivals. For example, humans tend to cooperate or interact with more “trustworthy” individuals in previous interactions. Some social animals, such as spotted hyenas, are observed to intend to cooperate with a particular group of individuals or higher ranking individuals more frequently. This intention will increase the payoff of hunting through increasing feeding tolerance. In our model, we introduce repeated affiliation with more trustworthy individuals according to previous interaction experience, when a supervisor agent \( x \) aggregates all the reported actions into an overall action \( a_x \).

Back to Algorithm 1. At each time step \( t \), the supervisor agent \( x \) collects all reported actions from subordinates. Agent \( x \) has its preference which is
represented by the decision weight $w_{t,i}$ regarding its subordinate agents’ actions. Agent $x$ measures $w_{t,i}$ according to the previous interaction experience with subordinate agent $i$. If a supervisor agent considers a subordinate agent’s action to be more trustworthy, it will assign a higher value to $w_{t,i}$ for this action. The overall action is the performance-based weighted aggregation action of reported actions. Specifically, weight $w_{t,i}$ is calculated by Equation 3:

$$w_{t,i} = \beta(s - w_{t-1,i}) + w_{t-1,i}$$  \hspace{1cm} (3)$$

where $\beta$ is an aggregation learning rate; the initialized decision weight $w_{0,i} = \frac{1}{|N_i|}$, $|N_i|$ indicates the number of subordinate $i$’s neighbors. This is influenced by the cluster structure, which will be described in the experimental section. $s = 1$ indicates the previous interaction at time $t - 1$ was successful, $s = 0$ indicates that the previous interaction was a failure. The interaction is successful if and only if agent $i$ cooperates with the supervisor agent $x$ in the $(t - 1)^{th}$ interaction [35].

3.3. Information Exchanging

The subordinate agents report the best-response actions and cumulative payoff after game playing. Supervisor agent $x$ holds an overall action $a_x$ which is aggregated from all reported actions. Supervisor $x$ then interacts with its randomly selected peer $y$ and updates $a_x$ based on the performance difference, i.e., average reported cumulative payoff $R_x$ and $R_y$ in their subordinate groups. In each time step, supervisor $x$ adopts peer $y$’s aggregated action with a probability $E$, which is calculated by Equation 4, then imitates to update $a_x$ into $a_x'$.

$$E = \frac{1}{1 + e^{-(R_y - R_x)/K}}$$  \hspace{1cm} (4)$$

Here $K$ is noise introduced for irrational choices [36], and we set $K = 0.1$.
in this model. Imitation behavior is one of the simplest ways of social learning. Previous literature suggested that social learning could extremely boost the evolution of a particular behavior [20, 34, 8].

3.4. Semi-supervised Adjusting Method

Supervisor $x$ passes down $a'_x$ to its subordinate agents $i$. At each time step $t$, based on this guidance information from supervisor $x$, agent $i$ adjusts its behavior. Many previous algorithmic frameworks can be used to model this semi-supervised learning with the self-adjustment process, such as MiniMax-Q Algorithm [37], Nash Q-learning Algorithm [38], and Friend-or-Foe Q-learning Algorithm [39]. All these previous works focused on maintaining Q-table including entire action space, state space, etc., and using mathematical programming based search (linear programming or quadratic programming) to find the best strategy. However, the inherited limitation “curse of dimensionality” emerges, i.e., if we assume action space $A$ and state space $S$ are discrete, a single agent needs $|S| \times |A|$ space to store Q-table, where $|S|$ and $|A|$ indicate the number of states and actions; $|N|$ indicates the number of agents. It is unrealistic especially facing large scale multi-agent games with large action space. In our model, we expect to reduce space cost into $|S| \times |A|$ (exponent is the most cost-consuming), which means agents can maintain Q-table only through its own action space. Besides that, agents should adjust behaviors locally according to supervisors’ guidance to facilitate global cooperation.

We introduce a simple but insightful philosophy, i.e., win stay, lose shift [40], to build this semi-supervised adjustment method. First, we should define two situations, “win” and “lose” respectively. If the reported action $a_i$ of subordinate $i$ is identical with the supervisor $x$’s final action $a'_x$ after aggregation and imitation, this situation is approved by the supervisor and regarded as “win”, and “lose” otherwise. The adjustment is conducted in the process of comparison of guidance information and the current situation of subordinates. Two primary parameters, i.e., learning rate $\alpha$ and exploration rate $\mu_t$ in Q-learning based interactions, will be adjusted as the entrance of accepting guidance. If
“win”, the focal agent will decrease both learning rate $\alpha$ and exploration rate $\mu_t$ to stay in the winning situation, otherwise increase these two parameters to escape from sub-optima, i.e., “shift”. In each step, the degree of adjustment is set to 10%.

4. Experiments and Results

In this section, we present the experiments and result analysis to illustrate our model’s performance and variations.

4.1. Experimental Setting

We clarify all the parameters in network structure, modified payoff matrix, and proposed algorithmic framework. For simplification reason, we test the entire society with two layers, subordinate and supervisor. A grid network structure is used to generate each layer. The layer is also separated into some grid networked clusters. In the modified payoff matrix, we set $a = 15, b = 4, d = 3, c = 2$. The mean stolen rate for defectors is set to 10% according to biological literature [41]. Notice this rate varies in different species, population density, space, etc. We approximately calculate average values. The disconnecting penalty $P_d$ is 0.1. In Q-learning algorithm, the learning rate $\alpha$ is set to 0.1. The initialized SA exploration rate $\mu_0$ is set to 0.144. We do not consider extension form of game playing which means default action space is 2. For reported information reprocessing among supervisors, the noise $k$ in imitation is set to 0.1. In repeated affiliation, the performance-based weighted aggregation learning rate $\beta$ is set to 0.8.

4.2. Results and Analysis

In this section, we test the system under different conditions and give explanations of different performance of our model. We firstly study whether cooperative hunting can emerge. A widely-adopted standard for measuring the evolution of cooperation is to test whether 90% or more of the entire individuals choose cooperation, since it is widely recognized that global cooperation rarely
appears considering the local interaction clusters (i.e., diversity) distributed in the society. We set 10000 time steps as the upper limit in a particular run. Otherwise, global cooperation is asserted as disappearance. We mainly focus on the average payoff, convergence speed, and convergence rate. Notice average payoff is calculated in the entire system including supervisors and subordinates. Convergence speed means the time steps the society needs to evolve cooperation-dominance. Convergence rate means the fraction of cooperators in the entire system.

4.2.1. Influence of Population Size

We fix cluster to a $4 \times 4$ grid network, which means 16 agents are within a small group and have a similar supervisor. We vary the subordinate agent population to $12 \times 12$ ($3 \times 3$ supervisors, total 153 agents), $16 \times 16$ ($4 \times 4$ supervisors, total 272 agents), $20 \times 20$ ($5 \times 5$ supervisors, total 425 agents), and $32 \times 32$ grid networks ($8 \times 8$ supervisors, total 1088 agents), respectively to study the influence of population size on the evolution of cooperative hunting, which is shown in Fig.3.

We find with a smaller population size, the higher level of cooperation can evolve. The potential reason is that when we set cluster size stable, a smaller population size means that the supervisor holds a broader view of a partial system, and this factor can boost complete semi-supervision. As a result, the evolution of cooperative hunting is facilitated.

4.2.2. Influence of Cluster Size

We fix subordinate population to a $32 \times 32$ grid network, vary the cluster size to $2 \times 2$ (with $16 \times 16$ supervisors), $4 \times 4$ (with $8 \times 8$ supervisors), $8 \times 8$ (with $4 \times 4$ supervisors), and $16 \times 16$ (with $2 \times 2$ supervisors), respectively, to study the influence of cluster size on the evolution of cooperative hunting, which is shown in Fig.4.

In general, we find with larger cluster size, the higher level of cooperation can evolve (such as the cases of cluster size $16 \times 16$, $8 \times 8$, and $4 \times 4$). The potential
reason is similar to the case of population size. Both small population size and large cluster size will lead to a broader view of a partial system for the focal supervisor, which facilitates the evolution of cooperative hunting. Additionally, the smaller cluster size leads to more local groups distributed in the entire system, and significantly increases the diversity of the system. To evolve global cooperation, it will take more effort to step across multiple sub-optima. This will bring a negative influence on the evolution of global cooperative hunting.

It is unusual for the case of cluster size $2 \times 2$. We find the curve of cluster size $2 \times 2$ seems to violate the general trends. That is because of the large number of supervisors. In our game settings, supervisors share a higher fraction of food than subordinates, and the number of supervisors is less than subordinates. For the case of cluster size $2 \times 2$, there are 256 supervisors and 1024 subordinates. The number of supervisors is significantly higher than that in other testing cases. This will lead to an increase in average payoff (both starting point and convergence value), and make up the negative influence caused by small cluster size.
4.2.3. Dynamics of Learning Rate and Exploration Rate

In our model, dynamics in both learning rate and exploration rate are introduced by “win stay, loose shift” rule and simulated annealing exploration. Based on a hierarchical grid network with 12 × 12 subordinates and 3 × 3 supervisors, we study parameter dynamics in reinforcement learning-based interactions shown in Fig. 5.

As shown in Fig. 5, the start of the exploration rate $\mu_t$ is slightly higher than the learning rate $\alpha$ because of the difference between initialized value. An initialized increasing but decreasing to almost 0 afterward can be seen in both learning rate $\alpha$ and exploration rate $\mu_t$. It indicates that agents initially do not know which action they can adopt, then they interact to try (“trial and error”), hence both $\alpha$ and $\mu_t$ increase. As the system evolves, agents realize which action they should adopt, in turn, both $\alpha$ and $\mu_t$ decrease until almost 0. Notice the increase at the start stage is slightly significant for the case of learning rate $\alpha$. This is because of simulated annealing exploration. Simulated annealing exploration introduces a continuous decrease in the exploration rate.
\( \mu_t \) as the system evolves. As a result, the difference between the learning rate \( \alpha \) and exploration rate \( \mu_t \) appears.

4.2.4. A Theoretical Analysis of Phase Transition

It is widely recognized that cooperative hunting increases the success rate and efficiency of hunting large prey. However, considering the social-rank based unequal prey sharing, few individual-benefits can be earned when low-ranking individuals participate in cooperative hunting in this society [42, 43]. These questions are interesting to us: Will subordinates choose to defect since they can not gain enough under unequal sharing? If so, what is the threshold of phase transition? In this subsection, we will give a theoretical explanation.

Following the experimental settings, we study the most straightforward situation where one layer of supervisors controls one layer of subordinates. Back to the modified payoff matrix (Table 2), for this concrete case, the payoff matrix for supervisors and subordinates can be specified as Table 3, Table 4, and Table 5 respectively. Notice we do not list the choice of (N/A) since we regard the disconnecting penalty as a mechanism to promote the evolution of cooperative hunting. Besides that, we do not consider mixed strategy Nash equilibrium since it is not evolutionarily stable [44].

The variations and phase transitions in hunting game settings are shown in
Cooperation    Defection
Cooperation  0.5a, 0.5a  0.5c, 0.9b
Defection    0.9b, 0.5c  0.9d, 0.9d

Table 3: Payoff matrix for supervisors.

Cooperation    Defection
Cooperation  0.25a, 0.25a  0.25c, 0.9b
Defection    0.9b, 0.25c  0.9d, 0.9d

Table 4: Payoff matrix for subordinates.

Fig. 6. We consider the entire society including supervisors and subordinates. We find different potential phenomena by adjusting the range of parameters, including cooperation dominance, defection dominance, and co-existence. When $0.9b > 0.5a \land 0.9d > 0.5c \ (a/b < 1.8 \land c/d < 1.8)$, defection is always a rational choice no matter what actions rivals adopt. Defection dominance appears. When $0.9b < 0.25a \land 0.9d > 0.25c \ (a/b > 3.6 \land c/d > 3.6)$, cooperation is always a rational choice no matter what actions rivals adopt. Cooperation dominance appears. For other ranges, the co-existence of cooperation and defection can be found in the entire system.

Additionally, there are many interesting concrete games for the case of co-existence. When $0.9b < 0.25a \land 0.9d > 0.5c \ (a/b > 3.6 \land c/d < 1.8)$, the strategy profiles (cooperation, cooperation) and (defection, defection) are both pure Nash equilibria. Rational players can not determine which equilibrium is better since one brings higher payoff (payoff dominant equilibrium), but the other is safer (risk dominant equilibrium). This game-theoretical setting can be extended as a coordination game with multiple-action space as well as multiple players. Notice for this extension, Nash equilibrium is always listed in the diagonal from top.
left to bottom right in the payoff matrix with sorted action spaces. Positive externalities are introduced where choosing the same action creates a benefit rather than a cost. However, experimental economics literature suggested that coordination failure is common in stag hunting and order-statistic coordination game without any external mechanisms introduced [45].

On the other hand, when $0.9b > 0.5a \land 0.9d < 0.25c$ ($a/b < 1.8 \land c/d > 3.6$), the strategy profiles (cooperation, defection) and (defection, cooperation) are both Nash equilibria, which is called anti-coordination game. A negative externality is introduced in this game setting where agents who choose coordination will be charged by a cost rather than gaining benefits. Anti-coordination game is a widely adopted tool to model conflict, e.g., Hawk-Dove game [46], crowding game [47], and El Farol Bar problem [48]. There is also a hybrid form of coordination game and anti-coordination game called “dis-coordination
game” (e.g., matching pennies game [49]). In this game setting, the intensive for one participant is obeying coordination while the other one wants to violate it. Discoordination games have no pure Nash equilibria following the same mathematical reasoning in our settings. Notice considering the basic settings $a > b$ and $d > c$ in Table 1 and 2, though we give a general analysis from game theory perspectives, global cooperation without any external incentives, or anti-coordination will not appear in the experiments. We can only find co-existence which reflects our parameter settings, and defection-dominance. The primary goal of this work is to design mechanisms to facilitate cooperation in the case of co-existence.

5. Related Work

The research on the evolution of cooperative behaviors, particularly cooperative hunting, can be traced to some early works in complexity sciences. Axelrod pioneered several interdisciplinary works on the evolution of cooperation both from theoretical simulation (notably agent-based models) and behavioral experiments [11, 50]. Skyrms [25] studied the evolution of social structure and social dynamics through stag hunting paradigms. This topic is also crucial in both evolutionary computation and multi-agent system research community. Many novel mechanisms can be found in previous literature to further extend Axelrod’s seminal work. Haynes et al. [14, 15, 17] did a series of early works to facilitate cooperation and coordination formation in hunting game settings through genetic programming. Spector et al. [51] combined multi-agent systems with genetic programming to study the evolution of cooperation and coordination in wolf-pack games. Olson et al. [12] used an agent-based model to study the co-adaptation and co-evolution of prey and predators in density-dependent predation behaviors. Rajagopalan et al. [16] paid more attention on influencing factors. They evaluated the influence of three factors, reward structure, coordination mechanism, and net return on the evolution of cooperation in hyena hunting situations through neuro-evolution. They additionally studied task de-
composition in extended predator-prey models. More recently, Leibo et al. applied a powerful deep network, i.e., Deep Q Network (DQN), to study behavior adaptation as a function of environmental factors including resource abundance in wolf-pack hunting game. Several behavior-inspired mechanisms have also been examined, e.g., imitation, penalty, and opinion diffusion. Bao et al. synthetically compared different mechanisms including learning, behavioral imitation, evolutionary selection, group voting, and their effects in multi-agent social simulation. Some biological literature also provided insights of evolutionary explanation behind cooperative hunting phenomena. All the precious works are carried out in a concrete setting. Different mechanisms are introduced through emergent approaches. In our model, based on a general setting that can be extended into different variables, we combined top-down semi-supervision and bottom-up emergent learning, which differs from existing models.

6. Conclusions

The evolution of cooperation is a crucial topic in multi-agent system and agent-based model research community. Previous works showed that individual learning-based interaction does facilitate the evolution of cooperation. However, this purely interactive emergent approach is inefficient, especially for large scale complex systems and widely-recognized local patterns. Centralized control is an efficient and accurate way while with expensive costs, much inaccessible information, and delayed communication. In this paper, we proposed a semi-supervised approach which combines both top-down steering and bottom-up emergent approaches. The experimental results show that this is an efficient and robust mechanism even when the temptation to defect (i.e., unequal payoff sharing for subordinates) is introduced. We synthetically study multiple related mechanisms, such as penalty and social learning. We additionally investigate the variables and phase transitions including cooperation dominance, defection dominance, and co-existence in this evolutionary game setting. This finding can
be extended to study many social science issues, such as the origins of inequality, social hierarchy, rebellion, and tyranny.

Many extensions can be done based on this general framework. For example, more layers can be introduced to build a more complex semi-supervised learning structure. Many network structures, e.g., small world and scale-free networks, can be introduced to represent agent-based artificial society. Some interesting factors, such as kin selection, can be investigated based on this framework. We made parameter approximations and simplifications in the assumptions. All of them also need to be examined to make the model more realistic. Plus, we give a theoretical analysis of the different values of the reward. However, the multi-layered sharing method and stolen rate for defectors will also have significant influences. They are regarded as in-built biologically-related parameters. The theoretical analysis of the two remaining parameters and the empirical work of this theoretical study should be completed with behavioral zoology researchers in the future.

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