An Empirical Study of Invasion and Resistance for Iterated Prisoner's Dilemma Strategies

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Abstract

The Iterated Prisoner's Dilemma is a well established framework for the study of emergent behaviour. In this paper an extensive numerical study of the evolutionary dynamics of this framework are presented. Fixation probabilities for Moran processes are obtained for 164 different strategies. We find that players with long memories and sophisticated behaviours outperform many strategies that perform well in a two player setting.

1 Introduction

The Prisoner's Dilemma (PD) [6] is a fundamental two player game used to model a large variety of strategic interactions. Each player can choose between cooperation (C) or defection (D). The decisions are made simultaneously and independently. The payoffs of the game are defined by the matrix $\begin{pmatrix} R & S \\ T & P \end{pmatrix}$, where $T > R > P > S$ and $2R > T + S$. The PD is a one round game, but is commonly studied in a manner where the prior outcomes matter. This extended form is called the Iterated Prisoner's Dilemma (IPD).

The Moran Process [15] is a model of evolutionary population dynamics that has been used to gain insights about the evolutionary stability and fixation of strategies in a number of settings. Similarly since the first Iterated Prisoner's Dilemma (IPD) tournament described in [4], the Prisoner's dilemma has been used to understand the evolution of cooperative behaviour in complex systems. Several earlier works have studied iterated games in the context of the prisoner's dilemma [16, 21].

This manuscript provides a detailed numerical analysis of **164** complex and adaptive strategies for the IPD. This is made possible by the Axelrod library [22], an effort to provide software for reproducible research for the IPD. The library now contains over 150 parameterized strategies including classics like TitForTat and WinStayLoseShift, as well as recent variants such as OmegaTFT, zero determinant and other memory one strategies, strategies based on finite state machines, lookup tables, neural networks, and other machine learning based strategies, and a collection of novel strategies. The library can conduct matches, tournaments and population dynamics with variations including noise and spatial structure.

We present fixation probabilities for all pairs of strategies in the library, identifying those are effective invaders and those resistant to invasion, for population sizes $N = 2$ to $N = 14$.

In particular we address the following questions:

1. What strategies are good invaders?
2. What strategies are good at resisting invasion?
3. How does the population size affect these findings?

While our results agree with some of the published literature, we find that:

1. Zero determinant strategies are not particularly effective for $N > 2$
2. Long memory strategies are generally more effective than short memory strategies
3. Complex strategies can be effective

1.1 The Moran Process

Figure 1 shows a diagrammatic representation of the Moran process, a stochastic birth death process on a finite population in which the population size stays constant over time. Individuals are **selected** according to a given fitness landscape. Once selected, the individual is reproduced and similarly another individual is chosen to be removed from the population.

In some settings mutation is also considered but without mutation (the case considered in this work) this process will arrive at an absorbing state where the population is entirely made up of players of one strategy. The probability with which a given strategy is the survivor is called the fixation probability. A more detailed analytic description of this is given in Section 3.

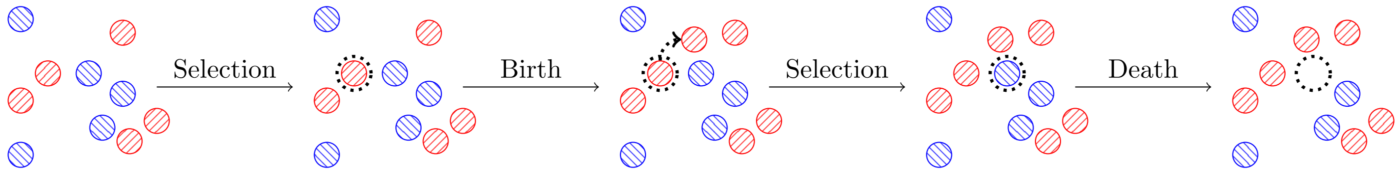


Figure 1: A diagrammatic representation of a Moran process

The Moran process was initially introduced in [15]. It has since been used in a variety of settings including the understanding of the spread of cooperative and non-cooperative behaviour such as cancer [24] and the emergence of cooperative behaviour in spatial topologies [2]. However these works mainly consider non-sophisticated strategies. Some work has looked at evolutionary stability of strategies within the Prisoner's Dilemma [12] but this is not done in the more widely-used setting of the Moran process, rather in terms of infinite population stability. In [5] Moran processes are studied in a theoretical framework for a small subset of strategies. The subset included memory one strategies, strategies that recall the events of the previous round only.

Of particular interest are the zero determinant strategies introduced in [17] and highly-praised [21] it was argued that generous ZD strategies are robust against invading strategies. However, in [10] a strategy using machine learning techniques was capable of resisting invasion and also able to invade any memory one strategy. Recent work [7] has investigated the effect of memory length on strategy performance and the emergence of cooperation but this is not done in Moran process context and only considers specific cases of memory 2 strategies. In [1] it was recognized that many zero determinant strategies do not fare well against themselves. This is a disadvantage for the Moran process where the best strategies cooperate well with other players using the same strategy.

The contribution of this work is a detailed and extensive analysis of absorption probabilities for 164 strategies. These strategies and the numerical simulations are from [22] which is an open source research library written for the study of the IPD. The strategies and simulation frameworks are automatically tested to an extraordinarily high degree of coverage in accordance with best research software practices. The large number of strategies are available thanks to the open source nature of the project with over 40 contributions made by different programmers and researchers.

Section 2 will explain the methodological approach used, Section 3 will validate the methodology by comparing simulated results to analytical results in some cases. The main results of this manuscript are presented in Section 4 which will present a detailed analysis of all the data generated. Finally, Section 5 will conclude and offer future avenues for the work presented here.

2 Methodology

To carry out this large numerical experiment, 164 strategies are used from the axelrod library: [22].

The axelrod library contains many machine learning based strategies trained with reinforcement learning algorithms. This work includes three additional strategies trained specifically to excel at the Moran process. Appendix A shows all the players in question. More information about each player can be obtained in the documentation for [22]. There are 43 stochastic and 121 deterministic strategies. Their memory depth, defined by the number of rounds of history used by the strategy each round, is shown in Table 1. The memory depth is infinite if the strategy uses the entire history of play (whatever its length). For example, a strategy that utilizes a handshaking mechanism where the opponents actions on the first few rounds of play determines the strategies subsequent behavior would have infinite memory depth.

All of the strategies are trained with an evolutionary algorithm that perturbs strategy parameters and optimizes an objective function, such as the mean total score against all other opponents or the mean fixation probability over a large number of Moran processes. The objective functions can include standard variations such as noisy matches, varying the number of rounds of play, and the other typical parameters used for the IPD. Variation is introduced via mutation and crossover of parameters, and the best performing strategies are carried to the next generation along with new variants. Similar methods appear in the literature [3].

All of our training code is available in the Axelrod repository with documentation to train new strategies easily. Training typically takes less than 200 iterations and can be completed within several hours on commodity hardware. The three strategies trained specifically for this study are Trained FSM 1, 2, and 3 (TF1 - TF3), based on finite state machines of 8, 16, and 16 states respectively (see Figures ??). These strategies were trained with the objective function of mean fixation probabilities for Moran processes starting at initial population states consisting of $N/2$ individuals of the training candidates and $N/2$ individuals of an opponent strategy, for all of the short run time strategies in the library (approximately 150 opponents at the time of training):

- TF1 $N = 8$, 1% noise, 100 repetitions per match
- TF2 $N = 10$, 0% noise, 10000 repetitions per match
- TF3 $N = 12$, 0% noise, 10000 repetitions per match

Each matchup of players was run to fixation for the specified number of repetitions to estimate the absorption probabilities. The trained algorithms were run for less than 50 generations.

TF1 cooperates and defects with various cycles depending on the opponent's actions. TF1 will mutually cooperate with any strategy and only tolerates a few defections before defecting for the rest of match. It is similar to but not exactly the same as Fool Me Once, a strategy that cooperates until the opponent has defected twice (not necessarily consecutively), and defects indefinitely thereafter. Though a product of training with a Moran objective, it was selected for inclusion because of the lack of an apparent handshake.

TF2 always starts with CD and will defect against opponents that start with DD. It plays CDD against itself and then cooperates thereafter. There is a longer complex handshake which eventually results in mutual cooperation with Firm but Fair, Fortress3, Fortress4, and Grofman (always) and Evolved HMM 5 and GTFT (depending on the random seed).

TF3 has an initial handshake of CCD and cooperates if the opponent matches. However if the opponent later defects, TF3 will respond in kind, so the handshake is not permanent. Only one player (Prober 4 [13]) manages to achieve cooperation with TF3 after about 20 rounds of play.

For both TF2 and TF3 a handshake mechanism naturally emerges from the structure of the underlying finite state machine. This behavior is an outcome of the evolutionary process and is in no way hard-coded or included via an additional mechanism. Some of the existing strategies in the library were trained on earlier versions of the library (smaller total opponents used in training) based on neural networks, lookup tables and stochastic variants trained with a particle swarm algorithm, finite state machines and a stochastic variant mimicking hidden Markov models, and neural networks. These strategies were trained to win IPD tournaments using an objective function that computes the mean match payoffs against a collection of opponents. Detailed descriptions and the performance of these strategies in IPD tournaments will be described in another manuscript.

Memory Depth	0	1	2	3	4	5	6	9	10	11	12	16	20	40	200	∞
Count	3	28	12	8	2	6	1	1	5	1	1	3	2	2	1	88

Table 1: Memory depth

Each strategy pair is run for 1000 runs of the Moran process to fixation with starting population distributions of $(1, N-1)$, $(N/2, N/2)$ and $(N-1, 1)$, for N from 2 through 14. The fixation probability is then empirically computed for each combination of starting distribution and value of N.

Our software can carry out exact simulations of the Moran process. Since some of the strategies have a high computational cost or are stochastic, we sample from a large number of match outcomes for the pairs of players for use in computing fitnesses in the Moran process. This approach was verified to agree with unsampled calculations to a high degree of accuracy in specific cases.

Figure 2 shows the distribution of the number of outcomes between all strategy pairs.

Section 3 will validate the methodology used here against known theoretic results.

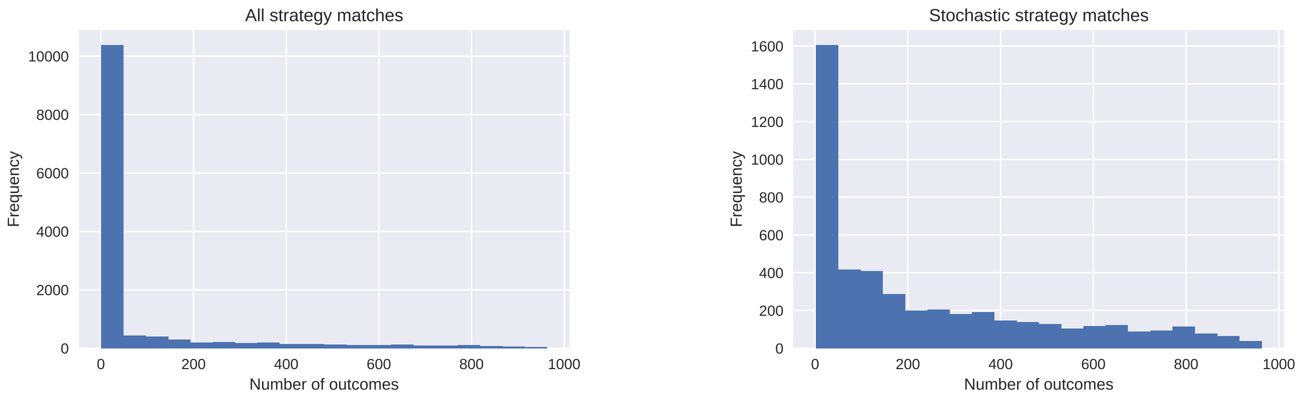
3 Validation

As described in [16] consider the payoff matrix:

$$M = \begin{pmatrix} a, b \\ c, d \end{pmatrix} \tag{1}$$

The expected payoffs of i players of the first type in a population with $N - i$ players of the second type are given by:

$$F_i = \frac{a(i-1) + b(N-i)}{N-1} \tag{2}$$



(a) All matches

(b) Stochastic matches

Figure 2: The distribution of the number of unique outcomes used as the cached results

$$G_i = \frac{ci + d(N - i - 1)}{N - 1} \tag{3}$$

With an intensity of selection ω the fitness of both strategies is given by:

$$f_i = 1 - \omega + \omega F_i \tag{4}$$

$$g_i = 1 - \omega + \omega G_i \tag{5}$$

The transitions within the birth death process that underpins the Moran process are then given by:

$$p_{i,i+1} = \frac{if_i}{if_i + (N - i)g_i} \frac{N - i}{N} \tag{6}$$

$$p_{i,i-1} = \frac{(N - i)g_i}{if_i + (N - i)g_i} \frac{i}{N} \tag{7}$$

$$p_{ii} = 1 - p_{i,i+1} - p_{i,i-1} \tag{8}$$

Using this it is a known result that the fixation probability of the first strategy in a population of i individuals of the first type (and $N - i$ individuals of the second. We have:

$$x_i = \frac{1 + \sum_{j=1}^{i-1} \prod_{k=1}^{j} \gamma_j}{1 + \sum_{j=1}^{N-1} \prod_{k=1}^{j} \gamma_j} \tag{9}$$

where:

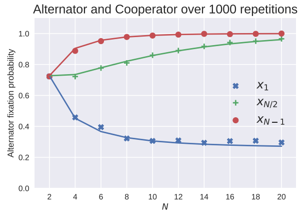
$$\gamma_j = \frac{p_{j,j-1}}{p_{j,j+1}}$$

A neutral strategy will have fixation probability $x_i = i/N$. Alternatively, we can frame the outcomes in terms of relative fitness. For a strategy of relative fitness r the fixation probability is well-known to be

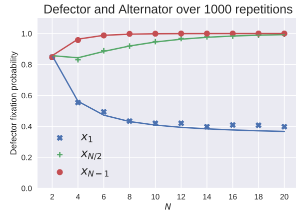
$$x_i = \frac{1 - r^{-i}}{1 - r^{-N}}$$

We can use this formula to compute a value r_i that produces the observed value x_i, noting that for arbitrary strategies the value of this effective relative fitness is dependent on i and N.

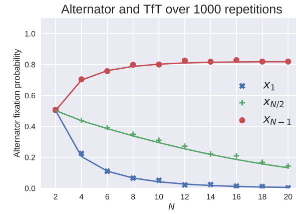
Comparisons of $x_1, x_{N/2}, x_{N-1}$ are shown in Figure 3. The points represent the simulated values and the line shows the theoretical value. Note that these are all deterministic strategies and show a perfect match up between the expected value of (9) and the actual Moran process for all strategies pairs.



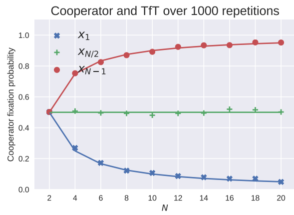
(a) Alternator and Cooperator



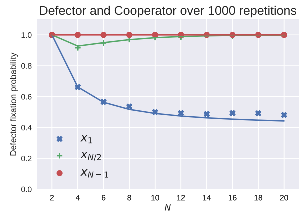
(b) Defector and Alternator



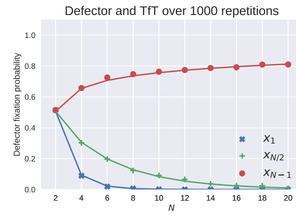
(c) Alternator and Tit For Tat



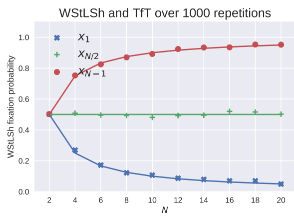
(d) Cooperator and Tit For Tat



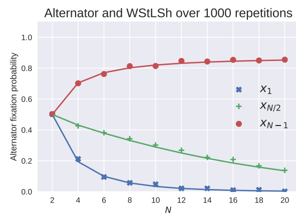
(e) Defector and Cooperator



(f) Defector and Tit For Tat



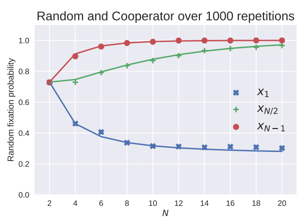
(g) Win Stay Lose Shift and Tit For Tat



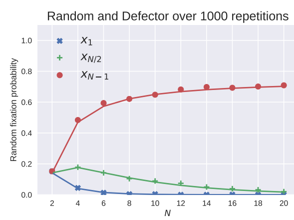
(h) Alternator and Win Stay Lose Shift

(i) Defector and Win Stay Lose Shift

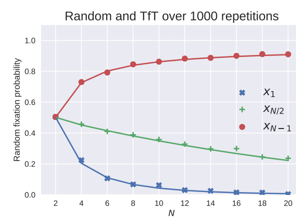
Figure 3: Comparison of theoretic and actual Moran Process fixation probabilities for **deterministic** strategies



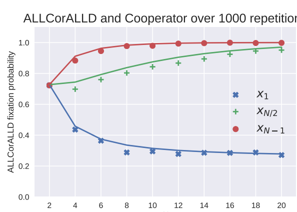
(a) Random and Cooperator



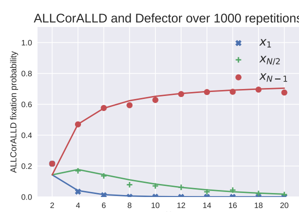
(b) Random and Defector



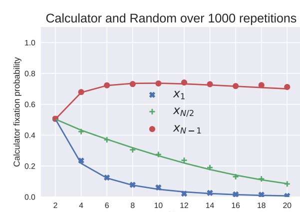
(c) Random and Tit For Tat



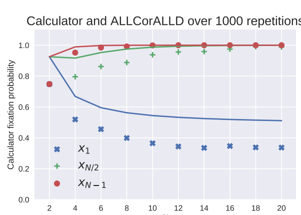
(d) All C or all D and Cooperator



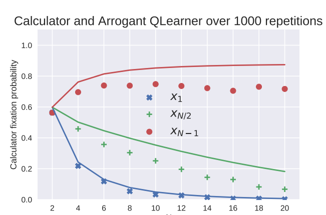
(e) All C or all D and Defector



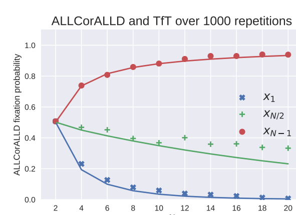
(f) Calculator and Random



(g) Calculator and All C or all D



(h) Calculator and Arrogant Q learner



(i) All C or all D and Tit For Tat

Figure 4: Comparison of theoretic and actual Moran Process fixation probabilities for **stochastic** strategies

Figure 4 shows the fixation probabilities for stochastic strategies. These are no longer a good match which highlights the weakness of the analytical formulae that relies on the average payoffs. A detailed analysis of the 164 strategies considered, using direct Moran processes will be shown in the next Section.

4 Empirical results

This section outlines the data analysis carried out:

- Section 4.1 considers the specific case of $N = 2$.
- Section 4.2 investigates the effect of population size on the ability of a strategy to invade another population. This will highlight how complex strategies with long memories outperform simpler strategies.
- Section 4.3 similarly investigates the ability to defend against an invasion.
- Section 4.4 investigates the relationship between performance for differing population sizes.

4.1 The special case of $N = 2$

When $N = 2$ the Moran process is effectively a measure of the relative mean payoffs over all possible matches between two players. The strategy that scores higher than the other more often will fixate more often.

Overall the main fixation probabilities of interest are x_1 and x_{N-1}, these reflect a strategy's ability to invade or resist invasion; for $N = 2$ these two cases coincide. Figure 5 shows all fixation probabilities for the strategies considered. This is summarised in Table 2.

1. The top strategy is the Collective Strategy (CS) which has a simple handshake mechanism (a cooperation followed by a defection on the first move). As long as the opponent plays the same handshake and does not defect in the future it cooperates. Otherwise it defects for all rounds [11]. This strategy was specifically designed for evolutionary processes.
2. The Defector: it always defects. As it has little potential interaction with itself, recall that $N = 2$ is considered, its aggressiveness is rewarded.
3. The Aggravater strategy which plays like Grudger (responding to any defections with unconditional defections throughout) however starts by playing 3 defections.
4. Predator, a finite state machine described in [3].
5. Handshake: a slightly less aggressive version of the Collective strategy [19]. As long as the initial sequence is played then it cooperates. Thus it will do well in a population consisting of many members of itself: just as the Collective strategy does. However it is not aggressive enough to invade other populations.

Player	Mean p_1	Memory Depth	Stochastic
CS	0.665141	∞	False
Defector	0.649638	0	False
Aggravater	0.632773	∞	False
Predator	0.630129	9	False
Handshake	0.623982	∞	False

Table 2: Summary of top five strategies for $N = 2$

As will be demonstrated in Section 4.4 the results for $N = 2$ differ from those of larger N. Hence our results do not concur with the literature which suggests that Zero Determinant strategies should be effective for larger population sizes, but we note that those analysis run each match to stationarity, while our matches run for a fixed number of rounds.

In the next sections we pay close attention to strategies who are strong invaders/resistors.

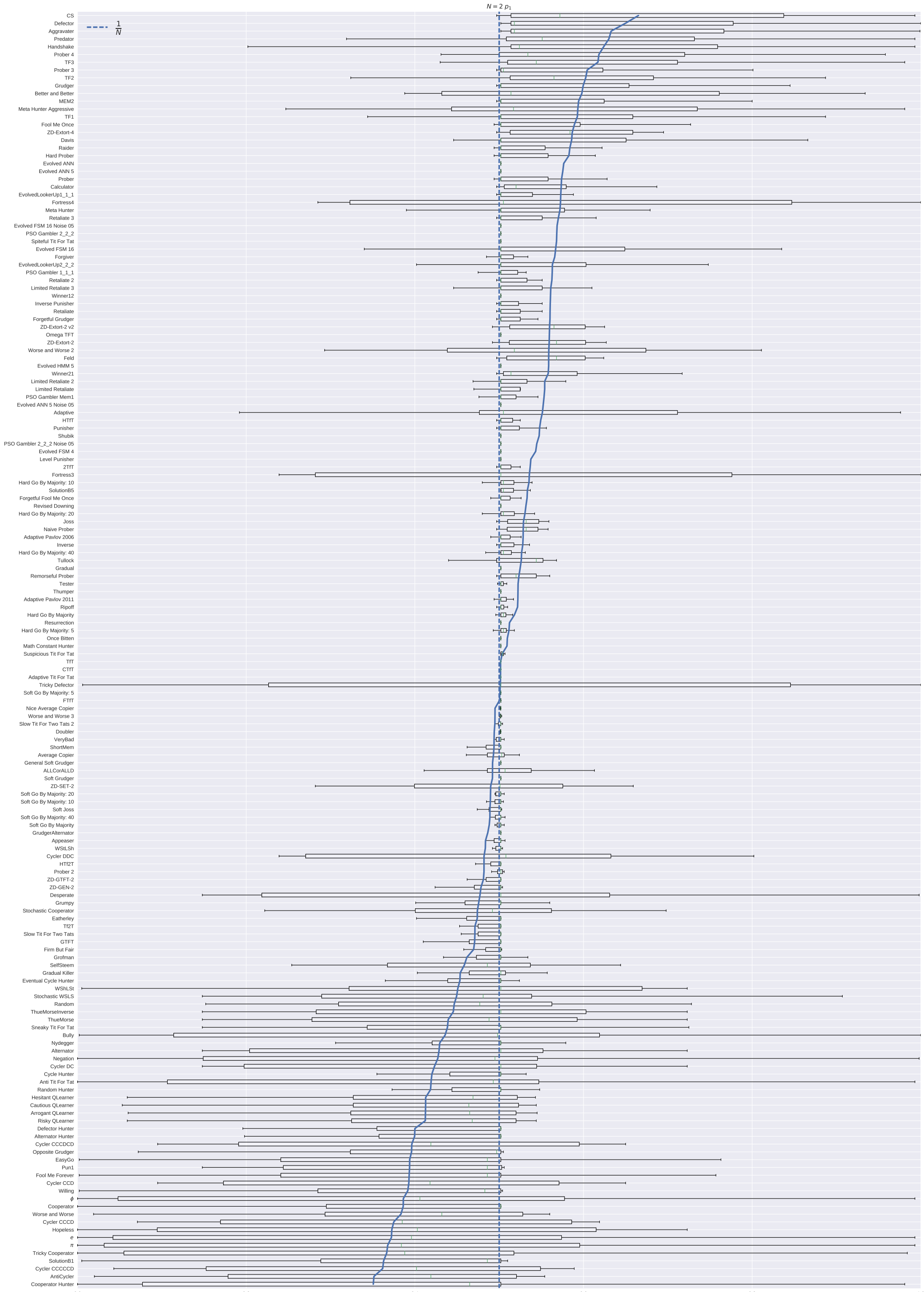


Figure 5: The fixation probabilities for $N = 2$

4.2 Strong invaders

In this section we focus on the ability of a mutant strategy to invade: the probability of 1 individual of a given type successfully becoming fixated in a population of $N-1$ other individuals, denoted by x_i. The fixation probabilities are shown in Figures 6, 7 and 8 for $N \in \{3, 7, 14\}$ showing the mean fixation as well as the neutral fixation for each given scenario.

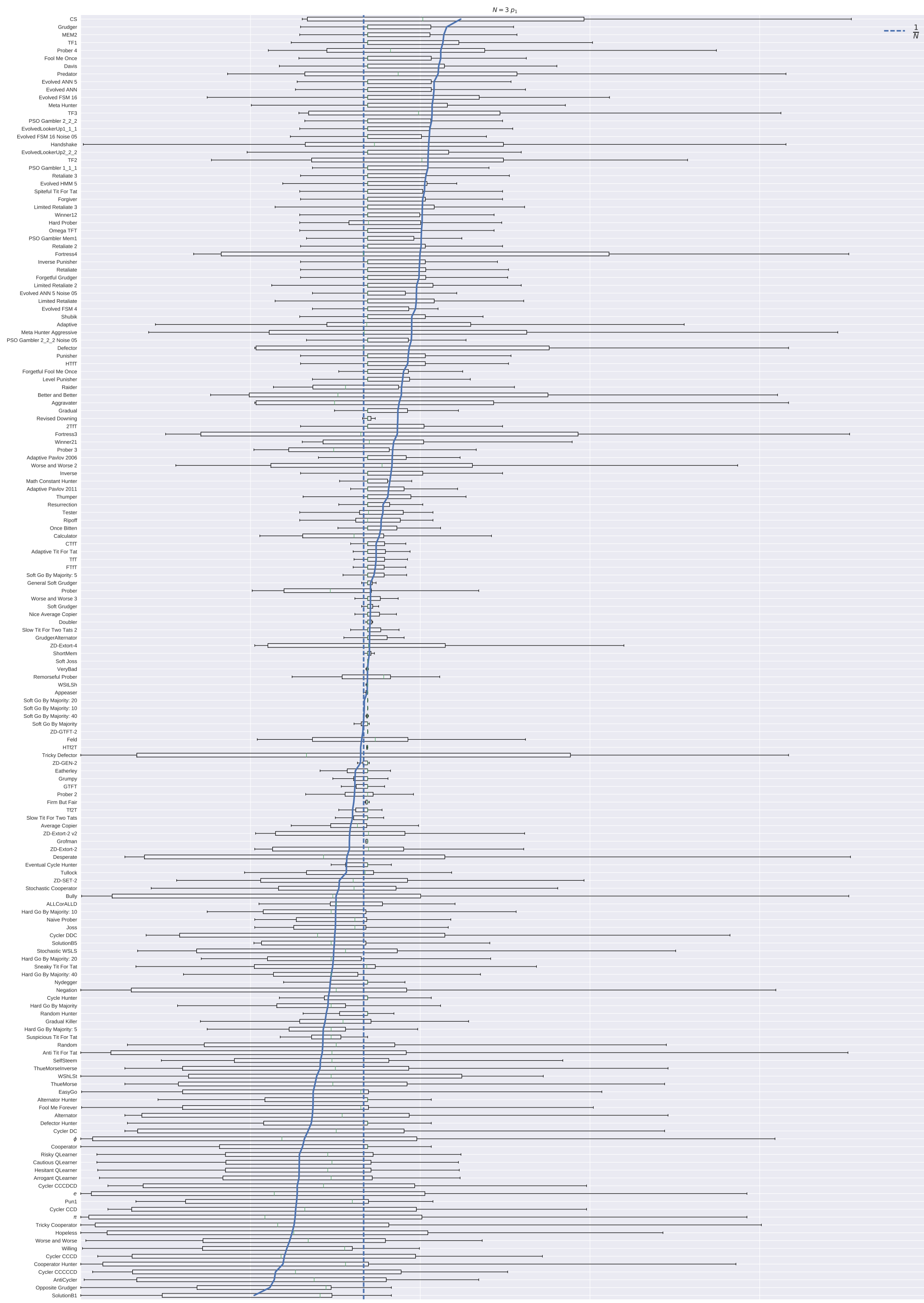


Figure 6: The fixation probability x_1 for $N = 3$

The top five strategies are given in Tables 3.

It can be seen that apart from CS, none of the strategies of Table 2 perform well for $N \in \{3, 7, 14\}$. The new high

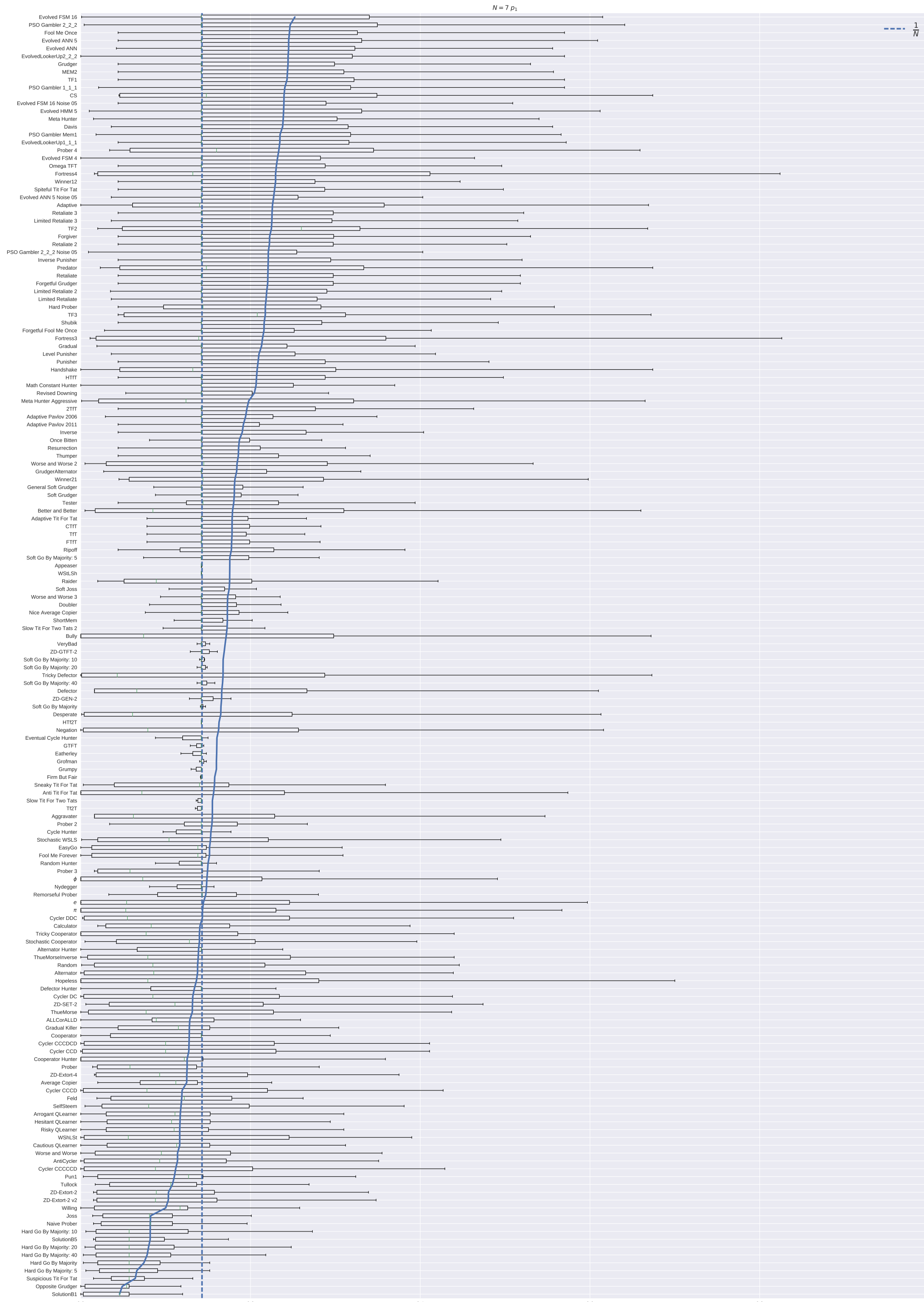


Figure 7: The fixation probability x_1 for $N = 7$

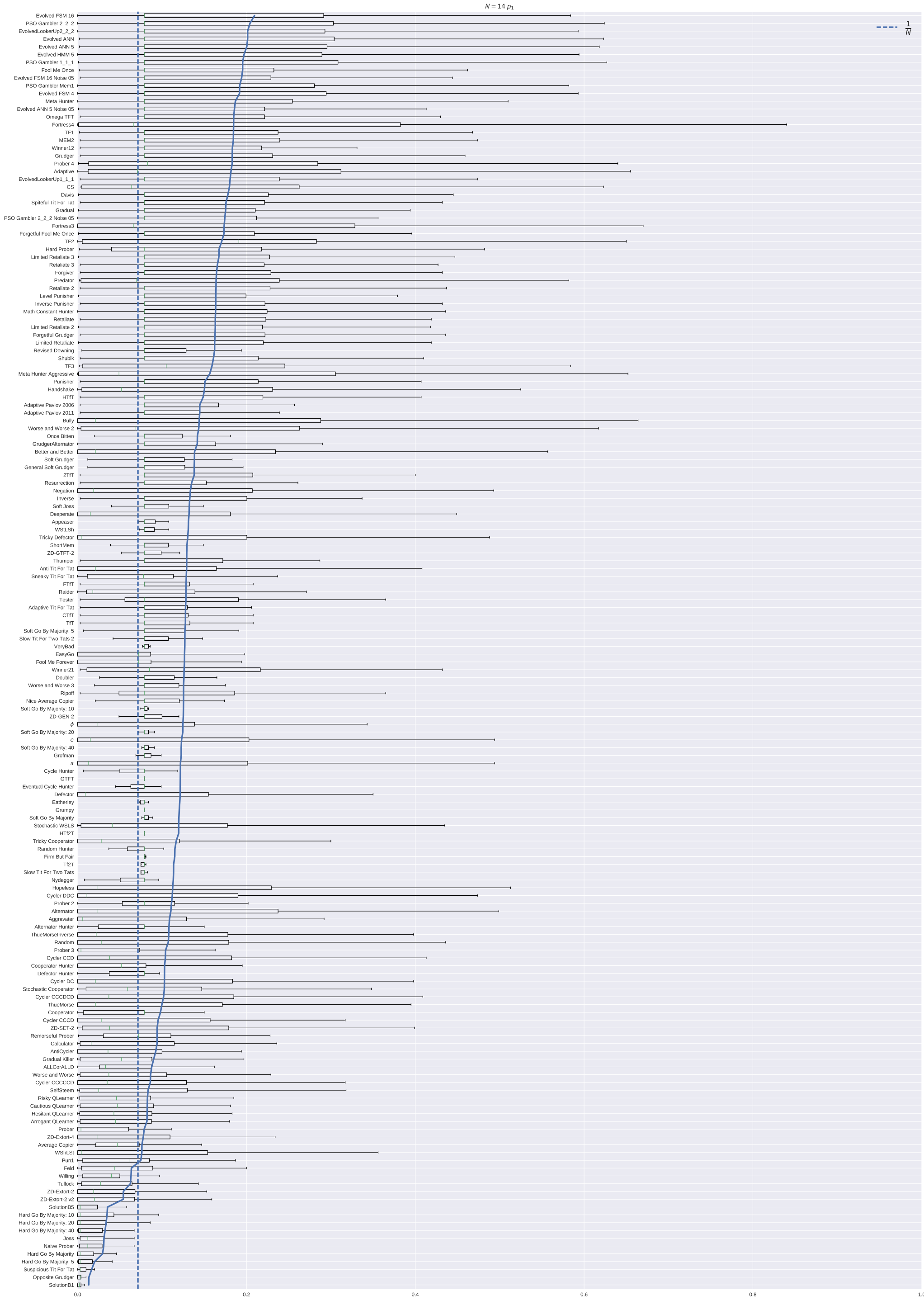


Figure 8: The fixation probability x_1 for $N = 14$

Player	Mean p_1	Memory Depth	Stochastic
CS	0.447761	∞	False
Grudger	0.431264	∞	False
MEM2	0.427804	∞	False
TF1	0.426736	16	False
Prober 4	0.424215	∞	False

(a) $N = 3$

Player	Mean p_1	Memory Depth	Stochastic
Evolved FSM 16	0.252282	16	False
PSO Gambler 2_2_2	0.246742	∞	True
Fool Me Once	0.245871	∞	False
Evolved ANN 5	0.244982	∞	False
Evolved ANN	0.244933	∞	False

(b) $N = 7$

Player	Mean p_1	Memory Depth	Stochastic
Evolved FSM 16	0.209564	16	False
PSO Gambler 2_2_2	0.204215	∞	True
EvolvedLookerUp2_2_2	0.201411	∞	False
Evolved ANN	0.201387	∞	False
Evolved ANN 5	0.200387	∞	False

(c) $N = 14$

Table 3: Properties of top five invaders

performing strategies are:

- Grudger (which only performs well for $N = 3$), starts by cooperating but will defect if at any point the opponent has defected.
- MEM2, an infinite memory strategy that switches between TfT, Tf2T, and Defector [12].
- TF1, the finite state machine trained specifically for Moran processes described in Section [**sec:introduction**].
- Prober 4, complex strategy with an initial 20 move sequence of cooperations and defections [13]. This initial sequence serves as approximate handshake.
- PSO Gambler and Evolved Lookerup 2 2 2: are strategies that make use of a lookup table mapping the first 2 moves of the opponent as well as the last 2 moves of both players to an action. The PSO gambler is a stochastic version which maps those states to probabilities of cooperating. The lookerup was described in [9].
- The evolved ANN strategies are neural networks that map a number of attributes (first move, number of cooperations, last move etc…) to an action. Both of these have been trained using an evolutionary algorithm and the ANN 5 was trained to perform well in a noisy tournament.
- The Evolved FSM 16 is a 16 state finite state machine trained to perform well in tournaments.

As well as noting that the memory length and complexity of these strategies are much greater than one, it is interesting to note that none of them are akin to memory one strategies. Only one is stochastic. The finite state machines trained specifically for Moran processes do not appear in the top 5: whereas strategies trained for tournament do. This is due to the nature of invasion: most of the opponents will initially be different strategies.

The strategies trained with the mean score objective are among the best invaders in the library but are not as resistant to invasion as the strategies trained using a Moran objective function. These strategies include trained finite state machine strategies, but they do not appear to have handshaking mechanisms. Therefore it is reasonable to conclude that the objective function is the cause of the emergence of handshaking mechanisms. The payoff maximizing strategies typically will not defect before the opponent's first defection, possibly because the training strategy collection contains a significant portion of strategies such as Grudger and Fool Me Once that retaliate harshly by defecting for the remainder of the match if the opponent has more than a small number of cumulative defections. Paradoxically it is necessary to defect in order to achieve mutual cooperation with opponents using the same strategy but not with other opponents. The importance of these handshakes will become apparent in the next Section.

4.3 Strong resistors

In addition to identifying good invaders, we also identify strategies resistant to invasion by other strategies by examining the distribution of x_{N-1} for each strategy. Note that this is equivalent to looking at x_1 for all opponents.

The fixation probabilities are shown in Figures 9, 7 and 11 for $N \in \{3, 7, 14\}$ showing the mean fixation as well as the neutral fixation for each given scenario.

Table 4 shows the top five strategies when ranked according to x_{N-1} for $N \in \{3, 7, 14\}$. Once again none of the short memory strategies from Section 4.1 perform well for high N.

Player	Mean p_{N-1}	Memory Depth	Stochastic
CS	0.835859	∞	False
Predator	0.812129	9	False
TF3	0.808736	∞	False
Handshake	0.801356	∞	False
TF2	0.795736	∞	False

(a) $N = 3$

Player	Mean p_{N-1}	Memory Depth	Stochastic
CS	0.976491	∞	False
TF3	0.971405	∞	False
TF2	0.967712	∞	False
Predator	0.967687	9	False
Handshake	0.954650	∞	False

(b) $N = 7$

Player	Mean p_{N-1}	Memory Depth	Stochastic
CS	0.998442	∞	False
TF3	0.997319	∞	False
TF2	0.994865	∞	False
Predator	0.994074	9	False
Prober 4	0.986301	∞	False

(c) $N = 14$

Table 4: Properties of top five resistors

There are are only two new strategies that appear in the top ranks for x_{N-1}: TF2 and TF3. These two strategies are with from CS the strongest resistors. They all have handshakes, and whilst the handshake that CS has was programmed, the handshakes of TF2 and TF3 evolved through an evolutionary process. It is also worth noting that none of the highly trained strategies of Section 4.2 perform as well as resistors. This indicates the subtlety needed to recognise true opponents.

Interestingly none of these strategies are stochastic: this is explained by the need of strategies to have a steady hand when interacting with their own kind. In essence: acting stochastically increase the chance of friendly fire. However it is possible to design a strategy with a "stochastic handshake" [10].

A handshake requires at least one defection and there is selective pressure to defect as few times as possible to achieve the self-recognition mechanism. It is also unwise to defect on the first move as some strategies additionally retaliate first round defections. So the handshakes used by TF2 and TF3, and CS, are in some sense optimal. These discoveries may have significant ramifications regarding the evolution of cooperation and forgiveness in biological organisms such as antibacterial resistant bacteria and social interactions between humans.

It is evident through Sections 4.1, 4.2 and 4.3 that performance of strategies not only depends on the initial population distribution but also that there seems to be a difference depending on whether or not $N > 2$. This will be explored further

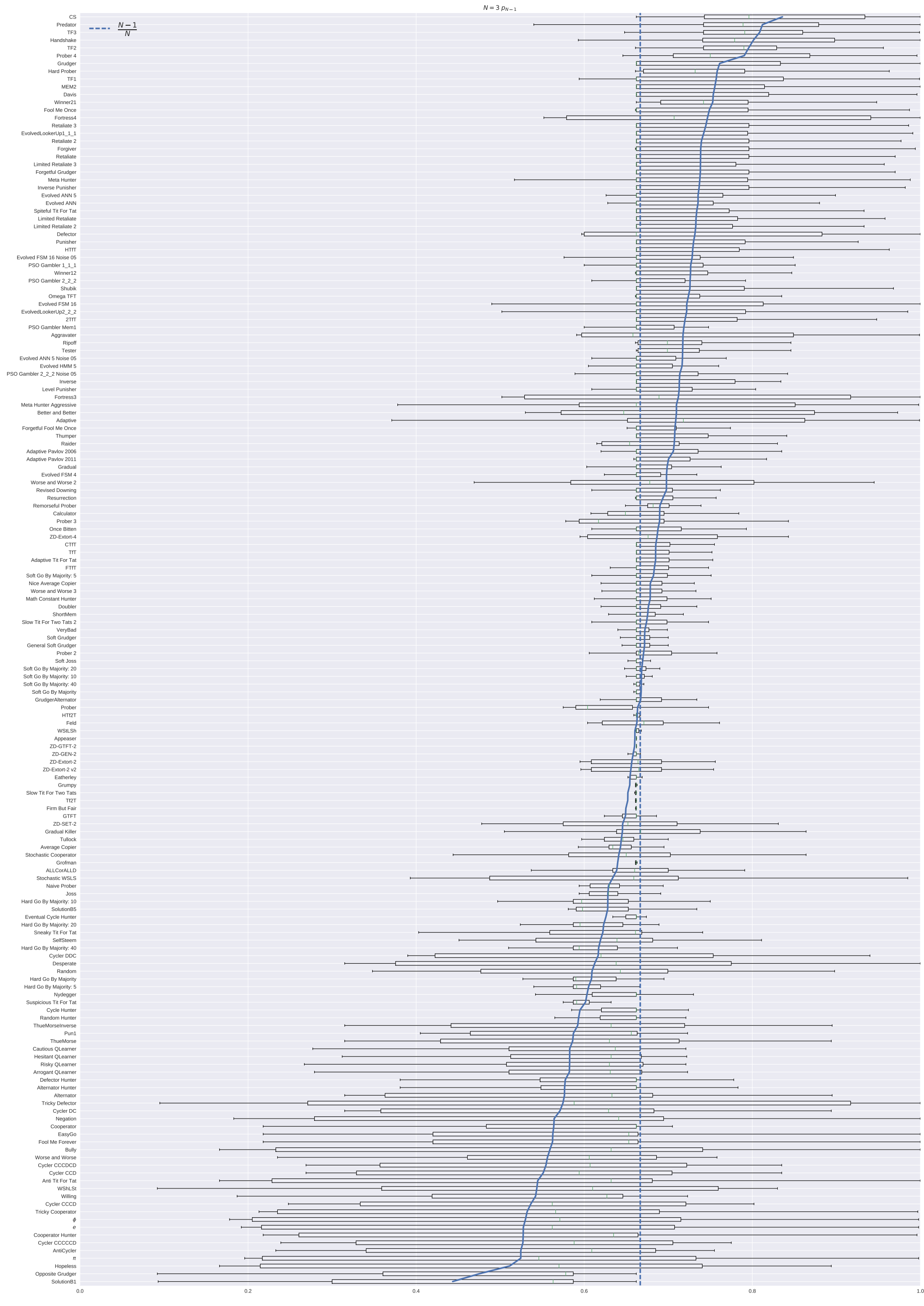


Figure 9: The fixation probability x_{N-1} for $N = 3$

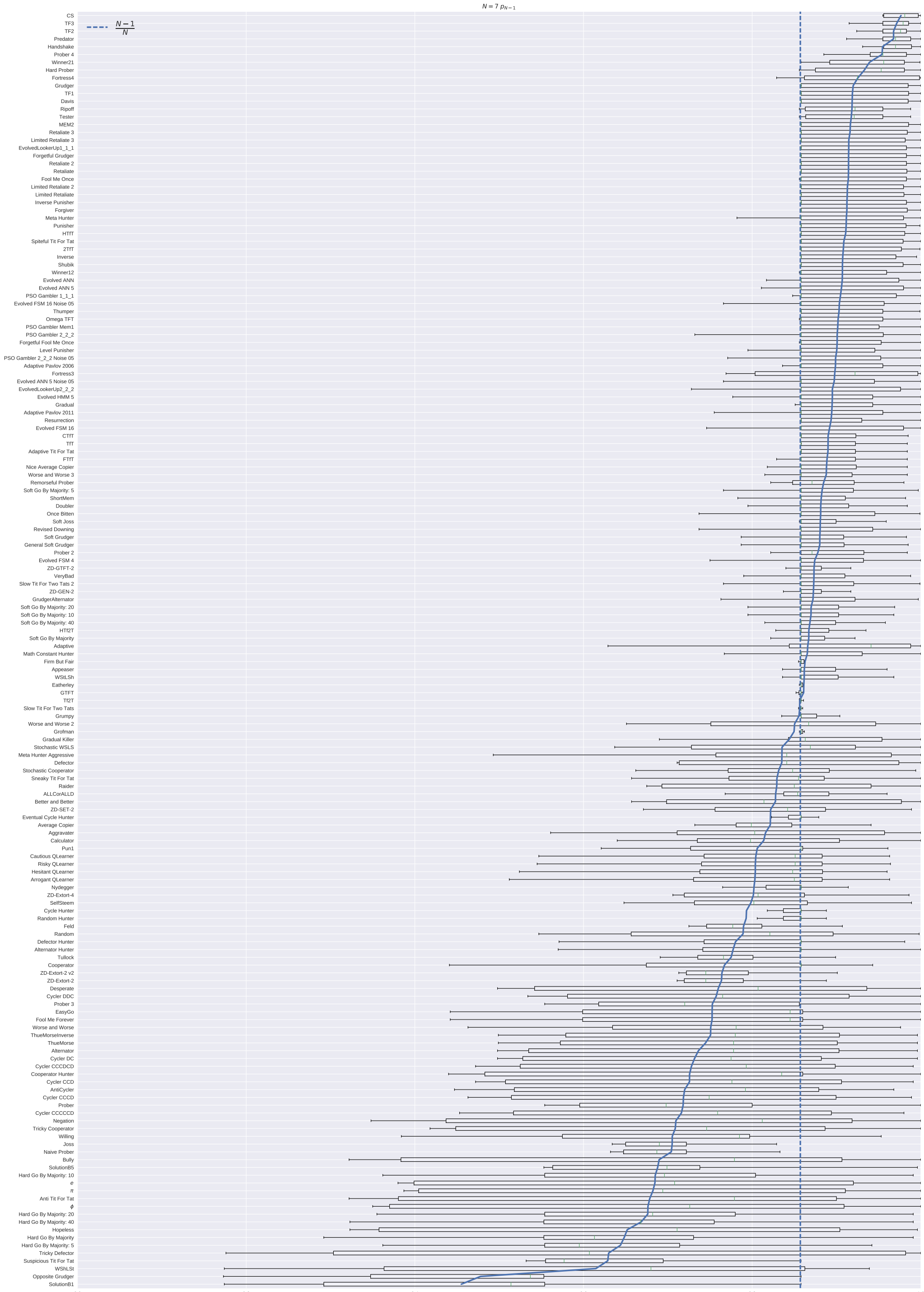


Figure 10: The fixation probability x_{N-1} for $N = 7$

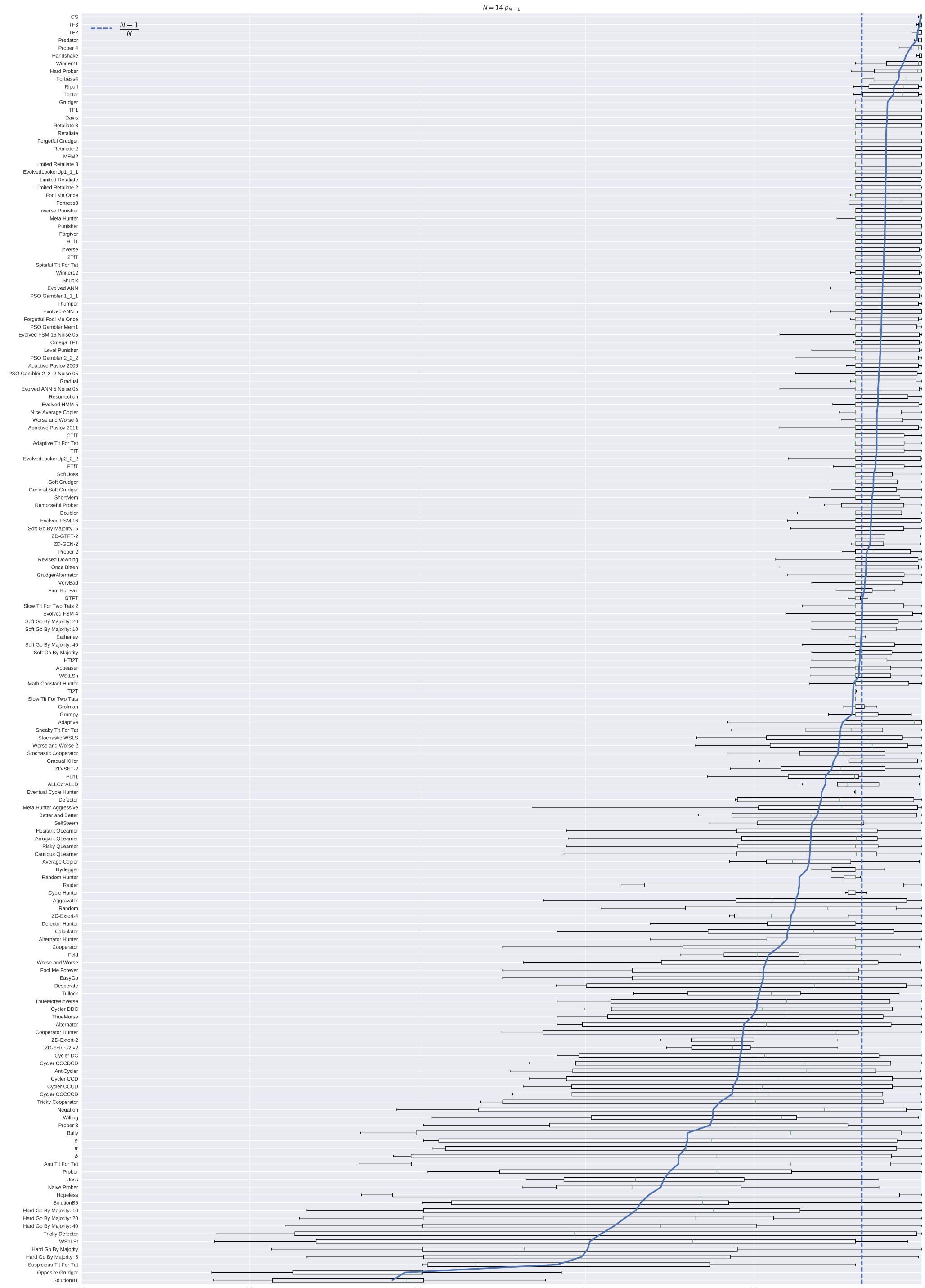


Figure 11: The fixation probability x_{N-1} for $N = 14$

in the next section.

4.4 The effect of population size

Figures 12, 13 and 14 show the median rank of each strategy against population size. For all starting populations $i \in \{1, N/2, N-1\}$ the ranks of strategies are relatively stable across the different values of $N > 2$ however for $N = 2$ there is a distinct difference. This confirms what has been discussed in previous sections.

Tables 5, 6 and 7 show the same information for the strategies that rated high for $N = 2$ and $N = 14$.

Player	2	3	4	5	6	7	8	9	10	11	12	13	14
CS	1.0	1.0	2.0	11.0	9.0	11.0	13.0	21.0	16.0	22.0	17.0	25.0	23.0
Defector	2.0	43.0	80.0	91.0	89.0	87.0	87.0	103.0	97.0	105.0	94.0	103.0	101.0
Aggravater	3.0	50.0	89.0	99.0	102.0	103.0	108.0	113.0	114.0	115.0	115.0	116.0	117.0
Predator	4.0	8.0	24.0	35.0	28.0	33.0	31.0	43.0	36.0	43.0	34.0	45.0	35.0
Handshake	5.0	17.0	40.0	46.0	43.0	46.0	46.0	49.0	48.0	49.0	47.0	50.0	49.0
Evolved FSM 16	31.0	11.0	6.0	2.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
PSO Gambler 2_2_2	29.0	14.0	10.0	6.0	4.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
EvolvedLookerUp2_2_2	33.0	18.0	11.0	9.0	10.0	6.0	6.0	5.0	3.0	5.0	3.0	3.0	3.0
Evolved ANN	20.0	10.0	8.0	7.0	8.0	5.0	3.0	3.0	4.0	3.0	4.0	4.0	4.0
Evolved ANN 5	21.0	9.0	7.0	8.0	7.0	4.0	5.0	4.0	5.0	4.0	5.0	5.0	5.0

Table 5: Ranks of some strategies according to x_1 for different population sizes

Player	2	3	4	5	6	7	8	9	10	11	12	13	14
CS	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Defector	2.0	29.0	55.0	79.0	94.0	97.0	98.0	98.0	102.0	101.0	103.0	100.0	102.0
Aggravater	3.0	42.0	71.0	97.0	101.0	106.0	107.0	111.0	113.0	113.0	116.0	115.0	115.0
Predator	4.0	2.0	3.0	3.0	3.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Handshake	5.0	4.0	5.0	5.0	5.0	5.0	5.0	6.0	6.0	6.0	6.0	6.0	6.0
TF3	7.0	3.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
TF2	10.0	5.0	4.0	4.0	4.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Prober 4	6.0	6.0	6.0	6.0	6.0	6.0	6.0	5.0	5.0	5.0	5.0	5.0	5.0

Table 6: Ranks of some strategies according to x_{N-1} for different population sizes

Player	2	4	6	8	10	12	14
CS	1.0	1.0	1.0	1.0	1.0	1.0	2.0
Defector	2.0	78.0	99.0	106.0	110.0	113.0	120.0
Aggravater	3.0	91.0	105.0	111.0	122.0	125.0	128.0
Predator	4.0	2.0	4.0	4.0	4.0	4.0	4.0
Handshake	5.0	6.0	5.0	6.0	6.0	6.0	6.0
TF2	9.0	4.0	3.0	2.0	2.0	2.0	1.0
TF3	7.0	3.0	2.0	3.0	3.0	3.0	3.0
Prober 4	6.0	5.0	6.0	5.0	5.0	5.0	5.0

Table 7: Ranks of some strategies according to $x_{N/2}$ for different population sizes

player	2	3	4	5	6	7	8	9	10	11	12	13	14
ZD-Extort-4	16.0	81.0	107.0	120.0	135.0	136.0	142.0	140.0	142.0	142.0	144.0	144.0	145.0
ZD-Extort-2 v2	41.0	105.0	126.0	140.0	152.0	152.0	153.0	152.0	153.0	153.0	153.0	152.0	153.0
ZD-Extort-2	43.0	107.0	125.0	139.0	151.0	151.0	152.0	153.0	152.0	152.0	152.0	153.0	152.0
ZD-SET-2	100.0	111.0	117.0	117.0	122.0	127.0	131.0	128.0	131.0	131.0	130.0	132.0	131.0
ZD-GTFT-2	112.0	92.0	82.0	80.0	81.0	82.0	84.0	72.0	81.0	71.0	78.0	72.0	70.0
ZD-GEN-2	113.0	96.0	87.0	83.0	85.0	88.0	90.0	82.0	87.0	82.0	86.0	83.0	91.0

Table 8: Ranks of Zero determinant strategies according to x_1 for different population sizes

Tables 11a, 11b and 11c show the correlation coefficients of the ranks of strategies in differing population size. This is shown graphically in Figure 15. It is immediate to note that how well a strategy performs in any Moran process for $N > 2$ has little to do with the performance for $N = 2$. This illustrates why the strong performance of zero determinant strategies predicted in [17] does not extend to larger populations. This was discussed theoretically in [1] however not observed empirically at the scale presented here.

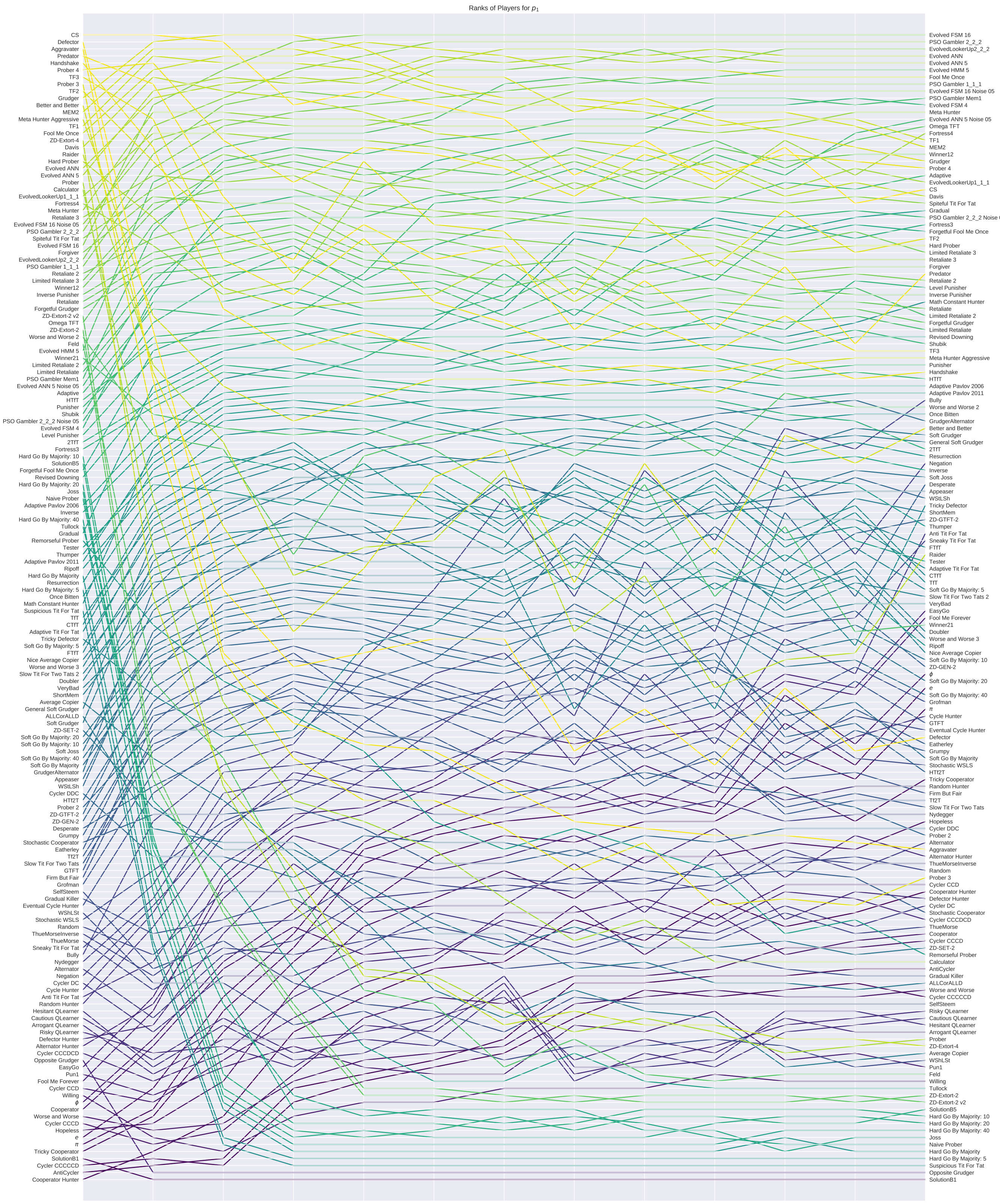


Figure 12: Ranks of all strategies according to x_1 for different population sizes

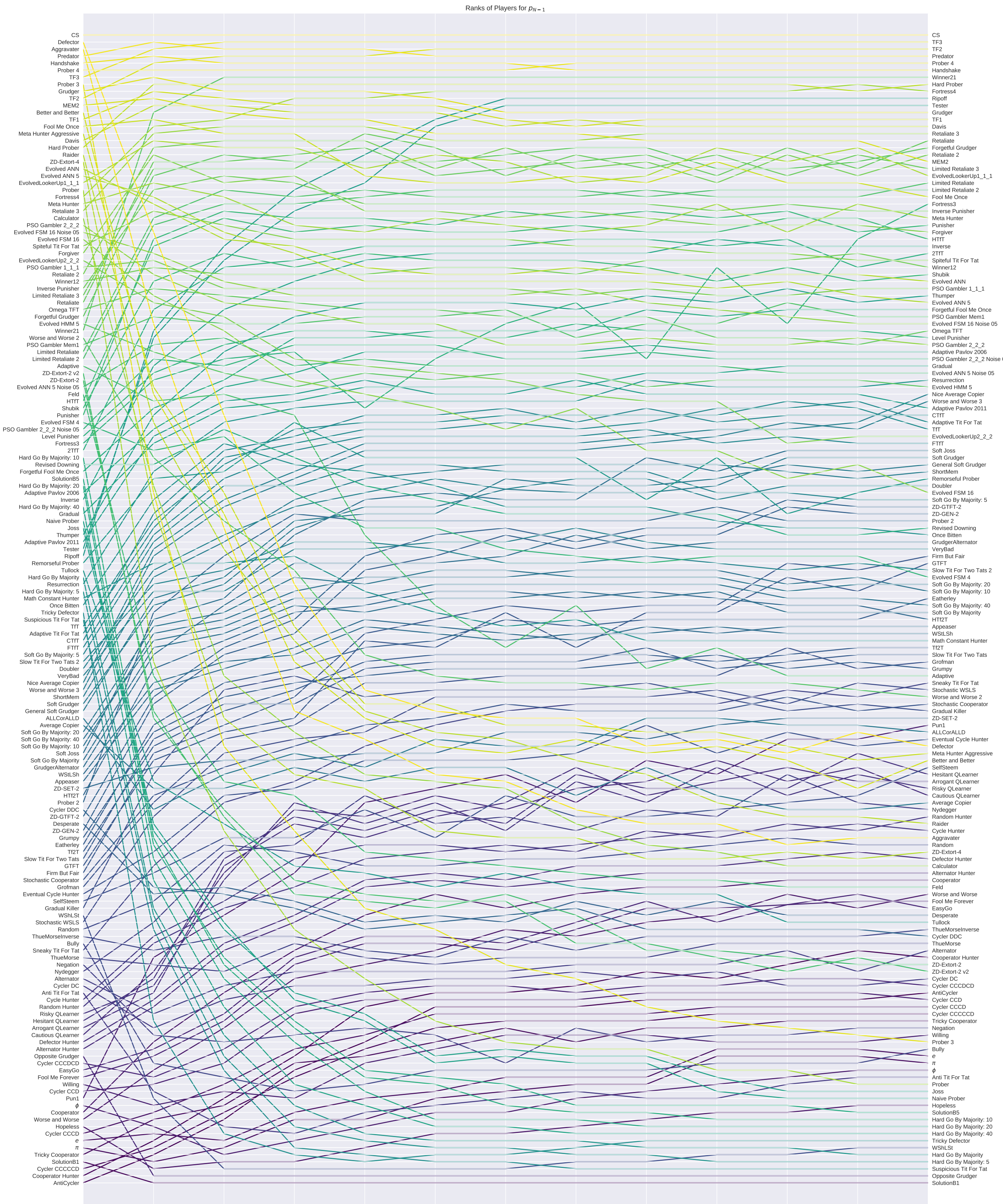


Figure 13: Ranks of all strategies according to x_{N-1} for different population sizes

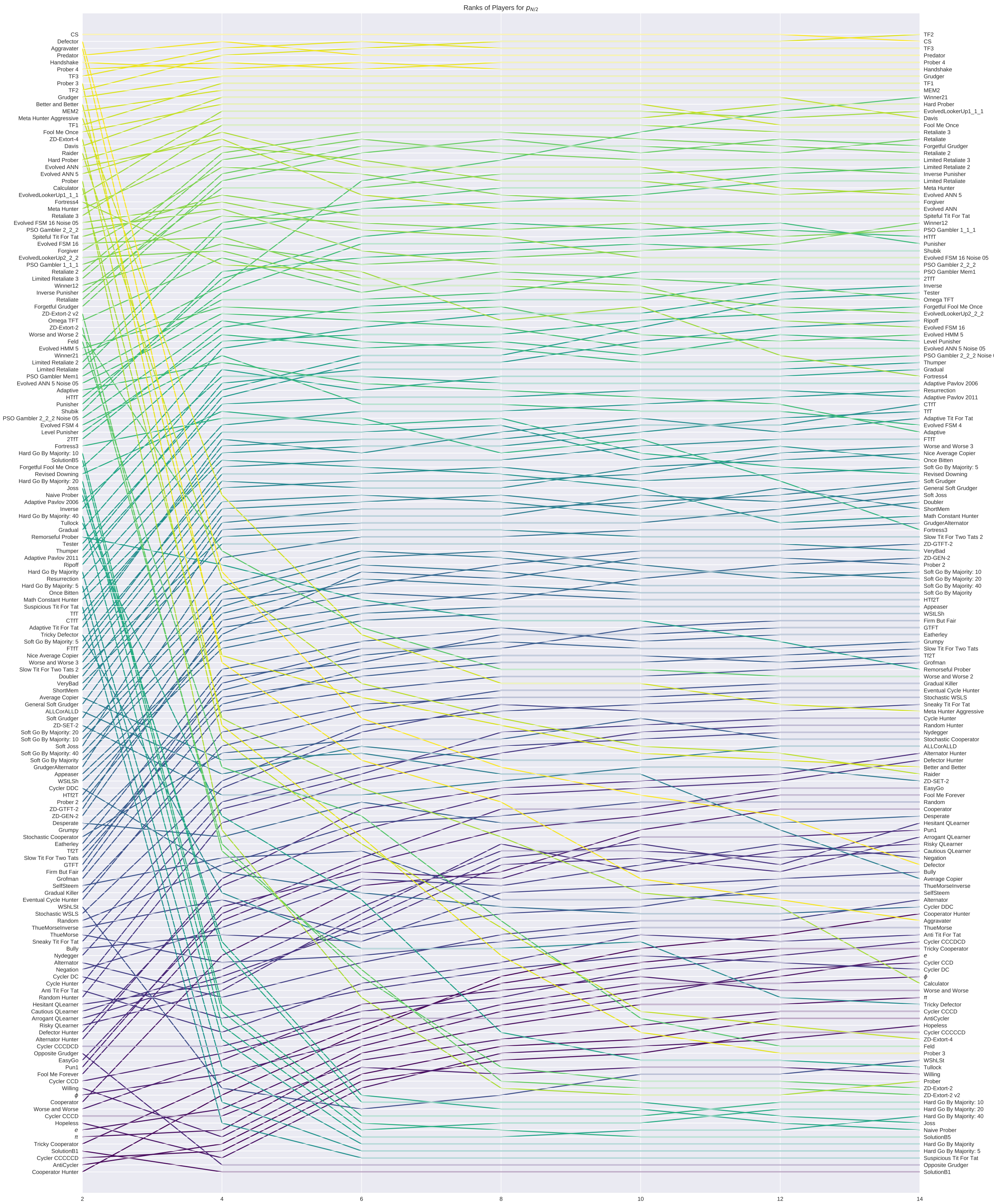


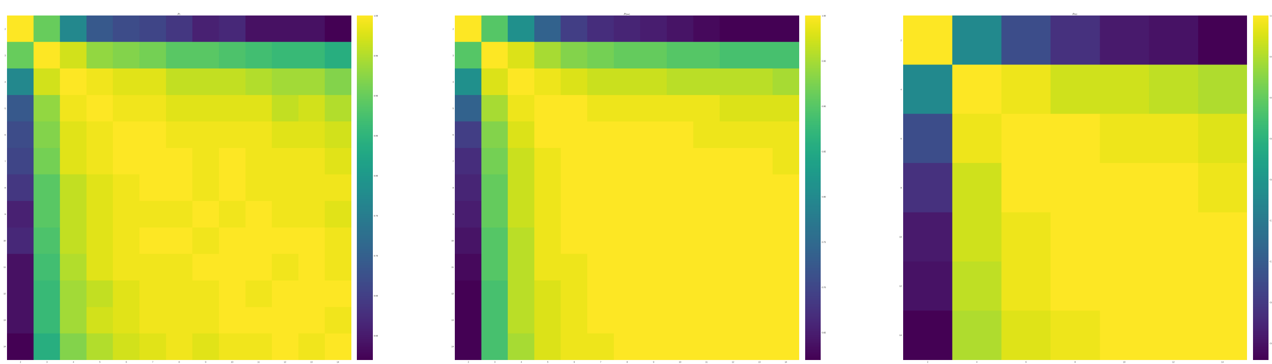
Figure 14: Ranks of all strategies according to $x_{N/2}$ for different population sizes

player	2	3	4	5	6	7	8	9	10	11	12	13	14
ZD-Extort-4	19.0	68.0	98.0	106.0	108.0	114.0	115.0	115.0	118.0	118.0	117.0	118.0	117.0
ZD-Extort-2 v2	49.0	98.0	111.0	121.0	123.0	124.0	124.0	130.0	130.0	132.0	134.0	132.0	134.0
ZD-Extort-2	50.0	97.0	112.0	123.0	124.0	125.0	123.0	126.0	131.0	131.0	132.0	133.0	133.0
ZD-SET-2	108.0	105.0	104.0	104.0	103.0	103.0	100.0	100.0	101.0	99.0	98.0	98.0	98.0
ZD-GTFT-2	112.0	95.0	88.0	84.0	75.0	72.0	71.0	73.0	71.0	71.0	67.0	68.0	68.0
ZD-GEN-2	114.0	96.0	89.0	86.0	77.0	75.0	72.0	74.0	72.0	72.0	68.0	69.0	69.0

Table 9: Ranks of Zero determinant strategies according to x_{N-1} for different population sizes

player	2	4	6	8	10	12	14
ZD-Extort-4	16.0	102.0	117.0	129.0	141.0	143.0	145.0
ZD-Extort-2 v2	41.0	118.0	135.0	151.0	152.0	152.0	153.0
ZD-Extort-2	43.0	117.0	136.0	149.0	151.0	151.0	152.0
ZD-SET-2	100.0	110.0	110.0	108.0	106.0	106.0	108.0
ZD-GTFT-2	112.0	82.0	80.0	77.0	75.0	75.0	74.0
ZD-GEN-2	113.0	85.0	81.0	82.0	79.0	77.0	76.0

Table 10: Ranks of Zero determinant strategies according to $x_{N/2}$ for different population sizes



(a) Rank based on x_1

(b) Rank based on x_{N-1}

(c) Rank based on $x_{N/2}$

Figure 15: Heatmap of correlation coefficients of rankings by population size

N	2	3	4	5	6	7	8	9	10	11	12	13	14
2	1.00	0.90	0.77	0.69	0.67	0.66	0.64	0.61	0.62	0.59	0.59	0.59	0.57
3	0.90	1.00	0.97	0.93	0.92	0.91	0.89	0.89	0.88	0.87	0.86	0.86	0.84
4	0.77	0.97	1.00	0.99	0.98	0.98	0.96	0.96	0.96	0.95	0.94	0.94	0.92
5	0.69	0.93	0.99	1.00	0.99	0.99	0.98	0.98	0.98	0.98	0.96	0.97	0.95
6	0.67	0.92	0.98	0.99	1.00	1.00	0.99	0.99	0.99	0.99	0.98	0.98	0.97
7	0.66	0.91	0.98	0.99	1.00	1.00	1.00	0.99	1.00	0.99	0.99	0.99	0.98
8	0.64	0.89	0.96	0.98	0.99	1.00	1.00	0.99	1.00	0.99	0.99	0.99	0.99
9	0.61	0.89	0.96	0.98	0.99	0.99	0.99	1.00	0.99	1.00	0.99	0.99	0.98
10	0.62	0.88	0.96	0.98	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99
11	0.59	0.87	0.95	0.98	0.99	0.99	0.99	1.00	1.00	1.00	0.99	1.00	0.99
12	0.59	0.86	0.94	0.96	0.98	0.99	0.99	0.99	1.00	0.99	1.00	1.00	1.00
13	0.59	0.86	0.94	0.97	0.98	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.99
14	0.57	0.84	0.92	0.95	0.97	0.98	0.99	0.98	0.99	0.99	1.00	0.99	1.00

(a) Correlation coefficients for ranks for invasion

N	2	3	4	5	6	7	8	9	10	11	12	13	14
2	1.00	0.90	0.81	0.74	0.69	0.67	0.66	0.65	0.64	0.63	0.62	0.62	0.62
3	0.90	1.00	0.98	0.95	0.93	0.92	0.91	0.91	0.90	0.90	0.89	0.89	0.89
4	0.81	0.98	1.00	0.99	0.98	0.97	0.97	0.97	0.96	0.96	0.96	0.96	0.95
5	0.74	0.95	0.99	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98
6	0.69	0.93	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
7	0.67	0.92	0.97	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99
8	0.66	0.91	0.97	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9	0.65	0.91	0.97	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10	0.64	0.90	0.96	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
11	0.63	0.90	0.96	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
12	0.62	0.89	0.96	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
13	0.62	0.89	0.96	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
14	0.62	0.89	0.95	0.98	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00

(b) Correlation coefficients for ranks for resistance

N	2	4	6	8	10	12	14
2	1.00	0.78	0.68	0.64	0.61	0.60	0.58
4	0.78	1.00	0.99	0.97	0.97	0.96	0.95
6	0.68	0.99	1.00	1.00	0.99	0.99	0.98
8	0.64	0.97	1.00	1.00	1.00	1.00	0.99
10	0.61	0.97	0.99	1.00	1.00	1.00	1.00
12	0.60	0.96	0.99	1.00	1.00	1.00	1.00
14	0.58	0.95	0.98	0.99	1.00	1.00	1.00

(c) Correlation coefficients for ranks for coexistance

Table 11: Correlation coefficients of rankings by population size

5 Conclusion

A detailed empirical analysis of 164 strategies of the IPD within a pairwise Moran process has been carried out. All $\binom{164}{2} = 13,366$ possible ordered pairs of strategies have been placed in a Moran process with different starting values allowing the each strategy to attempt to invade the other.

This is the largest such experiment carried out and has lead to many insights.

When studying evolutionary processes it is vital to consider $N > 2$ as the special case for $N = 2$ cannot be used to extrapolate performance in bigger populations. This was shown both observationally in Sections 4.2 and 4.3 but also by considering the correlation of the ranks in different population sizes in Section 4.4.

Memory one strategies do not perform well, as predicted by [17]. However, there are no memory one strategies in the top 5 performing strategies for $N > 3$. This is due to their lack of sophistication which allows them to recognise and adjust to their opponent. Some very sophisticated strategies proves to be high performers for invasion: these are infinite memory strategies which have been trained using a number of reinforcement learning algorithms. Interestingly they have been trained to perform well in tournaments and not Moran processes which highlights the potentially for improvement.

It is felt that these findings are important for the ongoing understanding of population dynamics and offer evidence for some of the shortcomings of short memory which has started to be recognised by the community [7].

All source code for this work has been written in a sustainable manner: it is open source, under version control and tested which ensures that all results can be reproduced [18, 20, 25]. The raw data as well as the processed data has also been properly archived.

There are various areas for further work to build on this. Firstly, an analysis of the effect of noise would offer insights about the stability of the findings. It would also be possible to consider three or more types of strategy in the population and finally mutation would also offer an interesting dimension to explore.

Acknowledgements

This work was performed using the computational facilities of the Advanced Research Computing @ Cardiff (ARCCA) Division, Cardiff University.

A variety of software libraries have been used in this work:

- The Axelrod library (IPD strategies and Moran processes) [22].
- The matplotlib library (visualisation) [8].
- The pandas and numpy libraries (data manipulation) [14, 23].

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A List of players

1. ϕ
2. π
3. e
4. ALLCorALLD
5. Adaptive
6. Adaptive Pavlov 2006
7. Adaptive Pavlov 2011
8. Adaptive Tit For Tat: 0.5
9. Aggravater
10. Alternator
11. Alternator Hunter
12. Anti Tit For Tat
13. AntiCycler
14. Appeaser
15. Arrogant QLearner
16. Average Copier
17. Better and Better
18. Bully

19. Calculator
20. Cautious QLearner
21. CollectiveStrategy (**CS**)
22. Contrite Tit For Tat (**CTfT**)
23. Cooperator
24. Cooperator Hunter
25. Cycle Hunter
26. Cycler CCCCCD
27. Cycler CCCD
28. Cycler CCCDCD
29. Cycler CCD
30. Cycler DC
31. Cycler DDC
32. Davis: 10
33. Defector
34. Defector Hunter
35. Desperate
36. Doubler
37. EasyGo
38. Eatherley
39. Eventual Cycle Hunter
40. Evolved ANN
41. Evolved ANN 5
42. Evolved ANN 5 Noise 05
43. Evolved FSM 16
44. Evolved FSM 16 Noise 05
45. Evolved FSM 4
46. Evolved HMM 5
47. EvolvedLookerUp1_1_1
48. EvolvedLookerUp2_2_2
49. FSM Player: [(0, 'C', 0, 'C'), (0, 'D', 3, 'C'), (1, 'C', 5, 'D'), (1, 'D', 0, 'C'), (2, 'C', 3, 'C'), (2, 'D', 2, 'D'), (3, 'C', 4, 'D'), (3, 'D', 6, 'D'), (4, 'C', 3, 'C'), (4, 'D', 1, 'D'), (5, 'C', 6, 'C'), (5, 'D', 3, 'D'), (6, 'C', 6, 'D'), (6, 'D', 6, 'D'), (7, 'C', 7, 'D'), (7, 'D', 5, 'C')], 0, C (**TF1**)
50. FSM Player: [(0, 'C', 13, 'D'), (0, 'D', 12, 'D'), (1, 'C', 3, 'D'), (1, 'D', 4, 'D'), (2, 'C', 14, 'D'), (2, 'D', 9, 'D'), (3, 'C', 0, 'C'), (3, 'D', 1, 'D'), (4, 'C', 1, 'D'), (4, 'D', 2, 'D'), (5, 'C', 12, 'C'), (5, 'D', 6, 'C'), (6, 'C', 1, 'C'), (6, 'D', 14, 'D'), (7, 'C', 12, 'D'), (7, 'D', 2, 'D'), (8, 'C', 7, 'D'), (8, 'D', 9, 'D'), (9, 'C', 8, 'D'), (9, 'D', 0, 'D'), (10, 'C', 2, 'C'), (10, 'D', 15, 'C'), (11, 'C', 7, 'D'), (11, 'D', 13, 'D'), (12, 'C', 3, 'C'), (12, 'D', 8, 'D'), (13, 'C', 7, 'C'), (13, 'D', 10, 'D'), (14, 'C', 10, 'D'), (14, 'D', 7, 'D'), (15, 'C', 15, 'C'), (15, 'D', 11, 'D')], 0, C (**TF2**)
51. FSM Player: [(0, 'C', 7, 'C'), (0, 'D', 1, 'C'), (1, 'C', 11, 'D'), (1, 'D', 11, 'D'), (2, 'C', 8, 'D'), (2, 'D', 8, 'C'), (3, 'C', 3, 'C'), (3, 'D', 12, 'D'), (4, 'C', 6, 'C'), (4, 'D', 3, 'C'), (5, 'C', 11, 'C'), (5, 'D', 8, 'D'), (6, 'C', 13, 'D'), (6, 'D', 14, 'C'), (7, 'C', 4, 'D'), (7, 'D', 2, 'D'), (8, 'C', 14, 'D'), (8, 'D', 8, 'D'), (9, 'C', 0, 'C'), (9, 'D', 10, 'D'), (10, 'C', 8, 'C'), (10, 'D', 15, 'C'), (11, 'C', 6, 'D'), (11, 'D', 5, 'D'), (12, 'C', 6, 'D'), (12, 'D', 9, 'D'), (13, 'C', 9, 'D'), (13, 'D', 8, 'D'), (14, 'C', 8, 'D'), (14, 'D', 13, 'D'), (15, 'C', 4, 'C'), (15, 'D', 5, 'C')], 0, C (**TF3**)
52. Feld: 1.0, 0.5, 200
53. Firm But Fair
54. Fool Me Forever
55. Fool Me Once
56. Forgetful Fool Me Once: 0.05
57. Forgetful Grudger
58. Forgiver
59. Forgiving Tit For Tat (**FTfT**)
60. Fortress3
61. Fortress4
62. GTFT: 0.33
63. General Soft Grudger: n=1,d=4,c=2
64. Gradual
65. Gradual Killer: ('D', 'D', 'D', 'D', 'D', 'C', 'C')
66. Grofman
67. Grudger
68. GrudgerAlternator
69. Grumpy: Nice, 10, -10
70. Handshake
71. Hard Go By Majority
72. Hard Go By Majority: 10
73. Hard Go By Majority: 20
74. Hard Go By Majority: 40
75. Hard Go By Majority: 5
76. Hard Prober
77. Hard Tit For 2 Tats (**HTf2T**)
78. Hard Tit For Tat (**HTfT**)
79. Hesitant QLearner
80. Hopeless
81. Inverse
82. Inverse Punisher
83. Joss: 0.9
84. Level Punisher
85. Limited Retaliate 2: 0.08, 15
86. Limited Retaliate 3: 0.05, 20
87. Limited Retaliate: 0.1, 20
88. MEM2
89. Math Constant Hunter
90. Meta Hunter Aggressive: 7 players
91. Meta Hunter: 6 players
92. Naive Prober: 0.1
93. Negation
94. Nice Average Copier
95. Nydegger
96. Omega TFT: 3, 8
97. Once Bitten

98. Opposite Grudger
99. PSO Gambler 1_1_1
100. PSO Gambler 2_2_2
101. PSO Gambler 2_2_2 Noise 05
102. PSO Gambler Mem1
103. Predator
104. Prober
105. Prober 2
106. Prober 3
107. Prober 4
108. Pun1
109. Punisher
110. Raider
111. Random Hunter
112. Random: 0.5
113. Remorseful Prober: 0.1
114. Resurrection
115. Retaliate 2: 0.08
116. Retaliate 3: 0.05
117. Retaliate: 0.1
118. Revised Downing: True
119. Ripoff
120. Risky QLearner
121. SelfSteem
122. ShortMem
123. Shubik
124. Slow Tit For Two Tats
125. Slow Tit For Two Tats 2
126. Sneaky Tit For Tat
127. Soft Go By Majority
128. Soft Go By Majority: 10
129. Soft Go By Majority: 20
130. Soft Go By Majority: 40
131. Soft Go By Majority: 5
132. Soft Grudger
133. Soft Joss: 0.9
134. SolutionB1
135. SolutionB5
136. Spiteful Tit For Tat
137. Stochastic Cooperator
138. Stochastic WSLS: 0.05
139. Suspicious Tit For Tat
140. Tester
141. ThueMorse
142. ThueMorseInverse
143. Thumper
144. Tit For 2 Tats (**Tf2T**)
145. Tit For Tat (**TfT**)
146. Tricky Cooperator
147. Tricky Defector
148. Tullock: 11
149. Two Tits For Tat (**2TfT**)
150. VeryBad
151. Willing
152. Win-Shift Lose-Stay: D (**WShLSt**)
153. Win-Stay Lose-Shift: C (**WStLSh**)
154. Winner12
155. Winner21
156. Worse and Worse
157. Worse and Worse 2
158. Worse and Worse 3
159. ZD-Extort-2 v2: 0.125, 0.5, 1
160. ZD-Extort-2: 0.1111111111111111, 0.5
161. ZD-Extort-4: 0.23529411764705882, 0.25, 1
162. ZD-GEN-2: 0.125, 0.5, 3
163. ZD-GTFT-2: 0.25, 0.5
164. ZD-SET-2: 0.25, 0.0, 2