COLLECTIVE BEHAVIOR AND KIN SELECTION IN EVOLUTIONARY ITERATED PRISONER’S DILEMMA

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Some strategies can be evolutionarily stronger than others although no evolutionarily stable strategy exists in iterated prisoner’s dilemma if the long-term payoff for each player is not insignificant. Li and Kendall (2009) introduce a so-called collective strategy for evolutionary iterated prisoner’s dilemma which plays a sequence of predefined moves and then identifies the opponent according to the response. It only cooperates with kin members and defects against any other strategies. A group of collective strategies is especially strong in evolution. In this paper, we study a mixed strategy that assigns probabilities to the collective strategy and the strategy that always defects. A population of mixed strategies has the advantage of expelling fake kin members so that other strategies do not have the chance to indirectly invade. Simulations show that it is evolutionarily strong in maintaining a homogeneous population. Kin selection favors collective behavior among group members which is not necessarily cooperation. We find that defection can also be a kin altruism and there is qualitative benefit as well as quantitative benefit from the altruistic behaviors.

Keywords: collective behavior, evolutionarily stable strategy, kin selection, prisoner’s dilemma
AMS Subject Classification: 91A22, 92D15

1. INTRODUCTION

The Iterated Prisoner’s Dilemma (IPD) is now regarded as an ideal experimental platform for the evolution of cooperation among selfish individuals and it attracts wide interest since Robert Axelrod’s IPD tournaments and ‘The Evolution of Cooperation’ [1,2,6,15]. The most successful strategy for IPD in Axelrod’s tournaments is ‘Tit for tat’ (TFT). Axelrod attributes the success of TFT to its properties of ‘nice’, ‘forgiving’, and ‘retaliating’. However, later researches have shown the weakness of TFT such as vulnerability to noise and being unable to exploit unconditional cooperators [14,23]. Therefore, there are still attempts to develop novel strategies that can outperform TFT either in round-robin tournaments or in evolutionary dynamics.

In recent iterated prisoner’s dilemma tournaments, there have appeared the strategies with identification mechanisms. By playing a determined sequence of moves and learning from their opponents’ response, these strategies managed to identify their opponents. In the 2004 IPD competition, a team from Southampton University led by N. Jennings introduced a group of strategies, which outperformed any singleton
strategy, and they won the top three positions in the competition [7,19]. The group of strategies were designed to recognise each other through a known series of five to ten moves at the start. Once two Southampton players recognized each other, they would act as a ‘master’ or ‘slave’ role - a master will always defect while a slave will always cooperate in order for the master to win the maximum points. If the program recognized that another player was not a Southampton entry, it would immediately defect to minimise the score of the opponent. In the 2005 IPD tournament, two types of competitions were held. One type of competition permitted multiple entrants (up to 20) submitted by the same competitor and the other only allowed one entrant per competitor. It was not surprising that group strategies again won the competitions with multiple entrants [22]. The winner of the competition that only allowed single entrant also applied an identification mechanism. This strategy divided possible strategies of the opponent into limited categories. By analyzing the moves made by both sides in the interaction, the category to which an opponent belonged could be identified, and then the corresponding optimal strategy could be applied. This strategy was able to identify the opponents and thus responded almost optimally in all games it participated in [9].

With identification mechanisms, it is possible for IPD strategies to behave collectively. Li and Graham [10] studied the so-called collective strategies that applied a simple identification mechanism to distinguish themselves from other strategies. A collective strategy (CS) only cooperates with its kin members and defects against any other strategies. This collective behavior makes the collective strategies especially strong in maintaining a stable population. Any strategy that can be distinguished by CS’s identification mechanism cannot invade a CS population. CS is especially strong in maintaining a homogeneous population, and it can be evolutionarily stable strategy in certain evolution dynamics.

However, a situation that CS cannot handle well is the misidentification of some strategies. For example, the strategy that automatically plays the sequence ‘CD-CCC’ will be identified as a kin member by CS. A homogeneous CS population cannot resist invasions from this type of ‘fake’ kin members, which leaves the possibility for other strategies to indirectly invade. In this study, a mixed strategy, $\epsilon$-CS, which assigns probabilities to CS and the strategy that always defects is developed. This strategy has the advantage of expelling those fake kin members under specific rules of natural selection. We compare it with some well known strategies and show that it is strong in maintaining a stable population.

One of the main objectives of studying strategies for IPD is to explain how cooperation emerges and evolves. A biological explanation of cooperation is based on kin selection [13,16]. Natural selection should eliminate altruistic behaviors in which an individual (the donor) performs an action that helps another individual (the recipient) with no advantage to itself, yet there are many examples in which animals appear to cooperate despite an apparent disadvantage to the donor, for example, alarm calling in squirrels and cooperative courtship in wild turkeys [8,21]. Hamilton explained these altruistic behaviors by means of inclusive fitness that incorporates the potential costs and benefits of an altruistic behavior to an individual and any of its genetic relatives [4,5]. The strategy developed in this paper, $\epsilon$-CS, shows that
kin selection can be achieved in evolutionary IPD and those strategies that maintain kin altruism within kin members can be stronger than others in evolution.

The strategies for IPD used in this paper are listed below.

- ALLC: always cooperates.
- ALLD: always defects.
- TFT: tit for tat, starts with cooperation, then copies the opponent’s move in previous round.
- GRIM: starts with cooperation. Once the opponent defects, it will always defect.
- TFTT: tit for two tats, behaves like TFT, but defects when the opponent has defected twice in succession.
- WSLS: win-stay, lose-shift, divides the result of each move into two groups: wins and loses. If the last result belongs to the win group it plays the same move. Otherwise it plays the other move.
- CD+ALLC: plays cooperation and defection in the first two rounds, and then behaves like ALLC.
- CDC+TFT: plays CDC in the first three rounds, and then behaves like TFT.
- CDC+WSLS: plays CDC in the first three rounds, and then behaves like WSLS.

2. EVOLUTIONARILY STABLE STRATEGY IN EVOLUTIONARY IPD

2.1. Prisoner’s Dilemma

The prisoner’s dilemma (PD) is a type of non-zero-sum game in which two players try to maximize their payoff by cooperating with, or betraying the other player. The classical PD is as follows:

Two suspects, A and B, are arrested by the police. The police have insufficient evidence for a conviction, and, having separated both prisoners, visit each of them to offer the same deal: if one testifies for the prosecution against the other and the other remains silent, the betrayer goes free and the silent accomplice receives the full 10-year sentence. If both stay silent, the police can sentence both prisoners to only six months in jail for a minor charge. If each betrays the other, each will receive a six-year sentence. Each prisoner must make the choice of whether to betray the other or to remain silent. However, neither prisoner knows for sure what choice the other prisoner will make. So the question this dilemma poses is: What will happen? How will the prisoners act?

PD can be represented as the following matrix (see Fig. 1) [20]:

<table>
<thead>
<tr>
<th>Prisoner 1</th>
<th>Cooperate</th>
<th>Defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooperate</td>
<td>(R, R)</td>
<td>(S, T)</td>
</tr>
<tr>
<td>Defect</td>
<td>(T, S)</td>
<td>(P, P)</td>
</tr>
</tbody>
</table>

Figure 1: Payoff matrix of the Prisoner’s Dilemma.
where R, S, T, and P denote Reward for mutual cooperation, Sucker’s payoff, Temptation to defect, and Punishment for mutual defection respectively, and $T > R > P > S$ and $R > \frac{1}{2}(S + T)$. The two constraints motivate each player to play non-cooperatively and prevent any incentive to alternate between cooperation and defection [18,19].

The "dilemma" faced by the prisoners is that, whatever the other does, each is better off to defect than to cooperate. However, the payoff when both defect is worse for each player than the outcome they would have received if they had cooperated. In the Iterated Prisoner’s Dilemma (IPD) game, two players have to choose their mutual strategy repeatedly, and they also have a memory of their previous behaviors and the behaviors of the opponents.

### 2.2. Evolutionarily stable group

An evolutionarily stable strategy (ESS) is a strategy such that, if all the members of a population adopt it, then no mutant strategy could invade the population under the influence of natural selection [12]. Suppose that there are two types of strategies in the population, A and B. Let $E(B, A)$ denote the payoff strategy B receives in interacting with strategy A. The strategy A is evolutionarily stable if both

\begin{align}
    a. & \quad E(A, A) \geq E(B, A), \text{ and} \\
    b. & \quad E(A, B) > E(B, B)
\end{align}

is true for all B. The concept of ESS considers those situations when a single mutant invades an infinite population of homogeneous strategies. It is not concerned with the structure of the population, the selection scheme, and other parameters of evolutionary dynamics. This definition is so strict that no known strategy is evolutionarily stable in IPD when players maintain long-term relationships [3,11].

Let’s consider a group of mutants (strategy A) invades a finite population of strategy B. Let $x$ and $y$ denote the number of strategy A and B respectively. The condition for A to successfully invade is

\[
x E(A, A) + y E(A, B) > x E(B, A) + y E(B, B)
\]

By using $\rho = \frac{x}{x + y}$ to denote the frequency of strategy A in the population, the above condition can be extended to the case of infinite populations. We have

\[
\rho E(A, A) + (1 - \rho) E(A, B) > \rho E(B, A) + (1 - \rho) E(B, B)
\]

or

\[
\rho(E(A, A) - E(B, B)) + (1 - \rho)(E(A, B) - E(B, B)) > 0
\]

We define the concept of an evolutionarily stable group (ESG) as follows. An **evolutionarily stable group** is a group of strategies such that, if the size of the group is no less than a certain percentage of the population, then it will outperform a group of another strategy under the influence of natural selection. A group of strategy A with the group size $\rho$ is ESG if (3) holds for any B.
The concept of ESG considers those situations when a group of mutants invades
an infinite (or finite) population of homogeneous strategies. An ESG can invade a
population of another strategy, or on the other hand, no other strategies can invade
a population of ESG if (3) is satisfied. The concept of ESG can also contribute to the
situations where there is competition between groups. In the following subsections
we introduce a mixed strategy which assigns probabilities to two pure strategies: the
collective strategy and ALLD, and a group of these strategies may be ESG under
specific evolutionary dynamics.

2.3. The collective strategy

The collective strategy (CS) has been studied in [10]. CS manages to identify the
opponent by using an identification mechanism, and then it cooperates with the
group members and defects against any others. A CS behaves in this way: it always
cooperates in the first move and defects in the second move. If the opponent also
cooperates in the first move and defects in second move, CS will cooperate until
the opponent defects. Otherwise, CS will always defect. A finite state machine
expression of CS is as shown in Fig. 2.

When two CSs meet, they both play a sequence of 'CDCCC...'. Because few
strategy plays the sequence of 'CD...' when interacting with CS, most known strate-
gies can be distinguished from CS after just two rounds. In this simple way, CS
manages to cooperate with its group members and defect against others.

The mechanism CS applies to identify the opponent can be expressed by a ma-
chine as shown in Fig. 2. From the viewpoint of biology, this can also be seen
as the 'genes' that differentiate the kin of CS from other strategies. Any strategy
without this structure of genes will be identified as a non-kin member by CS.

It have been proved that any strategy identified as non-kin member by CS cannot
invade a population of CS if the number of CS is not less than 50% of the population.
However, a situation that CS cannot handle well is the invasion of strategies that
cannot be successfully identified. Those strategies with the identification mechanism
as shown in Fig. 2, but different from CS with respect to other genes, will be
identified as kin members and they can invade a population of CS. Some of these
Figure 3: Identification mechanism of CS (any IPD strategy contains this structure will be considered as a kin member by CS).

strategies are CD+AllC, CDC+TFT, and CDC+GRIM, whose finite state machines are shown in Fig. ??). CD+AllC is a deterministic strategy that automatically plays the sequence ‘CDCCC...’. CDC+TFT plays ‘CDC’ in the first three rounds and then behaves like TFT. CDC+GRIM plays ‘CDC’ in the first three rounds and then behaves like GRIM. If there are continuous invasions of such strategies, some may remain and accumulate in the population. When the quantity of such strategies reach a significant level, CS will not perform well and some other strategies may invade. Therefore, a group of CS is not ESG.

Figure 4: Some strategies that cannot be identified by CS. (a) CD+AllC. (b) CDC+TFT. (c) CDC+GRIM.

However, periodical mutants or invasions of AllD can help CS to expel these ‘fake’ kin members from the population. When there are a small number of ALLD in the population, those fake kin members achieve a lower fitness than CS. If the selection rate is larger than the frequencies of ALLD in the population, the fake kin members will be killed under the pressure of natural selection. Therefore, a population of CS can remain evolutionarily stable in specific evolutionary dynamics where there are
periodical mutants of ALLD.

In this paper we study a mixed strategy which assigns probabilities to the CS and ALLD. Let $\epsilon$-CS denote the mixed strategy that assigns $(1-\epsilon)$ probability to CS and $\epsilon$ probability to ALLD (1 > $\epsilon$ > 0). Here, a $\epsilon$-CS maintains its strategy during each generation of IPD, or in other words, a $\epsilon$-CS will behave like ALLD when interacting with all other players in a generation if it is assigned to be ALLD. By applying a small positive value of $\epsilon$, a population of $\epsilon$-CS not only inherits the strength of CS but also has the ability to expel the strategies like CD+AllC and CDC+TFT. In the following section, $\epsilon$-CS is compared with some known strategies in evolutionary IPD. It shows that a group of $\epsilon$-CS can be ESG in specific evolutionary dynamics.

3. EVOLUTIONARY IPD SIMULATIONS

In these evolutionary IPD simulations, every individual strategy plays with all others, and then reproduces and dies according to the payoff (fitness) it earns. Consider a population consisting of two pure strategies, $A$ and $B$. $p_A$ and $p_B$ are the frequencies of $A$ and $B$ in the population respectively. The IPD between two strategies can be denoted by the payoff matrix:

\[
\begin{pmatrix}
A & B \\
A & (a & b) \\
B & (c & d)
\end{pmatrix}
\]

According to (3), for $A$ to dominate $B$ there should be,

\[
p_A(a - c) + p_B(b - d) > 0
\]

(4)

Suppose that $A$ is a mixed strategy which assigns $\epsilon$ and $(1 - \epsilon)$ probabilities to the pure strategies $A_1$ and $A_2$ respectively. Because $A_1$ and $A_2$ may gain different payoffs in interacting with $B$, $\epsilon$ will have an influence on the fitness of different groups in the population when evolutionary selection is taken into consideration. The IPD between a mixed strategy $A$ and a pure strategy $B$ can be expressed as,

\[
\begin{pmatrix}
A & B \\
A_1 & A_2 \\
A_1 & (a_1 & a_2 & b_1) \\
A_2 & (a_1 & a_4 & b_2) \\
B & (c_1 & c_2 & d)
\end{pmatrix}
\]

Let $E(A_1)$, $E(A_2)$ and $E(B)$ denote the fitness of $A_1$, $A_2$ and $B$ respectively. We have,

\[
E(A_1) = \epsilon P_Aa_1 + (1 - \epsilon)P_Aa_2 + P_Bb_1
\]

\[
E(A_2) = \epsilon P_Aa_3 + (1 - \epsilon)P_Aa_4 + P_Bb_2
\]
\[ E(B) = \epsilon P_A c_1 + (1 - \epsilon) P_A c_2 + P_B d \]

Without loss of generality, assume that \( E(A_1) \leq E(A_2) \). If \( E(A_1) > E(B) \), \( A \) will dominate \( B \) no matter what the selection rate is. If \( E(A_2) < E(B) \), \( A \) will definitely be dominated by \( B \). When \( E(A_1) \leq E(B) < E(A_2) \), which strategy can be dominant depends on the selection rate and \( \epsilon \).

### 3.1. \( \epsilon \)-CS vs. ALLD

Against ALLD, \( \epsilon \)-CS is playing in the worst position against defecting strategies because any other defecting strategy will not receive higher payoffs than ALLD in interacting with \( \epsilon \)-CS. When \( A \) and \( B \) denote the strategies of \( \epsilon \)-CS and ALLD respectively, their fitness can be computed as,

\[
E(A_1) = (\epsilon P_A + P_B)P + \frac{1}{n}(1 - \epsilon)P_A(T + (n - 1)P)
\]

\[
E(A_2) = \frac{1}{n}(\epsilon P_A + P_B)(S + (n - 1)P) + \frac{1}{n}(1 - \epsilon)P_A(P + (n - 1)R)
\]

\[
E(B) = (\epsilon P_A + P_B)P + \frac{1}{n}(1 - \epsilon)P_A(T + (n - 1)P)
\]

where \( n \) is the number of rounds for each IPD and \( T, R, P, \) and \( S \) are payoffs as defined in Fig. ???. Because there must be \( E(A_2) > E(B) = E(A_1) \), \( \epsilon \)-CS can dominate ALLD whatever the selection rate is.

Fig. ?? shows the relationship between the least \( p_A \) needed for \( \epsilon \)-CS to dominate ALLD and \( n \), provided \( T = 5, R = 3, P = 1, S = 0 \) and \( n > \frac{T}{R} - \frac{P}{R} \). For example, a group of \( \epsilon \)-CS whose size is no less than 7.94% will dominate ALLD provided \( n = 10 \) and \( \epsilon = 0.1 \). Note that the least frequency for ALLD to dominate \( \epsilon \)-CS is \( p_B = 1 - p_A \).

![Figure 5: The least frequency for \( \epsilon \)-CS to dominate ALLD in evolutionary IPD without noise.](image-url)
3.2. $\epsilon$-CS vs. TFT

Against TFT, $\epsilon$-CS is playing in the worst position against cooperating strategies because any other cooperating strategy will not receive higher payoffs than TFT in interacting with $\epsilon$-CS. When $A$ and $B$ denote the strategies of $\epsilon$-CS and TFT respectively, the strategies in the population consists of ALLD, CS, and TFT whose frequencies are $\epsilon P_A$, $(1 - \epsilon) P_A$, and $P_B$ respectively. The IPD between three types of strategies can be expressed as

\[
\begin{array}{ccc}
\text{ALLD} & \text{CS} & \text{TFT} \\
\hline
nP & T + (n-1)P & T + (n-1)P \\
S + (n-1)P & P + (n-1)R & R + T + (n-2)P \\
S + (n-1)P & R + S + (n-2)P & nR \\
\end{array}
\]

The fitness of each type of strategy is,

\[
E(\text{ALLD}) = \epsilon P_A P + \frac{1}{n} ((1 - \epsilon) P_A + P_B)(T + (n - 1)P) \\
E(\text{CS}) = \frac{1}{n} \epsilon P_A (S + (n-1)P) + \frac{1}{n} (1- \epsilon) P_A (P + (n-1)R) + \frac{1}{n} P_B (R + T + (n - 2)P) \\
E(\text{TFT}) = \frac{1}{n} \epsilon P_A (S + (n-1)P) + \frac{1}{n} (1- \epsilon) P_A (R + S + (n - 2)P) + P_B R
\]

There is $E(\text{TFT}) > E(\text{ALLD})$ provided $\epsilon << 1$. If the selection rate is smaller than $\epsilon$ in this case, the evolutionary selection tends to eliminate those $\epsilon$-CS acting as ALLD. If the selection rate is more than $\epsilon$, however, TFT may be eliminated by the evolutionary selection. Fig. ?? shows the relationship between the least $p_A$ needed for $\epsilon$-CS to expel TFT and $n$, provided $T = 5$, $R = 3$, $P = 1$, $S = 0$ and $n > \frac{T - P}{R - P}$. For example, a group of $\epsilon$-CS whose size is no less than 48.35% will dominate TFT provided $n = 10$ and $\epsilon = 0.05$.

3.3. $\epsilon$-CS vs. CDC+TFT

CDC+TFT is chosen as the representative for those strategies that differentiate from CS but could be identified as kin members by CS. $\epsilon$-CS has the ability to expel those strategies from the population if $\epsilon$ is smaller than the selection rate of evolution. The IPD between ALLD, CS, and CDC+TFT is as below,

The fitness of each type of strategy is,

\[
E(\text{ALLD}) = \epsilon P_A P + \frac{1}{n} (1- \epsilon) P_A (T + (n - 1)P) + \frac{1}{n} P_B (2T + (n - 2)P) \\
E(\text{CS}) = \frac{1}{n} \epsilon P_A (S + (n-1)P) + \frac{1}{n} ((1 - \epsilon) P_A + P_B)(P + (n-1)R) \\
E(\text{CDC + TFT}) = \frac{1}{n} \epsilon P_A (2S + (n - 2)P) + \frac{1}{n} ((1 - \epsilon) P_A + P_B)(P + (n-1)R)
\]
Figure 6: The least frequency for $\epsilon$-CS to dominate TFT in evolutionary IPD without noise.

There is $E(\text{CS}) > E(\text{CDC} + \text{ALLD}) > E(\text{ALLD})$ if $n > \frac{2(T-P)}{R-P} + 1$, and $E(\text{CS}) > E(\text{ALLD}) > E(\text{CDC} + \text{ALLD})$ holds if $n < \frac{2(T-P)}{R-P} + 1$.

Fig. ?? shows the fitness of each type of strategy provided $T = 5$, $R = 3$, $P = 1$, $S = 0$, $\epsilon = 0.1$, and $p_A = 80\%$. ALLD makes the fitness of CS higher than the fitness of CDC+TFT. When $\epsilon$ is smaller than the selection rate and the selection favors those strategies with the highest fitness produce offsprings, CDC+TFT can be expelled and a population of $\epsilon$-CS will remain stable. Fig. ?? shows $\epsilon$-CS expels CDC+TFT under the selection dynamics in which the strategies with the $\gamma$ highest fitness duplicate and those with the $\gamma$ lowest fitness die out during a generation.

### 3.4. Sensitivity to noise

Noise in IPD means occasional mistakes in the interactions between players. It has a certain probability of occurrence and is fixed throughout a game. In this paper, two noise levels are applied: 1% and 5%. 1% noise means that for each intended choice there is a 1% chance that the opposite choice will actually be implemented.

$\epsilon$-CS performs well in evolutionary IPD with noise. We have compared $\epsilon$-CS with strategies such as TFTT, GTFT and WSLS that are considered to be good strategies in a noisy IPD. Simulations show that $\epsilon$-CS can defeat all those strategies in evolutionary IPD if its frequency is no less than 50% in the population. Fig. ?? shows $\epsilon$-CS expels WSLS in evolutionary IPD with noise. Notice that the fitness of those $\epsilon$-CS that behave as CS keep stable in the evolution because CS can exploit...
Collective behavior and kin selection in evolutionary IPD

Figure 7: The fitness of CS, ALLD and CDC+TFT provided $T = 5$, $R = 3$, $P = 1$, $S = 0$, $\epsilon = 0.01$, and $p_A = 80\%$.

Figure 8: $\epsilon$-CS expels CDC+TFT. The evolution starts with a population of 55% $\epsilon$-CS and 45% CDC+TFT. (a) $\epsilon = 0.01$ and the selection rate $\gamma = 0.03$. (b) $\epsilon = 0.018$ and the selection rate $\gamma = 0.02$.

WSLS.

Interestingly, noise helps $\epsilon$-CS to eliminate fake kin members. In evolutionary IPD with noise a population of $\epsilon$-CS can resist the invasion of fake kin strategies even if $\epsilon = 0$. Fig. ?? shows that $\epsilon$-CS expels CDC+WSLS in evolutionary IPD with noise. CDC+WSLS is chosen as the representative because it not only implements cooperation when interacting with $\epsilon$-CS but also maintains WSLS’s advantage of recovering from occasional errors. Simulations show that a population of $\epsilon$-CS can prevent both fake kin members and those strategies identified as non-group members from invasion in noisy IPD so that a stable population can be maintained.
Figure 9: $\epsilon$-CS expels WSLS in evolutionary IPD with 5% noise. The evolution starts with a population of 50% $\epsilon$-CS ($\epsilon = 0.01$) and 50% WSLS and the selection rate is $\gamma = 0.02$. (a) Frequency change of the strategies. (b) Fitness of the strategies.

Figure 10: $\epsilon$-CS expels CDC+WSLS in evolutionary IPD with 1% noise. The evolution starts with a population of 50% $\epsilon$-CS and 50% CDC+WSLS and the selection rate is $\gamma = 0.02$. (a) $\epsilon = 0.01$. (b) $\epsilon = 0$.

### 3.5. Kin selection in evolutionary IPD

Defection can also be an altruistic behavior in evolutionary IPD. Each $\epsilon$-CS behaves as either CS or ALLD in a generation of evolution. When a $\epsilon$-CS behaves as ALLD, it is very likely to receive a low fitness and be eliminated under the pressure of selection. On the other hand, those $\epsilon$-CS behaving as CS receive a higher probability of surviving. If a $\epsilon$-CS can choose the value of $\epsilon$, it is better off choosing $\epsilon = 0$ so as to maximize its fitness. If all $\epsilon$-CS choose to be CS, however, the population cannot persist the invasion of those fake kin members. Therefore, acting as ALLD is a kin altruism by which other members of the group of $\epsilon$-CS benefit.

Kin altruism is common in nature and it can be explained by means of kin selection. Hamilton states that the selection of genes due to one or more individuals favoring or disfavoring the survival and reproduction of relatives who possess the same genes by common descent. Kin altruism happens only when the donor and the receiver are members of the same species. In Hamilton’s model, the coefficient of relatedness $r$, must exceed the cost to benefit ratio of the altruistic act [5]:

$$r > \frac{c}{b}$$
where relatedness is defined as the probability of sharing a gene.

The finite state machine structure of ϵ-CS as shown in Fig. ?? can be considered as its genes. So two ϵ-CS have 100% relatedness. The genes of strategies relate with certain behavior that can be identified. ϵ-CS adopts the identification mechanism as shown in Fig. ?? which acts as the identity genes of kin members. With identity genes, kin recognition is acquired and then cooperation is established between kin members.

Hamilton’s rule represents the quantitative effect of kin altruism by which certain kin members benefit directly. The behavior of ϵ-CS, however, shows that kin altruism may be of qualitative benefit to other kin members as well. Consider a population of ϵ-CS in an evolutionary IPD. Let $E(\epsilon-CS)$ denote the expected fitness of ϵ-CS. We have,

$$E(\epsilon-CS) = (1 - \epsilon)E(CS) + \epsilon E(ALLD)$$

where $E(CS)$ and $E(ALLD)$ are the fitness of those ϵ-CS behaving as CS and the fitness of those ϵ-CS behaving as ALLD respectively.

$$E(CS) = \frac{1}{n}(1 - \epsilon)(P + (n - 1)R) + \frac{1}{n}\epsilon(S + (n - 1)P)$$

$$E(ALLD) = \frac{1}{n}(1 - \epsilon)(T + (n - 1)P) + \epsilon P$$

As the value of $\epsilon$ increases, $E(\epsilon-CS)$ decreases as shown in Fig. ???. When $\epsilon = 0$, $E(\epsilon-CS)$ reaches the maximum, which means that those ϵ-CS behaving as CS with 100% probability receive the highest fitness. Those ϵ-CS behaving as ALLD receive the lowest fitness and they lower the average fitness of the whole population.

Figure 11: $E(\epsilon-CS)$ decreases when $\epsilon$ increases provided $T = 5$, $R = 3$, $P = 1$, $S = 0$, and $n = 50.$
It is altruistic behavior for a $\epsilon$-CS to choose $\epsilon > 0$ because individual selection favors $\epsilon = 0$. However, the benefit from this kin altruism is not easy to be quantified. It prevents the spread of the fake kin members in the population so that other strategies cannot indirectly invade and a population of $\epsilon$-CS can maintain stable. If this qualitative benefit is not taken into consideration, $\epsilon > 0$ is not worthy according to Hamilton’s rule (5).

We leave the problems of how to evaluate the qualitative benefit of kin altruism, how kin altruism evolves in evolutionary dynamics, and how to explain the collective behavior by evolutionary game theory for future research.

4. CONCLUDING REMARKS

$\epsilon$-CS is evolutionarily stronger than those non-group strategies. Like CS, $\epsilon$-CS identifies the opponent and then maintains cooperation with kin members and defects against any others. This collective behavior makes a group of $\epsilon$-CS maximize the fitness of kin members and minimize the fitness of others. Therefore, $\epsilon$-CS is especially strong once a group is formed.

Unlike pure CS, $\epsilon$-CS can expel those fake kin strategies so that it prevents other strategies from indirectly invasion, which is important for a population to maintain stability. When those fake kin strategies, CD+ALLC and CDC+TFT for example, have occupied a significant percentage of the population, some other strategies can then invade the population of CS.

$\epsilon$-CS performs well in the noisy environment. Once a mistake happens, $\epsilon$-CS will then behave like ALLD. The influence of noise on $\epsilon$-CS is equivalent to the increase of the value of $\epsilon$.

$\epsilon$-CS shows that the approaches of kin altruism may be diverse. First, defection can be a kin altruism in kin selection. A $\epsilon$-CS with $\epsilon = 0$ maximizes its fitness. However, a population of $\epsilon$-CS with $\epsilon = 0$ is vulnerable to invasions of fake kin strategies. Thus, $\epsilon$-CS that behaves as ALLD is a kin altruism that benefits other kin members. Second, the benefit from kin altruism may be qualitative. Acting as ALLD neither increases other kin members’ fitness nor necessarily eliminates fake kin strategies (if there is no fake kin strategy in the population). It helps to maintain a homogeneous population by relieving the threat of possible invasions.

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REFERENCES


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