Engineering Design of Strategies for Winning Iterated Prisoner's Dilemma Competitions

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Engineering Design of Strategies for Winning Iterated Prisoner's Dilemma Competitions

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Abstract - **We investigate winning strategies for round-robin iterated prisoner's dilemma (IPD) competitions and evolutionary IPD competitions. Since the outcome of a single competition depends on the composition of the population of participants, we propose a statistical evaluation methodology that takes into account outcomes across varying compositions. We run several series of competitions in which the strategies of the participants are randomly chosen from a set of representative strategies. Statistics are gathered to evaluate the performance of each strategy. With this approach, the conditions for some well-known strategies to win a round-robin IPD competition are analyzed. We show that a strategy that uses simple rule based identification mechanisms to explore and exploit the opponent outperforms well-known strategies such as tit-for-tat in most round-robin competitions. Group strategies have an advantage over non-group strategies in evolutionary IPD competitions. Group strategies adopt different strategies in interacting with kin members and non-kin members. A simple group strategy, Clique, which cooperates only with kin members, performs well in competing against well-known IPD strategies. We introduce several group strategies developed by combining Clique with winning strategies from round-robin competitions and evaluate their performance by adapting three parameters; sole survivor rate, extinction rate, and survival time. Simulation results show that these group strategies outperform well-known IPD strategies in evolutionary IPD competitions.**

Index Terms— **opponent identification, group strategy, iterated prisoner's dilemma, game theory**

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I. Introduction

The prisoner's dilemma is a fundamental problem in game theory that has been heavily studied in economics, machine learning, and evolutionary computation. Two players have to decide whether to cooperate (C) with an opponent, or defect (D). Both players make their choices simultaneously and the choice is made independently, without being able to exchange information with the other player. When both players have made their choices, their payoffs will be determined according to the payoff matrix in Figure 1. Each player is attempting to maximize their own payoff.

Player II

		Cooperate	Defect
Player I	Cooperate	***R*=3** (Player II); ***R*=3** (Player I)	***T*=5** (Player II); ***S*=0** (Player I)
	Defect	***S*=0** (Player II); ***T*=5** (Player I)	***P*=1** (Player II); ***P*=1** (Player I)

Fig. 1. Payoff matrix of the Prisoner's Dilemma.

If both players cooperate, they both receive a Reward (*R*) of 3 points. If one player defects and the other cooperates then the defector receives the Temptation to defect (*T*) payoff of 5 points and the cooperator receives the Sucker (*S*) payoff (zero in this case). If both players defect, they both receive the Penalty (*P*) payoff (1 in this case).

It is clear that each player is better off choosing to defect no matter what the other player chooses. However, both players would have been better off if they chose to cooperate with each other. Game theory predicts that both players will choose to defect if they are self-interested. Mutual defection (D, D) is the unique Nash equilibrium of this game, which denotes a steady state in which no player has the incentive to deviate from their strategy, even when the decision of the other player is known.

In an iterated prisoner's dilemma (IPD), two players play prisoner's dilemma repeatedly, and they have the option to retain a memory of the previous actions of both players. The payoffs should satisfy the conditions that $T > R > P > S$ and $R > 1/2(T+S)$, which motivates each player to play non-cooperatively and prevents any incentive to alternate between cooperation and defection. Thus each player has an opportunity to punish the other player for previous non-cooperative play. If the precise length of an IPD is known to the players, the optimal strategy for both players is to defect on each move. This is deduced by means of so-called backward induction: Both players will choose to defect in the final iteration because the opponent will not be able to subsequently punish the player. Given mutual defection in the final iteration, the optimal strategy in the penultimate iteration is defection for both players, and so on, back to the initial iteration. If the precise length of an IPD is infinite, or unknown, mutual cooperation can also be an equilibrium.

However, many experiments have revealed that cooperation between human players at an early stage of a finite IPD can be achieved if there are sufficient iterations [1]-[3]. Some explanations of cooperation in IPD include altruism, bounded rationality, incomplete information, and reputation. An empathy-induced altruism model claims that empathic concern for the needs of another person leads to altruistic behaviours [4]. Bounded rationality assumes that decision makers lack the ability and resources to arrive at the optimal solution, and cooperation is the result of non-rationality [5]. If players are not sure that their opponent will always defect and they believe that there is a small probability that their opponent is a Tit-for-Tat type player, finite IPD turns out to be a repeated game of incomplete information and cooperation can be an equilibrium [6]. The reputation model assumes that players believe that a fraction of their opponents are altruists and each player has a reputation that reflects their past choices. Reputation motivates self-interested players to choose cooperation [7].

Axelrod was the first to attempt to search for efficient strategies by means of IPD competitions [8, 9]. Since his famous book '*The Evolution of Cooperation*', Tit-for-Tat (TFT) is often considered to be the most successful strategy in IPD [10]. TFT always cooperates in the first move and then mimics whatever the opponent did in the previous move. According to Axelrod, several characteristics make TFT successful: TFT is Nice, Retaliating and Forgiving. TFT is not a Nash equilibrium and there is always a sub-game perfect equilibrium that dominates TFT, according to the Folk Theorem in game theory [11, 12]. On the other hand, whether or not TFT is the most efficient strategy in IPD is still unclear. Some strategies perform better than TFT in specific environments [13-17]. Therefore, researchers are attempting to develop novel strategies that can outperform TFT either in round-robin tournaments or in evolutionary dynamics.

In recent IPD competitions, strategies have appeared with identification mechanisms. With a rule based identification mechanism, a strategy called APavlov won competition four of the 2005 IPD competition [18]. Furthermore, many of the top listed strategies more or less explore the opponent by using some simple mechanisms [19, 20]. This shows that strategies that *explore and then exploit* the opponent can outperform any single non-group strategy in round-robin IPD tournaments.

A strategy with a simple identification mechanism, named 'handshake' [21], appeared in evolutionary IPD. This strategy just defects at the first move and cooperates on the second move. If the opponent behaves the same as handshake, it will keep cooperating in the following moves. Otherwise, it will always defect. This 'initial defect then cooperate' can be seen as a password. Any strategy that knows this password (or behaves the same by chance) may evoke handshake's cooperation while others trigger defection. Handshake has an effect on promoting cooperation in evolutionary IPD [22, 23].

In the 2004 IPD competition, a team from Southampton University led by Jennings introduced a group of strategies, which outperformed all singleton strategies, and won the top three positions. These strategies were designed to recognize each other through a predetermined sequence of 5-10 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 opponent was recognized as not being a Southampton entry, it would immediately defect to minimize the score of the opponent [24]. The importance of group strategies lies in their evolutionary features. A simple group strategy that just cooperates with kin members and defects against any non-kin could be strong in maintaining a stable population in evolution [25, 26]. Recent surveys on IPD and the introduction of some group strategies appearing in recent IPD competitions can be found in [27, 42, 43].

Since Axelrod, two types of approaches are used to test the efficiency or robustness of a strategy and to derive optimal strategies:

(1) Round-robin IPD competitions, and

(2) Evolutionary IPD competitions.

In round-robin IPD, the interactions between different strategies can be observed and analyzed. In evolutionary IPD, a population of strategies plays IPD with one another and each strategy has the chance to produce offspring proportional to its fitness (payoff) [28]. The strategies with higher fitness reproduce and replace those with lower fitness at each time step. The population converges to strategies with higher fitness. Round-robin competitions show the efficiency of a strategy in competing with others, while evolutionary competitions illustrate the evolutionary robustness of a strategy in terms of the number of offspring or survivability in a certain environment.

We adopt a statistical evaluation methodology to measure the performance of IPD strategies in both round-robin and evolutionary environments. The main motivation of this evaluation methodology is to provide a performance measure for IPD strategies by running a series of competitions in which different compositions of IPD strategies are taken into consideration. In [29], the generalization performance of a strategy is defined as its average performance against all test strategies. The estimated value of generalization performance is computed by using a small sample of randomly chosen test strategies. It is proven that the difference between the estimated value and the true value can be tiny if the size of the set of test strategies is large. This provides the theoretical basis for the proposed evaluation methodology. Comparing with [29], we adopt different parameters and use IPD competitions, rather than IPD games, to evaluate the performance of IPD strategies.

The contribution of this study is two-fold.

(1) It offers a methodological contribution to evolutionary game theory. The proposed statistical methodology not only measures the performance of IPD strategies in different circumstances but also the conditions under which a strategy outperforms others in an IPD competition. For example, we have computed the conditions for TFT to outperform GRIM and TFTT.

(2) It introduces strategies that have the potential to outperform well-known strategies, such as TFT, in both round-robin and evolutionary IPD competitions. Strategies with identification mechanisms to explore and exploit the opponent perform well in round-robin IPDs. Group strategies that adopt different strategies in interacting with kin members and non-kin members outperform non-group strategies in evolutionary IPDs. The performances of these strategies are computed by means of the proposed statistical methodology.

The remainder of this paper is arranged as follows. In section II, we first run a series of round-robin IPD competitions to evaluate IPD strategies. The conditions for well-known strategies such as TFT to win competitions are analyzed. We show that a strategy with an identification mechanism to explore and exploit the opponent outperforms well-known strategies in most round-robin competitions. In section III, we introduce several group strategies. The performances of IPD strategies in evolutionary dynamics are evaluated by a series of competitions. It is shown that group strategies outperform well-known IPD strategies in evolutionary competitions. We conclude the paper and suggest possibilities for future work in the last section.

II. Design of Winning Strategies for Round-robin IPD Competitions

Consider a round-robin IPD competition where there are a total of m players. The players play an n-round IPD with one another where n is unknown to each player. The winner is the player who receives the highest aggregated payoff in all IPDs. Obviously, a strategy could be the winning strategy if it interacts with most of the other strategies optimally. We note that winning an IPD competition is based on average IPD payoff per game, rather than the number of wins in the games.

In this section, we show that a strategy with an identification mechanism outperforms well-known strategies such as TFT in round-robin IPD competitions.

A. *Identifying the Opponent*

In order to interact with an IPD player optimally, we first need to know what strategy it adopts. For players that adopt a predetermined sequence of moves, for example AllC and AllD, the optimal strategy to deal with them is AllD. For strategies that are nice and retaliating, for example TFT and GRIM, the optimal strategy is AllC. So an identification mechanism is needed in order for a strategy to win an IPD competition.

It is theoretically impossible to identify an arbitrary IPD strategy in a finite number of moves because even pure IPD strategies are numerous. However, identifying some known IPD strategies is still practical because,

a. Most IPD strategies are not likely to appear in a competition.

b. We do not need to know an IPD strategy exactly in order to deal with it optimally.

We list 32 IPD strategies that can be found in the scientific literature in Appendix A. Some of them, TFT, GRIM and Pavlov for example, are heavily studied and have been proven to be efficient in some past competitions. These strategies, and their mutants, are much more likely to be adopted in an IPD competition than other strategies. Strategies that are not likely to win are less likely to be adopted. Thus, identifying the opponent is possible if we concentrate on those strategies with a high possibility of being adopted in competitions.

Furthermore, we do not need to know an IPD strategy exactly before adopting the optimal counter-strategy. For example, consider two random strategies. Strategy one cooperates with 30% probability and defects 70% of the time. Strategy two cooperates with 40% probability and defects with 60% probability. It is not easy to distinguish these two strategies from each other in a limited number of moves. However, since AllD is the optimal strategy in dealing with both strategies, we just need to distinguish them from other strategies and then adopt AllD.

A strategy with an identification mechanism that plays ‘DDCC’ in first four moves can identify most cooperative strategies shown in Appendix A in these four moves. When interacting with this strategy, TFT responds with ‘CDDC’ and GRIM responds ‘CDDD’ and Pavlov responds ‘CDCC’ and TFTT responds ‘CCDC’ and etc. It needs 6-8 moves to distinguish the 32 IPD strategies in Appendix A.

There is the problem of exploitation versus exploration in identifying the opponent. For example, both GRIM and AllC remain cooperative if their opponents cooperate. In order to make clear which strategy the opponent is, we need to defect at least once. If we do so, however, we trigger GRIM’s defection and lose the chance to maintain future cooperation. To avoid the revenge of GRIM, we should not start defecting. However, we lose the chance to exploit AllC in this situation. Whether we should explore or exploit depends on our prior knowledge of which strategies are likely to occur. It is worth exploring if the probability that the opponent is GRIM is less than that of AllC.

B. *IPD Strategies*

In a round-robin IPD competition, the participants can be expressed by $\{S, \rho\}$, where $S = \{S_1, \cdots, S_n\}$ denotes a limited set of possible IPD strategies and ρ is the percentage distribution of different strategies.

$$\text{An unknown population} = \begin{cases} S_1, & \rho_1 \\ S_2, & \rho_2 \\ \vdots & \vdots \\ S_n, & \rho_n \end{cases}$$

A winning strategy should interact with most of the strategies optimally and its performance depends on the types of strategies and their frequencies in the population.

Cooperative strategies dominate in most IPD competitions. Cooperative strategies are those strategies that remain cooperative if their opponents do not start defecting. Typical cooperative strategies include TFT, GRIM, and TFTT. There has been controversy for some time as to which strategy is the best for IPD competitions. A situation that TFT cannot handle well is a long series of mutual retaliations evoked by a singleton defection. The deadlock can be broken if it cooperates one more time. TFTT performs well in this situation because it is more forgiving than TFT. However, it can be exploited by strategies that alternately play C and D. Compared to TFT, GRIM is not forgiving so cooperation is impossible when it meets non-cooperative strategies. These strategies are indistinguishable in interacting with cooperative strategies. Table 1 shows the result of 50 rounds of IPD between these strategies and some non-cooperative strategies.

The non-cooperative strategies in Table 1 can be divided into three categories:

1. Those strategies that attempt to exploit the opponent and try to recover cooperation if the exploitation attempt fails.

2. Those strategies that start defecting but cooperation can be achieved if their opponents try to recover cooperation.

3. Random strategies, deterministic strategies that play predetermined moves, and strategies that adopt an unreasonable logic such as RTFT.

Category 1 contains Adaptive and Prober. In dealing with this type of strategy, TFT is the best counter-strategy (of those considered) while TFTT is exploited and receives the lowest payoff. Category 2 contains STFT and HM. In interacting with this type of strategy, TFTT is the best while GRIM is the worst. TFT falls into a deadlock of mutual retaliations in this situation. GRIM performs well in dealing with the strategies of Category 3. Thus, which strategy wins depends on the makeup of the population.

It is possible to develop a strategy that outperforms TFT by using an identification mechanism. Consider a strategy that shifts between TFT, TFTT and GRIM according to which category (1, 2 or 3) the opponent belongs to. This strategy will outperform TFT in most situations in which both strategies are involved. In the following sections, we introduce a strategy with a rule based identification mechanism and run a series of competitions to investigate its performance in IPD competitions.

C. APavlov Strategy

APavlov, a strategy with a simple rule based identification mechanism, won the competition that mirrored Axelrod's 1980 IPD competition at the 2005 IEEE Symposium on Computational Intelligence and Games [18]. APavlov adopts a simple 'if-then' identification mechanism. It adopts TFT in the first six moves and identifies the opponent according to the result of the interaction. In the following six rounds, a corresponding reaction will be adopted. The possible strategies of the opponent are divided into four categories: cooperative, AllD, STFT, and Random. If the opponent does not start defecting, it is identified to be cooperative and then APavlov will behave as TFT. If the opponent defects more than four times in six consecutive moves, it is identified as an AllD type and then APavlov will always defect. If the opponent just defects three times in six moves, it is identified as STFT type and then APavlov will adopt TFTT in order to recover mutual cooperation. Any strategy that does not belong to the former three categories will be identified as a random type. In this situation, APavlov will always defect. In order to deal with the situations in which the opponents may change their actions, the average payoff is computed every six rounds. If it is lower than a threshold, the process of opponent identification will restart. The strategy of APavlov can be expressed in a flowchart as

Table 1 Comparison between TFT, GRIM and TFTT.

	AllD	TFT	GRIM	TFTT	STFT	Hand	PCD	HM	Adaptive	RTFT	For3	For4	Prob	RAND
TFT	**49**	150	150	150	125	52	123	125	**139**	109	80	73	**149**	118
GRIM	**49**	150	150	150	*53*	**53**	**147**	*53*	95	**241**	**97**	**85**	65	**135**
TFTT	*48*	150	150	150	**147**	*49*	*75*	**147**	*66*	*90*	*64*	*63*	*51*	*98*

See Appendix A for the description of these strategies. Hand: Hand shake; Prob: Prober. The values in bold show the highest payoffs received in interacting with a non-cooperative strategy while the values in italic show the lowest payoffs.

Table 2 Categories of non-cooperative strategies.

Category	IPD strategies	Optimal counter-strategy
1	Adaptive, Prober	TFT
2	STFT, HM	TFTT
3	Random, AllD, PCD, RTFT, Handshake, Fortress	GRIM*

* AllD is the optimal counter-strategy in this case. However, GRIM is 'practically' optimal because we cannot know the strategy of an opponent in advance.

shown in Figure 2.

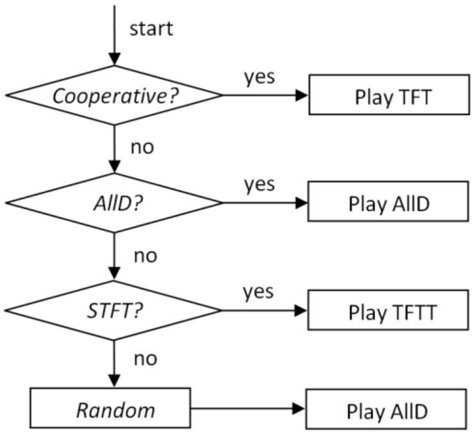


Fig. 2. A strategy with simple rule based identification mechanism.

We played 50 rounds IPD games between 33 strategies (those in Appendix A, plus APavlov). The result shows that APavlov receives equal or higher payoff than TFT against every other strategy except Adaptive, and APavlov receives the highest aggregated payoffs in this competition.

The frequencies of strategies, ρ, has a crucial influence on the result of an IPD competition. A single competition is not enough to prove the efficiency of any one strategy. In the following section, we present a series of competitions to show that APavlov outperforms other strategies in most situations.

III. Evaluation Methodology for IPD Strategies

Since a single competition is not enough to evaluate the efficiency of a strategy, we ran a series of competitions in which different compositions of IPD strategies used. In this proposed evaluation methodology, many competitions are run between different, randomly chosen subsets of the strategies under consideration. The performance of a strategy is evaluated based on its *average payoff* and its *win rate*. Average payoff denotes average payoff per move in all competitions that it is involved in and win rate is the frequency of achieving the highest payoff in single competition.

This methodology is an adaptation of the generalization performance measure described in [29]. It is proven that the difference between the estimated value and the true value of the generalization measure can be tiny if the size of the set of test strategies is large.

Let G denote the true value of the generalization measure, $\hat{G}$ the estimated value of G. The absolute difference, $|\hat{G}-G|$, is a random variable with distribution P_N taken on a compact interval $[G_{\min}, G_{\max}]$. We have,

$$P_N(|\hat{G}-G| \geq \varepsilon) \leq \frac{R^2}{4N\varepsilon^2} \quad (1)$$

where $R = G_{\max} - G_{\min}$, N is the number of random test strategies, ε is a small positive number ($\varepsilon > 0$) [29].

A biased sample of test strategies is adopted in computing the generalization measure because participants in games are more interested in the performance against those 'good' strategies. We extend the biased sample idea by testing on multiple random selections. The performance of a strategy in an IPD competition depends on the composition of the strategies of participants. Instead of a fixed sample, we use a large number of groups of strategies randomly selected from a set of well-known IPD strategies, against which the performance of strategies is evaluated.

In simulations 1-3, we use 10 strategies randomly drawn from a set of IPD strategies in order to simulate the circumstances in which there are limited types of strategy. In simulation 4, we use 100 strategies to simulate the circumstances in which different distributions of IPD strategies are adopted. In each of the examples that follow, 100,000 competitions were run.

a. Simulation 1.

For each competition, we choose ten IPD strategies, each of which is randomly chosen from the set of strategies shown in Appendix A. The strategies play 50 rounds of IPD with each other and the winner is the strategy that receives the highest average payoff in those games in which it is involved. Figure 3 shows the result of competitions. APavlov receives the highest average payoff per move (2.74). CTFT receives the second highest payoff (2.64) and the highest win rate (it wins about 16.7% of the competitions in which it is involved).

We have tried different numbers of participants for the competitions and receive similar results.

b. Simulation 2.

In this simulation, ten strategies are randomly chosen from an extended set of IPD strategies. This extended set includes not only the strategies in Appendix A but also ten random strategies (mixed strategies with different probabilities of choosing C or D) and ten predetermined strategies (with randomly created sequences of C and D). Obviously, strategies such as AllD and GRIM have an advantage over others in interacting with those newly added strategies. The result is shown in Figure 4. Again, APavlov receives the highest average payoff per move (2.72) and the highest win rate (12.6%). GRIM receives the second highest average payoff (2.67) and win rate (11.2%).

c. Simulation 3.

In this simulation, strategies are evaluated in an environment with noise. Noise in IPD means occasional mistakes in the interaction between players and it has a certain probability of occurrence throughout a game. Two levels of noise are applied: 2% and 10%. 2% noise means that for each intended choice there is 2% chance that the opposite choice will actually be implemented. We randomly choose ten strategies from the extended set of IPD strategies. The result

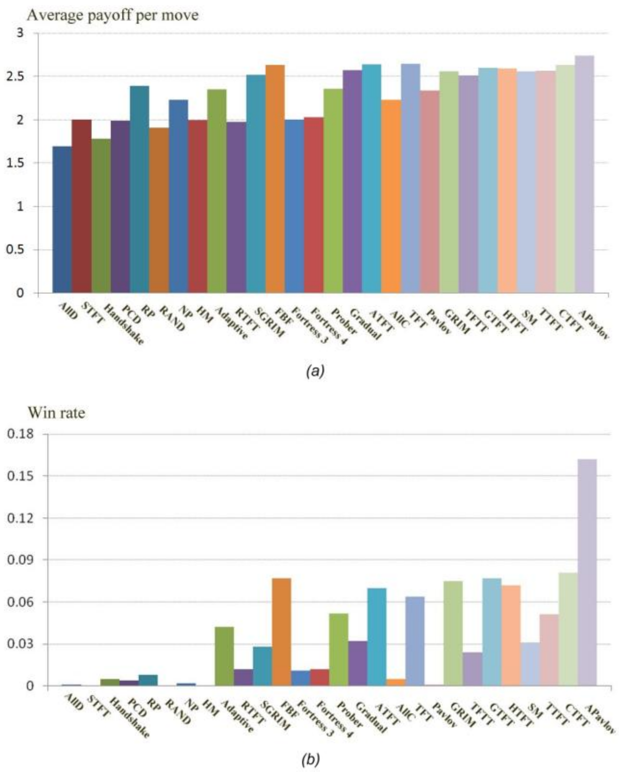


Fig. 3. (*a*) Average payoffs per move. (*b*) Win rate in the competitions in which the strategy is involved. The competition is repeated 100,000 times, in which 10 strategies are randomly chosen from the set of strategies shown in Appendix A plus APavlov.

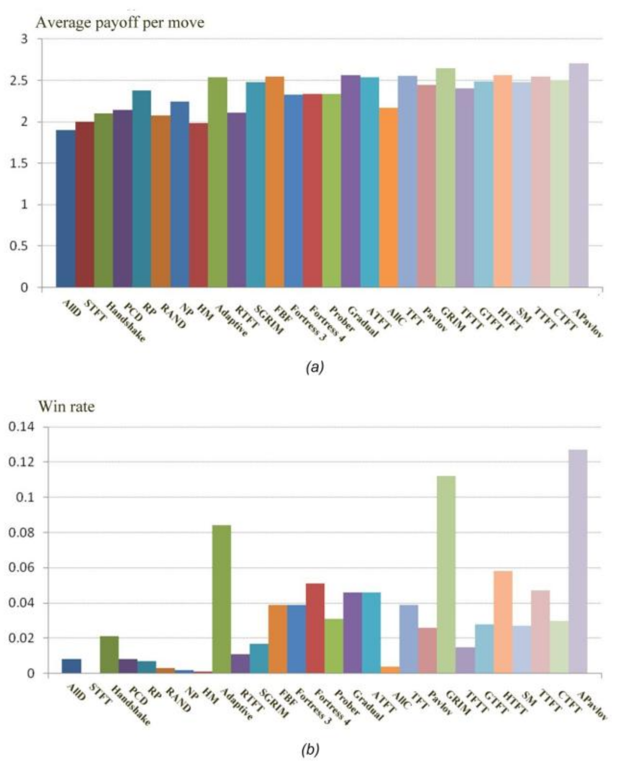


Fig. 4. (*a*) Average payoffs per move. (*b*) Win rate in the competitions that the strategy is involved in. The competition is repeated 100,000 times, in which 10 strategies are randomly chosen from an extended set of IPD strategies.

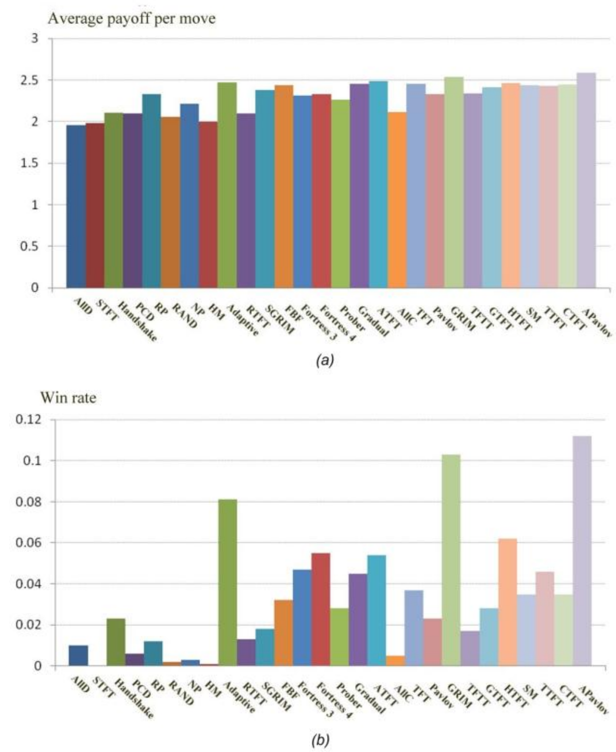


Fig. 5. The result of competitions with 2% noise. (*a*) Average payoffs per move. (*b*) Win rate in the competitions in which the strategy is involved.

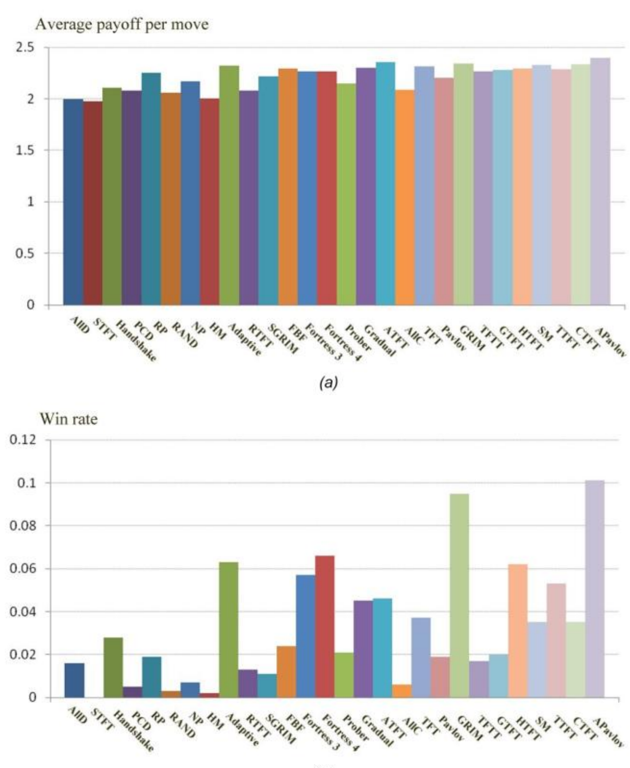
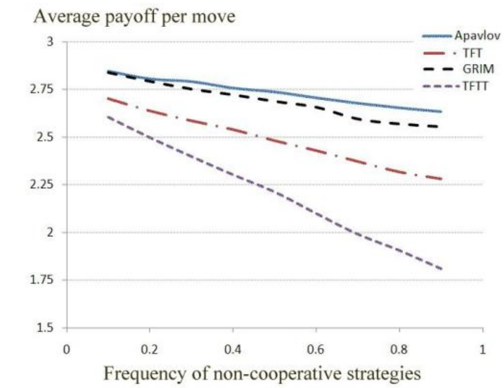
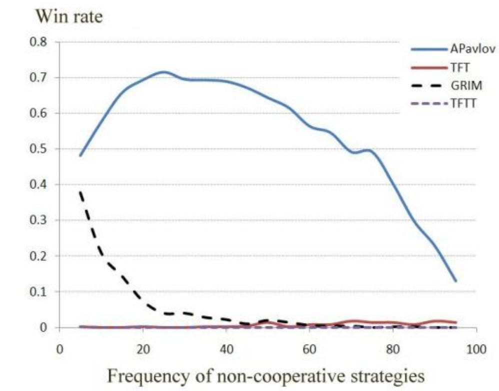


Fig. 6. The result of competitions with 10% noise. (*a*) Average payoffs per move. (*b*) Win rate of winning in the competitions in which the strategy is involved.

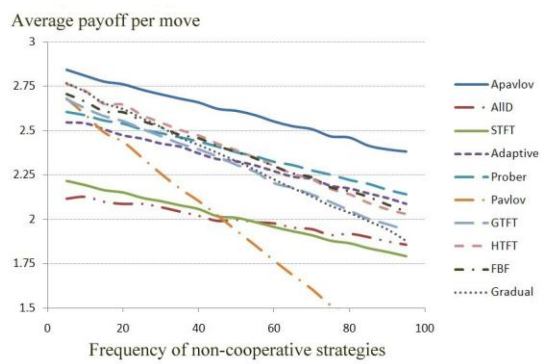


(a)



(b)

Fig. 7. APavlov outperforms TFT, GRIM and TFTT. There are totally 100 randomly chosen strategies in which the percentage of non-cooperative strategies is fixed. The competition is repeated 100,000 runs.



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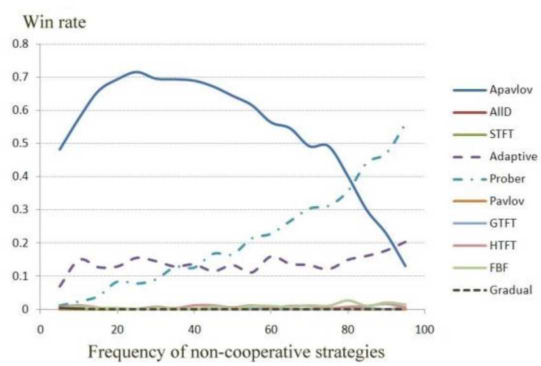
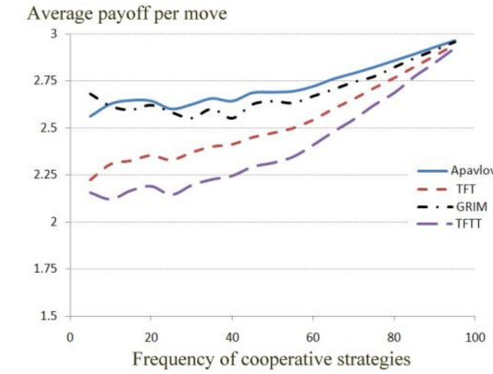


(b)

Fig. 8. APavlov outperforms Adaptive and other IPD strategies when the percentage of non-cooperative strategies is less than 80%.



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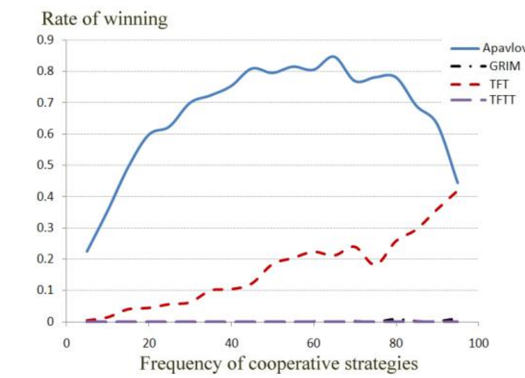
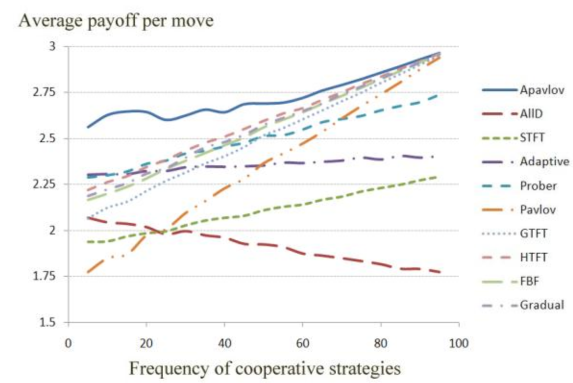


(b)

Fig. 9. APavlov outperforms TFT, GRIM and TFTT. There are totally 100 randomly chosen strategies in which the percentage of cooperative strategies is fixed. The competition is repeated 100,000 runs.



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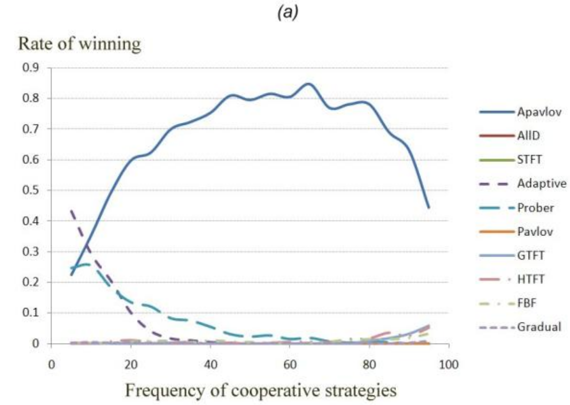

(b)

Fig. 10. APavlov outperforms Adaptive and other IPD strategies when the percentage of cooperative strategies is greater than 10%.

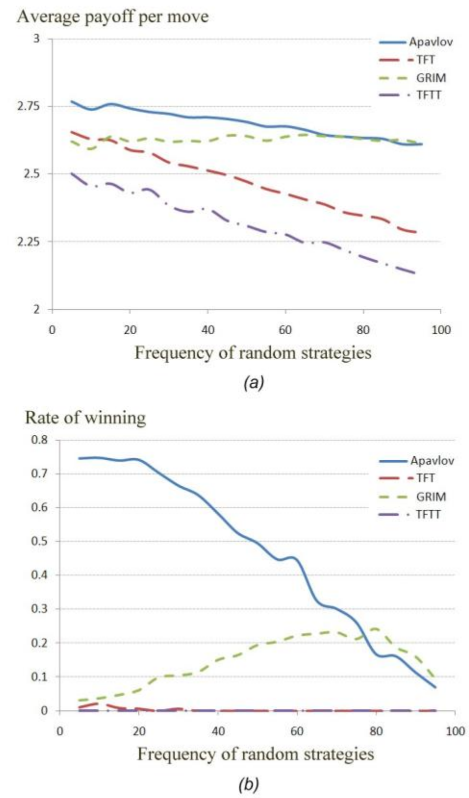

Fig. 11. APavlov outperforms TFT, GRIM and TFTT when the percentage of random strategies is less than 75%. There are in total 100 randomly chosen strategies in which the percentage of random strategies is fixed. The competition is repeated 100,000 runs.

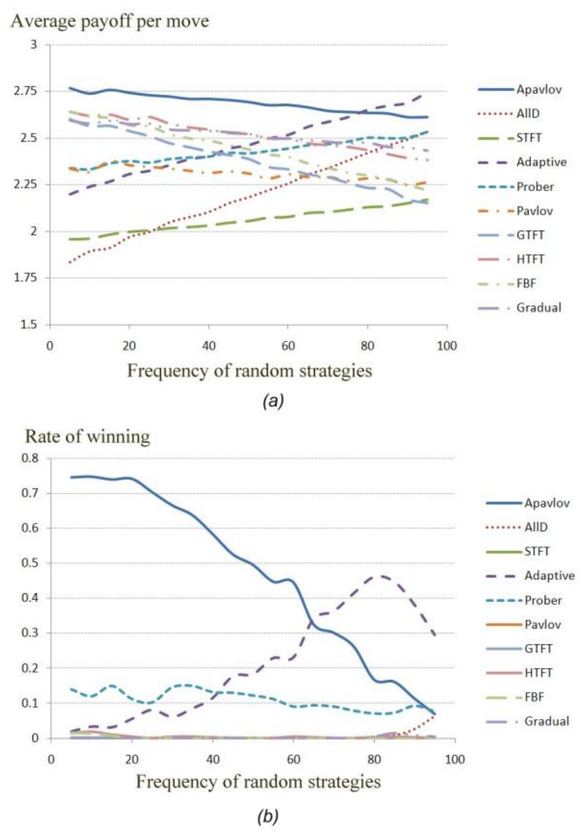

Fig. 12. APavlov outperforms Adaptive, Prober and other IPD strategies when the percentage of random strategies is less than 65%.

shows that APavlov performs well in IPD competitions with noise. As shown in Figures 5 and 6, APavlov receives the highest average payoff and highest win rate in both low noise and high noise environments.

d. Simulation 4.

In this simulation, the IPD strategies are divided into three groups: Cooperative, Non-cooperative and Random. The objective is to investigate the influence of the composition of the population. The cooperative group contains 15 strategies: AllC, TFT, Pavlov, GRIM, TFTT, CTFT, GTFT, HTFT, SM, TTFT, ATFT, SGRIM, FBF, Gradual, and APavlov. The Non-cooperative group contains ten strategies: AllD, STFT, Handshake, PCD, HM, Prober, RTFT, Adaptive, For3, and For4. The random group contains 11 strategies: NP, RP, Rand1, ··· Rand9 (these random strategies are mixed strategies with different cooperation rates). Each competition includes a population of 100 strategies. In the following competitions, the percentages of different types of strategies in the initial population are fixed. For example, 40% cooperative strategies means that there are exactly 40 cooperative strategies in the initial population and the other 60 strategies are non-cooperative and random. We first fix the percentage of non-cooperative strategies in the population and randomly choose the rest from the Cooperative and Random groups. Figures 7 and 8 show the results of these competitions with different percentages of non-cooperative strategies. APavlov outperforms other IPD strategies when the percentage of non-cooperative strategies is less than 80%. In competitions where there are more than 80% non-cooperative strategies, Prober and Adaptive have a higher chance of winning. However, APavlov still receives the highest average payoff per move in these situations, which shows that APavlov is competitive in a non-cooperative environment as well.

Figures 9 and 10 show the results of competitions with different percentages of cooperative strategies. APavlov outperforms other IPD strategies when the percentage of cooperative strategies is greater than 10%.

The results of competitions with different percentages of random strategies are shown in Figures 11 and 12. APavlov outperforms other IPD strategies when the percentage of random strategies is less than 65%. In the competitions where there are more than 65% random strategies, Adaptive is the best strategy that has the highest average payoff and highest probability of winning. GRIM outperforms APavlov in competitions with a high percentage (more than 75%) of random strategies since GRIM is the second best strategy when interacting with random strategies (the best strategy is AllD).

Different IPD strategies favour competitions with different compositions of the population. TFT performs well in competitions where there is a high percentage of cooperative strategies and a low percentage of random strategies. GRIM performs well in competitions where there is a low percentage of non-cooperative strategies and a high percentage of random strategies. Adaptive performs well in the competitions where there is a high percentage of non-cooperative strategies and a high percentage of random strategies. The reason why TFT performed well in past IPD competitions is that there were high percentages of cooperative strategies and low percentages of random strategies. As some cooperative strategies are more likely to win a competition than non-cooperative strategies and random strategies, it is natural that most players prefer adopting cooperative strategies.

APavlov outperforms well-known IPD strategies in most of the round-robin IPD competitions in which it is involved.

IV. Design of Winning Strategy for Evolutionary IPD Competitions

In an evolutionary IPD competition, a population of IPD playing agents compete with each other. The population consists of agents belonging to a number of distinct species. Each species adopts its own specific IPD strategy. The agents play IPD games with one another and produce offspring proportional to their fitness (average payoffs) received in game playing. The species with higher fitness, at each time step, reproduce and replace those with lower fitness.

A. *Competition between Well-known IPD Strategies*

An evolutionarily stable strategy (ESS) is a strategy which, if adopted by a population of players, cannot be invaded by any other strategy that is initially rare. Although no known IPD strategy is ESS [30], a population of group strategies can be in an evolutionarily stable state in some circumstances [31].

We ran a competition that includes all the strategies listed in Appendix A. The initial population contains 33 species and each species includes 20 identical IPD strategies. The discount rate of IPD is 0.98, which means that the average length of the IPD is 50 moves. The results are not affected by this setting since the performance of the strategies is measured by the average payoff per move. Stochastic universal sampling is used to select parents for the next generation. The parents simply copy their strategies to produce offspring and no mutation is carried out. The competition is run for 100 generations. As the outcome of any single competition is affected by chance, we repeat the competition 10 times, and gather statistics on the outcomes.

The result is shown in Figure 13 (for reasons of space, we only show seven strategies). The figure shows that cooperative strategies dominate non-cooperative strategies. Non-cooperative strategies go extinct quickly and then cooperative strategies reach some kind of dynamical equilibrium. It is not surprising that TFT performs well because it is favoured in environments where the population contains a high percentage of cooperative strategies, as we have demonstrated in the previous section.

In order to investigate the influence of the initial composition of the population, we ran a series of 10,000 competitions. In each competition, six strategies are randomly chosen from a set of IPD strategies that includes all strategies

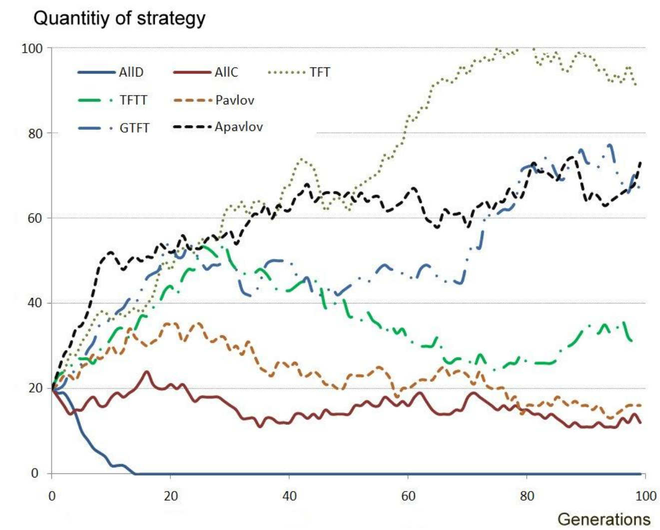

Fig. 13. Mean numbers of IPD strategies over 100 generations. The initial population contains 33 species and each species includes 20 identical IPD strategies.

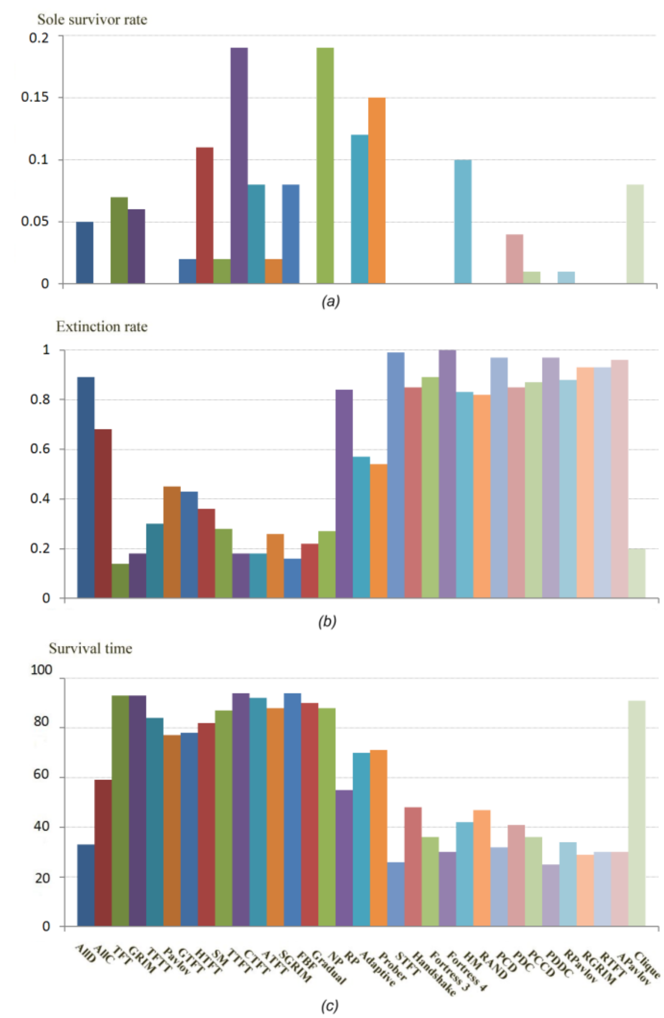

Fig. 14. IPD strategies compete in evolutionary dynamics. The initial population contains six types of randomly chosen strategies and each type has 20 copies. The competition is repeated 10,000 times.

listed in Appendix A and APavlov. Each strategy has 20 copies in the initial population.

The payoffs of the strategies vary in the process of evolution because the composition of the population changes. The average payoff of a strategy does not reflect its performance over generations. We use three measures to evaluate the performance of a strategy. If only one species survives for the whole period of evolution, it is called the *sole survivor*. A sole survivor is obviously the winner of an evolutionary IPD. The sole survivor rate is the ratio of the number of times a strategy becomes the sole survivor to the number of competitions it participates in, which denotes how frequently a strategy wins. The extinction rate denotes the frequency with which a strategy goes extinct. The survival time is the average length of survival in 100 generations.

The results of this simulation are shown in Figure 14. TTFT, Gradual and Adaptive have higher rates of sole survivor than other strategies. Although TFT, GRIM and APavlov have relatively long survival times and low extinction rates, they are average in terms of sole survivor rate. Thus, the winning strategies in round robin competitions do not necessarily have an advantage over others in evolutionary competitions.

B. *Group Strategies*

The motivation of studying group strategies is to develop efficient strategies that are suitable for evolutionary dynamics. We first show that a very simple group strategy can be strong in evolutionary IPD competitions.

Clique is a group strategy that cooperates only with other members of the Clique group [25]. Clique depends on 'tags' that denote heritable indicators of relatedness between kin members to identify the opponent. It attempts to give maximum assistance to clique members while decreasing the fitness of outsiders to a minimum. A similar definition to Clique is *evolution dominator*, which highlights the objective of the strategy [23].

Again, we run a series of competitions. In each competition, six strategies are randomly chosen from the set of IPD strategies that includes Clique, APavlov and all the strategies listed in Appendix A. Each species is assigned a distinct name by which an individual can recognize the members of its species. Each species will have 20 copies in the initial population. The result is shown in Figure 15. It shows that Clique has an obviously higher rate of sole survivor than other strategies. Clique wins about 38% of competitions it participates in.

It is easy to verify that Clique will be the sole survivor if its frequency in the population is ever greater than 50%. There are two types of strategies in the population, *A* (Clique) and *B* (all others). Let $\rho\,(1 \geq \rho \geq 0)$ denote the frequency of *A* in the population, and $1-\rho$ the frequency of *B*. Let *n* be the number of rounds in a game of IPD, and let $E(x, y)$ be the average score of a type x strategy against a type y strategy. The

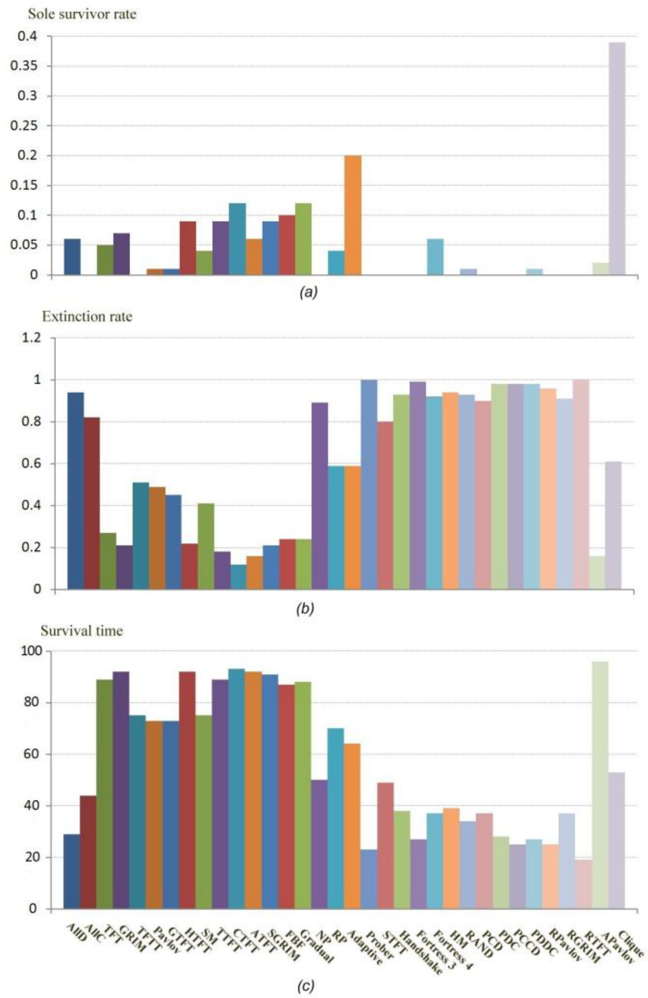

Fig. 15. Clique has higher rate of sole survivor than non-group IPD strategies. The initial population contains six types of randomly chosen strategies and each type has 20 copies. The competition is repeated 10,000 times.

average fitness of *A* and *B*, E_A and E_B, can be expressed by,

$$E_A = \rho E(A, A) + (1-\rho)E(A, B) \tag{2}$$

$$E_B = \rho E(B, A) + (1-\rho)E(B, B) \tag{3}$$

Because *A* will always cooperate with *A* and defect against *B*, we have $E(A, A) = nR$, $E(A, B) \geq nP$, $E(B, A) \leq nP$, and $E(B, B) \leq nR$ for any *B*. Thus, we have,

$$E_A - E_B \geq (2\rho - 1)n(R - P) \tag{4}$$

Thus, $E_A > E_B$ always holds if ρ>1/2 and we have $E_A = E_B$ only if *B* is also a Clique strategy. This is the reason why Clique has a high sole survivor rate.

The weakness of Clique lies in its inability to obtain a good reward from cooperative strategies that retaliate. This leads to the high extinction rate (60%) and relatively short survival time (about 52, which means that Clique survives on average 52 generations in 100 generations).

Clique needs tags to recognize kin members. It cannot work in an environment where there is no tag. Strategies such as APavlov have identification mechanisms that can also be used to recognize kin members. We introduce a strategy called APavlov-Clique that combines APavlov and Clique in order to retain the advantage of both strategies.

The APavlov-Clique strategy shifts between APavlov and Clique. It adopts the APavlov strategy if its frequency in the population is less than 50%. Otherwise, it adopts the Clique strategy. Its frequency in the population is estimated by computing the frequency of encountering kin members in each generation. APavlov-Clique does not require extra information to evaluate the frequency of kin members. Because APavlov-Clique identifies opponents using an identification mechanism, it is easy to extract the frequency information from the results of identification. Furthermore, this strategy has a memory that stores the moves of (15) recently identified strategies, so that the process of identification can be saved for the next time an identified strategy is encountered.

APavlov-Clique performs well in evolutionary IPD competitions. We run a series of competitions with similar settings to the above competitions. Six strategies are randomly chosen from the set of IPD strategies that includes APavlov-Clique, Clique, APavlov and all strategies listed in Appendix

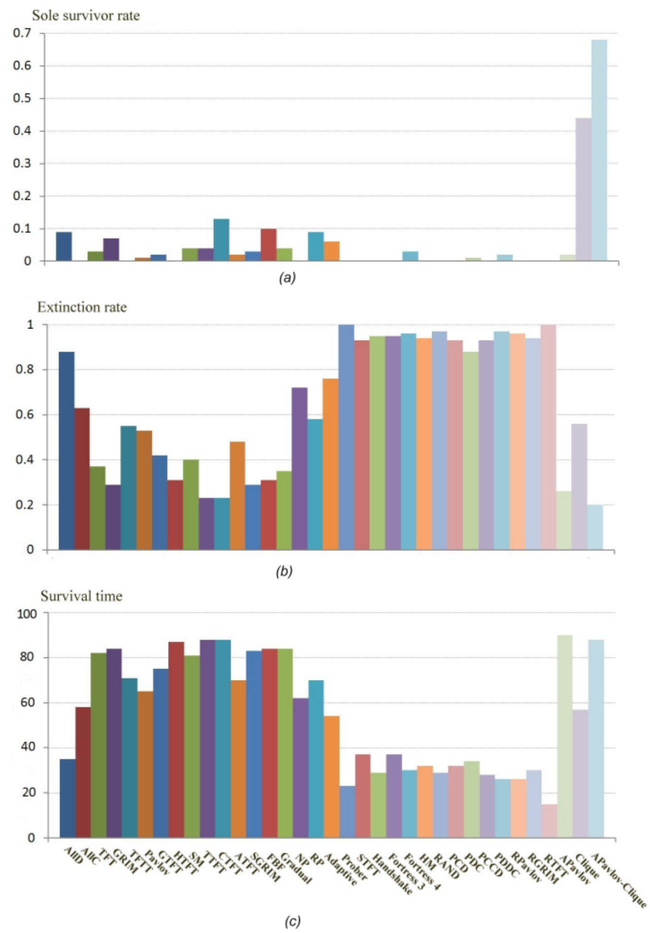

Fig. 16. APavlov-Clique has higher rate of sole survivor and lower rate of extinction than others. The initial population contains six types of randomly chosen strategies and each type has 20 copies. The competition is repeated 10,000 times.

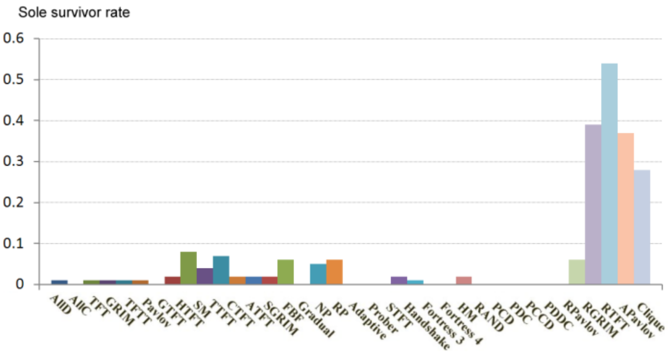

Fig. 17. Group strategies dominate non-group strategies in evolutionary IPD. The initial population contains six types of randomly chosen strategies and each type has 20 copies. The competition is repeated 10,000 times.

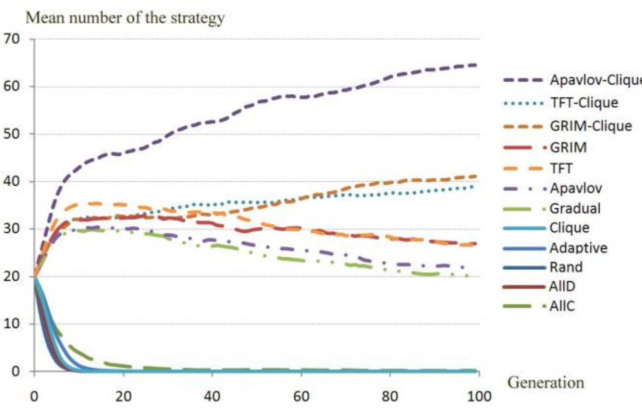

Fig. 18. Mean numbers of IPD strategies over 1,000 competitions. The initial population contains 12 species (4 group strategies and 8 non-group strategies) and each species has 20 members.

A. As shown in Figure 16, APavlov-Clique has a significantly higher sole survivor rate than the others. It wins about 68% of the competitions and goes extinct in about 20% competitions in which it is involved.

When there are group strategies in the population, they dominate non-group strategies. We run a series of 10,000 competitions in which the initial population contains six randomly chosen strategies. Four group strategies are included in the set of IPD strategies: Clique, APavlov-Clique, TFT-Clique and GRIM-Clique. TFT-Clique adopts TFT if its frequency in the population is less than 50%. Otherwise, it adopts the Clique strategy. Similarly, GRIM-Clique adopts GRIM if its frequency in the population is less than 50 percent. Otherwise, it adopts the Clique strategy. As shown in Figure 17, group strategies have significantly higher rates of sole survivor than non-group strategies.

APavlov-Clique, TFT-Clique and GRIM-Clique are superior to Clique because they receive higher fitness in the early stages of evolution by cooperating with the strategies of other species. Clique frequently goes extinct if the number of unconditional cooperators in the initial population is small. In a typical competition in which all the four group strategies are involved, Clique is expelled as well as those non-cooperative strategies (as shown in Figure 18). This also shows that group strategies outperform cooperative strategies. Group strategies coexist with cooperative strategies if the size of their group is small. Once a group grows large enough, it expels other groups and finally becomes the sole survivor. Thus, group strategies have a higher rate of winning than any singleton IPD strategy.

V. Conclusion and Future Work

We have introduced a statistical evaluation approach to analyze strategies for both round-robin and evolutionary IPD competitions, which takes into account outcomes of a large quantity of IPD competitions with varying compositions. Using our approach, we have shown that APavlov, a strategy with a simple identification mechanism to explore and exploit the opponent, outperforms well-known IPD strategies in most round-robin competitions and group strategies outperform well-known IPD strategies in evolutionary competitions. Thus, the winning strategy for IPD competitions should have the ability to classify and identify the opponent and then to adopt the optimal action.

We have studied several simple group strategies. It may be worth developing more complex group strategies since APavlov-Clique is obviously not optimal for evolutionary IPD. For example, it is not necessary that APavlov-Clique should shift to Clique only after its frequency is greater than 50% in the population. More than 50% is a sufficient but not a necessary condition for APavlov-Clique to win. Some representation schemes, for example binary string and fingerprinting [23, 32], could be used, together with the proposed approach, in order to take into consideration more IPD strategies. Also, the diversity of the initial population in evolutionary IPD could have an influence on the performance of group strategies. These topics will be the focus of our future research.

Appendix A

The main IPD strategies used in this article are listed here. We also give the literature citations for the initial introduction of some of the strategies.

1) **Adaptive**: Starts with C,C,C,C,C,C,D,D,D,D,D and then takes choices which have given the best average score re-calculated after every move.

2) **Adaptive Tit For Tat** (**ATFT**): An adaption rate *r* is computed by means of history moves of the opponent and the behavior of the opponent, whether cooperative or defecting, is estimated according to *r*. If the opponent is cooperative, it cooperates. Otherwise, it defects. [17]

3) **Always Cooperate** (**AllC**): Cooperates on every move.

4) **Always Defect** (**AllD**): Defects on every move.

5) **Contrite TFT** (**CTFT**): Same as TFT when no noise. In a noisy environment, once it receives *T* because of error, it will choose cooperate twice in order recover mutual cooperation. [34]

6) **Firm But Fair** (**FBF**): Cooperates on the first move, and cooperates except after receiving a sucker payoff. [38]

7) **Fortress3** (**For3**): Like Handshake, it tries to recognize kin member by playing D,D,C. If the opponent plays the same sequence of D,D,C, it cooperates until the opponent defects. Otherwise, it defects until the opponent defects on continuous two moves, and then it cooperates on the following move. [37]

8) **Fortress4** (**For4**): Same as Fortress3 except that it plays D,D,D,C in recognizing kin members. If the opponent plays the same sequence of D,D,D,C, it cooperates until the opponent defects. Otherwise, it defects until the opponent defects on continuous three moves, and then it cooperates on the following move. [37]

9) **Generous TFT** (**GTFT**): Same as TFT, except that it cooperates with a probability *q* when the opponent defects. [35]

10) **Gradual**: Cooperates on the first move, and cooperates as long as the opponent cooperates. After the first defection of the other player, it defects one time and cooperates two times; ... After the *n*th defection it reacts with *n* consecutive defections and then calms down its opponent with two cooperations. [14]

11) **Grudger** (**GRIM**): Cooperates, until the opponent defects, and thereafter always defects.

12) **Handshake**: Defects on the first move and cooperates on the second move. If the opponent behaves the same as Handshake does, it always cooperates. Otherwise, it always defects. [36]

13) **Hard Majority** (**HM**): Defects on the first move, and defects if the number of defections of the opponent is greater than or equal to the number of times it has cooperated, else cooperates. [40]

14) **Hard Tit for Tat** (**HTFT**): Cooperates on the first move, and defects if the opponent has defects on any of the previous three moves, else cooperates.

15) **Naive Prober** (**NP**): Like Tit for Tat, but occasionally defects with a small probability.

16) **Pavlov**: Cooperates on the first move. If a reward or temptation payoff is received in the last round then repeats last choice, otherwise chooses the opposite choice. [41]

17) **Periodic player CCD** (**PCCD**): Plays C, C, D periodically.

18) **Periodic player CD** (**PCD**): Plays C, D periodically.

19) **Periodic player DC** (**PDC**): Plays D, C periodically.

20) **Periodic player DDC** (**PDDC**): Plays D, D, C periodically.

21) **Prober**: Starts with D,C,C and then defects if the opponent has cooperated in the second and third move; otherwise, it plays TFT.

22) **Random Player** (**RAND**): Makes a random move.

23) **Remorseful Prober** (**RP**): Like Naive Prober, but it tries to break the series of mutual defections after defecting.

24) **Reverse Grudger** (**RGRIM**): Defects on the first move, then defects until the opponent cooperates, and thereafter always cooperates.

25) **Reverse Pavlov** (**RPavlov**): It does the reverse of Pavlov. It defects on the first move, then only repeats last choice if a punishment or sucker payoff is scored.

26) **Reverse Tit for Tat** (**RTFT**): It does the reverse of TFT. It defects on the first move, then mimics the opponent's last move in reverse.

27) **Soft Grudger** (**SGRIM**): Like GRIM except that the opponent is punished with D,D,D,D,C,C.

28) **Soft Majority** (**SM**): Cooperates on the first move, and cooperates as long as the number of times the opponent has cooperated is greater than or equal to the number of times it has defected, else it defects. [40]

29) **Suspicious Tit for Tat** (**STFT**): Same as TFT, except that it defects on the first move. [39]

30) **Tit for Tat** (**TFT**): Cooperates on the first move, then copies the opponent's last move. [33]

31) **Tit for Two Tats** (**TFTT**): Cooperates on the first move, and defects only when the opponent defects two times.

32) **Two Tits for Tat** (**TTFT**): Same as Tit for Tat except that it defects twice when the opponent defects.

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Prof. Kendall is a Member of the Automated Scheduling, Optimization, and Planning Research Group. He is a Fellow of the Operational Research Society. He is an Associate Editor of seven international journals, including two IEEE journals: IEEE Transactions on Evolutionary Computation and IEEE Transactions on Computational Intelligence and Artificial Intelligence in Games. He chaired the Multidisciplinary International Conference on Scheduling: Theory and Applications in 2003, 2005, 2007, 2009, 20111 and has chaired several other international conferences, which has included establishing the IEEE Symposium on Computational Intelligence and Games. He chaired this symposium in 2005 and 2006. He has been a Member of the program (or refereeing) committees of over 160 international conferences over the last few years. He has been awarded externally funded grants worth over £6 million from a variety of sources including Engineering and Physical Sciences Research Council (EPSRC) and commercial organizations. He is a Director of three companies (EventMAP Ltd., Nottingham, U.K.; Aptia Solutions Ltd., Nottingham, U.K. and Nottingham MyRIAD Solutions Sdn Bhd, Malaysia).