# A meta analysis of tournaments and an evaluation of performance in the Iterated Prisoner's Dilemma.

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**Abstract**

The Iterated Prisoner's Dilemma has been used for decades as a model of behavioural interactions. From the celebrated performance of Tit for Tat, to the introduction of the zero-determinant strategies, to the use of sophisticated structures such as neural networks, the literature has been exploring the performance of strategies in the game for years. The results of the literature, however, have been relying on the performance of specific strategies in a finite number of tournaments, whereas this manuscript evaluates 195 strategies' effectiveness in more than 40000 tournaments. The top ranked strategies are presented, and moreover, the impact of features on their success are analysed using machine learning techniques. The analysis determines that the cooperating ratio of a strategy in a given tournament compared to the mean and median cooperator is the most important feature. The conclusions are distinct for different types of tournaments. A strategy with a theory of mind would aim to be the mean/median cooperator in standard tournaments, whereas in tournaments with probabilistic ending it would aim to cooperate 10% of the times the median cooperator did. In tournaments with noise and a probability of ending an effective strategy cooperates 60% of the times the median/mean cooperator did, and in tourmanents with only noise or even in a setting that the tournament can be any of the above a strategy should aim to play 67% as a median/mean cooperator.

## 1 Background

The Iterated Prisoner's Dilemma (IPD) is a repeated two player game that models behavioural interactions, and more specifically, interactions where self-interest clashes with collective interest. At each turn of the game both players, simultaneously and independently, decide between cooperation (C) and defection (D) whilst having memory of their prior interactions. The payoffs for each player, at each turn, is influenced by their own choice and the choice of the other player. The payoffs of the game are generally defined by:

$$\begin{pmatrix} R & S \\ T & P \end{pmatrix}$$

where $T > R > P > S$ and $2R > T + S$. The most common values used in the literature [17] are $R = 3, P = 1, T = 5, S = 0$. These values are also used in this work.

Conceptualising strategies and understanding the best way of playing the game has been of interest to the scientific community since the formulation of the game in 1950 [29]. Following the computer tournaments of Axelrod in the 1980's [15, 16], a strategy's performance in a round robin computer tournament became a common evaluation technique for newly designed strategies. Today more than 200 strategies exist in the literature and several tournaments, excluding Axelrod's, have been undertaken [20, 34, 38, 58, 59].

In the 80's, Axelrod performed two computer tournaments [15, 16]. The contestants were strategies submitted in the form of computer code. They competed against all other entries, a copy of themselves and a random strategy. The winner was decided on the average score a strategy achieved. The winner of both tournaments was the simple strategy Tit For Tat which cooperated on the first turn and then simply copied the previous action of it's opponent. Due to the strategy's strong performance in both tournaments, and moreover in a series of evolutionary experiments [17], Tit For Tat was thought to be the most robust basic strategy in the IPD.

However, further research proved that the strategy had weakness, and more specifically, it was shown that the strategy suffered in environments with noise [20, 28, 48, 57]. This was mainly due to the strategy's lack of generosity and contrition. The strategy was quick to punish a defection, and in a noisy environment it could lead to a repeated cycle of defections and cooperations. Some new strategies, more robust in tournaments with noise, were soon introduced and became the new protagonists of the game. These include Nice and Forgiving [20], Pavlov [50] and Generous Tit For Tat [51].

In 2004, a 20$^{\text{th}}$ Anniversary Iterated Prisoner Dilemma Tournament took place with 233 entries. This time the winning strategy was not designed on a reciprocity based approach but on a mechanism of teams [26, 27, 55]. A team from Southampton University took advantage of the fact that a participant was allowed to submit multiple strategies. They submitted a total of 60 strategies that could recognised each other and colluded to increase one members score. This resulted with three of the strategies to be ranked in the top spots. The performance of the Southampton University team received mixed attention, though they had won the tournament as stated in [25] "technically this strategy violates the spirit of the Prisoner's Dilemma, which assumes that the two prisoners cannot communicate with one another".

Another set of IPD strategies that have received a lot of attention are the zero-determinant strategies (ZDs) [53]. By forcing a linear relationship between the payoffs ZDs can ensure that they will never receive less than their opponents. The American Mathematical Society's news section stated that "the world of game theory is currently on fire". ZDs are indeed a set of mathematically unique strategies and robust in pairwise interactions, however, their simplicity and extortionate behaviour have been tested. In [34] a tournament containing over 200 strategies, including ZDs, was ran and none of the them ranked in top spots. Instead, the top ranked strategies were a set of trained strategies based on lookup tables [14], hidden markov models [34] and finite state automata [46].

Though only a select pieces of work have been discussed, the IPD literature is rich, and new strategies and competitions are being published every year. The question, however, still remains the same: what is the best way to play the game? Compared to other works, whereas a few selected strategies are evaluated on a small number of tournaments, this manuscript evaluates the performance of 195 strategies in 45686 tournaments. These tournaments do not consist by just standard round robin tournaments, but also by tournaments with noise and tournaments with a probabilistic ending. The later part of the paper, evaluates the impact of features on the performance of the strategies using modern machine learning techniques. These features include measures regarding a strategy's behaviour and measures regarding the tournaments. The data set used in this work has been made publicly available [33] and can be used for further analysis and insights.

The different tournament types as well as the data collection, which is made possible due an open source package called Axelrod-Python [4], are covered in Section 2. Section 3, focuses on the best performing strategies for each type of tournament and overall. Section 4, explores the traits which contribute to good performance, and finally the results are summarised in Section 5. This manuscripts uses several parameters. These are introduced in the following sections, however, the full set of parameters and their definitions are given in Appendix A.

# 2 Data collection

For the purposes of this manuscript a data set containing results of IPD tournaments has been generated and is available at [33]. This was done using the open source package Axelrod-Python [4], and more specifically, version 3.0.0. Axelrod-Python allows for different types of IPD computer tournaments to be simulated whilst containing a list of over 180 strategies. Most of these are strategies described in the literature with a few exceptions being strategies that have been contributed specifically to the package. This paper make use of 195 strategies implemented in version 3.0.0. A list of the strategies is given in the Appendix B. Though Axelrod-Python features several tournament types, this work considers only standard, noisy, probabilistic ending and noisy probabilistic ending tournaments.

**Standard tournaments**, are tournaments similar to that of Axelrod's in [15]. There are $N$ strategies which all play an iterated game of $n$ number of turns against each other. Note that self interactions are not included. Similarly, **noisy tournaments** have $N$ strategies and $n$ number of turns, but at each turn there is a probability $p_n$ that a player's action will be flipped. **Probabilistic ending tournaments**, are of size $N$ and after each turn a match between strategies ends with a given probability $p_e$. Finally, **noisy probabilistic ending** tournaments have both a noise probability $p_n$ and an ending probability $p_e$. For smoothing the simulated results a tournament is repeated for $k$ number of times. This was allowed to vary in order to evaluate the effect of smoothing. The winner of each tournament is based on the average score a strategy achieved and not by the number of wins.

The process of collecting tournament results implemented in this manuscript is described by Algorithm 1. For each trial a random size $N$ is selected, and from the 195 strategies a random list of $N$ strategies is chosen. For the given list of strategies a standard, a noisy, a probabilistic ending and a noisy probabilistic ending tournament are performed and repeated $k$ times. The parameters for the tournaments, as well as the number of repetitions, are selected once for each trial. The parameters and their respective minimum and maximum values are given by Table 1.

| parameter | parameter explanation | min value | max value |
|---|---|---|---|
| $N$ | number of strategies | 3 | 195 |
| $k$ | number of repetitions | 10 | 100 |
| $n$ | number of turns | 1 | 200 |
| $p_n$ | probability of flipping action at each turn | 0 | 1 |
| $p_e$ | probability of match ending in the next turn | 0 | 1 |

Table 1: Data collection; parameters' values

The source code for the data collection, as well as the source code for the analysis, which will be discussed in the following sections, have been written following best practices [5, 21]. It has been packaged and is available here.

A total of 11420 trials of Algorithm 1 have been run. For each trial the results for 4 different tournaments were collected, thus a total of 45686 ($11420 \times 4$) tournament results have been retrieved. Each tournament outputs a result summary in the form of Table 2. Each strategy have participated on average in 5154 tournaments of each type. The strategy with the maximum participation in each tournament type is Inverse Punisher with 5639 entries. The strategy with the minimum entries is EvolvedLookerUp 1 1 1 which was selected in 4693 trials.

The result summary, Table 2, has $N$ number of rows because each row contains information for each strategy that participated in the tournament. The information includes the strategy's rank, median score, the rate with which the strategy cooperated ($C_r$), its match win count and the probability that the strategy cooperated in the opening move. Moreover, the probabilities of a strategy being in any of the four states ($CC, CD, DC, DD$),

**Algorithm 1:** Data collection Algorithm

**foreach** *seed* $\in [0, 11420]$ **do**

  $N \leftarrow$ randomly select integer $\in [N_{min}, N_{max}]$;

  players $\leftarrow$ randomly select $N$ players;

  $k \leftarrow$ randomly select integer $\in [k_{min}, k_{max}]$;

  $n \leftarrow$ randomly select integer $\in [n_{min}, n_{max}]$;

  $p_n \leftarrow$ randomly select float $\in [p_{n\,min}, p_{n\,max}]$;

  $p_e \leftarrow$ randomly select float $\in [p_{e\,min}, p_{e\,max}]$;

  result standard $\leftarrow$ Axelrod.tournament(players, $n, k$);

  result noisy $\leftarrow$ Axelrod.tournament(players, $n, p_n, k$);

  result probabilistic ending $\leftarrow$ Axelrod.tournament(players, $p_e, k$);

  result noisy probabilistic ending $\leftarrow$ Axelrod.tournament(players, $p_n, p_e, k$);

**return** *result standard, result noisy, result probabilistic ending, result noisy probabilistic ending*;

and the rate of which the strategy cooperated after each state. A measure that has been manually included is the **normalised rank**. The normalised rank, denoted as $r$, is calculated as a strategy's rank divided by the tournament's size ($N$). In the next section the performance of these strategies is evaluated based on their normalised rank.

| | | | | | | Rates | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rank | Name | Median score | Cooperation rating ($C_r$) | Win | Initial C | CC | CD | DC | DD | CC to C | CD to C | DC to C | DD to C |
| 0 | EvolvedLookerUp2 2 2 | 2.97 | 0.705 | 28.0 | 1.0 | 0.639 | 0.066 | 0.189 | 0.106 | 0.836 | 0.481 | 0.568 | 0.8 |
| 1 | Evolved FSM 16 Noise 05 | 2.875 | 0.697 | 21.0 | 1.0 | 0.676 | 0.020 | 0.135 | 0.168 | 0.985 | 0.571 | 0.392 | 0.07 |
| 2 | PSO Gambler 1 1 1 | 2.874 | 0.684 | 23.0 | 1.0 | 0.651 | 0.034 | 0.152 | 0.164 | 1.000 | 0.283 | 0.000 | 0.136 |
| 3 | PSO Gambler Mem1 | 2.861 | 0.706 | 23.0 | 1.0 | 0.663 | 0.042 | 0.145 | 0.150 | 1.000 | 0.510 | 0.000 | 0.122 |
| 4 | Winner12 | 2.835 | 0.682 | 20.0 | 1.0 | 0.651 | 0.031 | 0.141 | 0.177 | 1.000 | 0.441 | 0.000 | 0.462 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |

Table 2: Output result of a single tournament.

# 3 Top ranked strategies

This section evaluates the performance of 195 IPD strategies. The performance of each strategy is evaluated in four tournament types, which were presented in Section 2, followed by an evaluation of their performance over all the 45686 simulated tournaments of this work.

Each strategy participated in multiple tournaments of the same type (on average 5154). For example Tit For Tat has participated in a total of 5114 tournaments of each type. The strategy's normalised rank distribution in these is given in Figure 1. A value of $r = 0$ corresponds to a strategy winning the tournament where a value of $r = 1$ corresponds to the strategy coming last. Because of the strategies' multiple entries their performance is evaluated based on the **median normalised rank** denoted as $\bar{r}$.

The top 15 strategies for each tournament type based on $\bar{r}$ are given in Table 3.

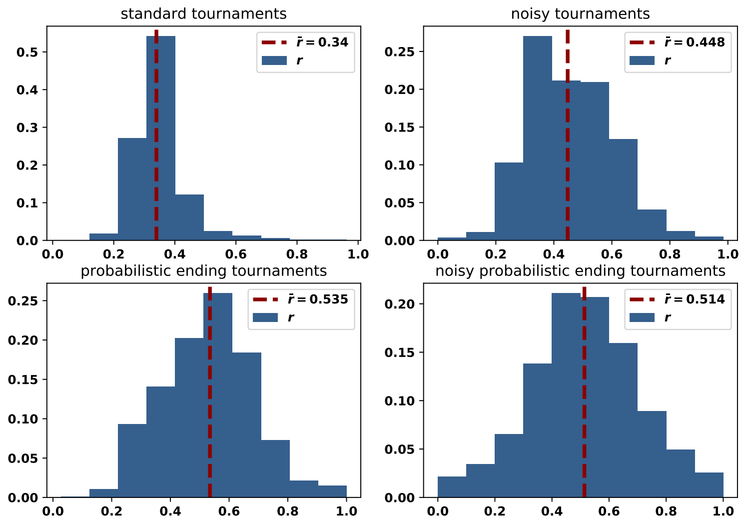



Figure 1: Tit For Tat's $r$ distribution in tournaments. The best performance of the strategy has been in standard tournaments where it achieved a $\bar{r}$ of 0.339.

| | Standard | | Noisy | | Probabilistic ending | | Noisy probabilistic ending | |
|---|---|---|---|---|---|---|---|---|
| | Name | $\bar{r}$ | Name | $\bar{r}$ | Name | $\bar{r}$ | Name | $\bar{r}$ |
| 0 | Evolved HMM 5 | 0.00667 | Grumpy | 0.14020 | Fortress4 | 0.01266 | Alternator | 0.30370 |
| 1 | Evolved FSM 16 | 0.00995 | $e$ | 0.19388 | Defector | 0.01429 | $\phi$ | 0.30978 |
| 2 | EvolvedLookerUp2 2 2 | 0.01064 | Tit For 2 Tats | 0.20617 | Better and Better | 0.01587 | $e$ | 0.31250 |
| 3 | Evolved FSM 16 Noise 05 | 0.01667 | Slow Tit For Two Tats | 0.20962 | Tricky Defector | 0.01875 | $\pi$ | 0.31686 |
| 4 | PSO Gambler 2 2 2 | 0.02143 | Cycle Hunter | 0.21538 | Fortress3 | 0.02174 | Limited Retaliate | 0.35263 |
| 5 | Evolved ANN | 0.02878 | Risky QLearner | 0.22222 | Gradual Killer | 0.02532 | Anti Tit For Tat | 0.35431 |
| 6 | Evolved ANN 5 | 0.03390 | Retaliate 3 | 0.22887 | Aggravater | 0.02778 | Retaliate 3 | 0.35563 |
| 7 | PSO Gambler 1 1 1 | 0.03704 | Cycler CCCCCD | 0.23507 | Raider | 0.03077 | Limited Retaliate 3 | 0.35563 |
| 8 | Evolved FSM 4 | 0.04891 | Retaliate 2 | 0.23913 | Cycler DDC | 0.04545 | Retaliate | 0.35714 |
| 9 | PSO Gambler Mem1 | 0.05036 | Defector Hunter | 0.24038 | Hard Prober | 0.05128 | Retaliate 2 | 0.35767 |
| 10 | Winner12 | 0.06011 | Retaliate | 0.24177 | SolutionB1 | 0.06024 | Limited Retaliate 2 | 0.36134 |
| 11 | Fool Me Once | 0.06140 | Hard Tit For 2 Tats | 0.25000 | Meta Minority | 0.06077 | Hopeless | 0.36842 |
| 12 | DBS | 0.07143 | ShortMem | 0.25286 | Bully | 0.06081 | Arrogant QLearner | 0.40651 |
| 13 | DoubleCrosser | 0.07200 | Limited Retaliate 3 | 0.25316 | Fool Me Forever | 0.07080 | Cautious QLearner | 0.40909 |
| 14 | BackStabber | 0.07519 | Limited Retaliate | 0.25706 | EasyGo | 0.07101 | Fool Me Forever | 0.41764 |

Table 3: Top performances for each tournament type based on $\bar{r}$.

In standard tournaments 10 out of the 15 top strategies are introduced in [34]. These are strategies based on finite state automata (FSM), hidden markov models (HMM), artificial neural networks (ANN), lookup tables (LookerUp) and stochastic lookup tables (Gambler) that have been trained using reinforcement learning algorithms (evolutionary and particle swarm algorithms). They have been trained to perform well against the strategies in [4] in a standard setting, thus their performance in the specific setting was anticipated. DoubleCrosser, and Fool Me Once, are strategies not from the literature but from [4]. DoubleCrosser is a strategy that makes use of the number of turns because is set to defect on the last two rounds. The strategy was expected to not perform as well in tournaments where the number of turns is not specified, but the strategy did not perform well in tournaments with noise either. Finally, Winner 12 [45] and DBS [13] are both from the the literature. DBS is strategy specifically designed for noisy environments, however, it ranks highly only in standard ones.

Figure 2 gives the distributions of $r$ for the top ranked strategies. The distributions are skewed towards zero and the highest median, of the top 15 strategies, is at 0.075. This indicates that the top ranked strategies perform well in any given standard tournament, despite the opponents and the number of turns.

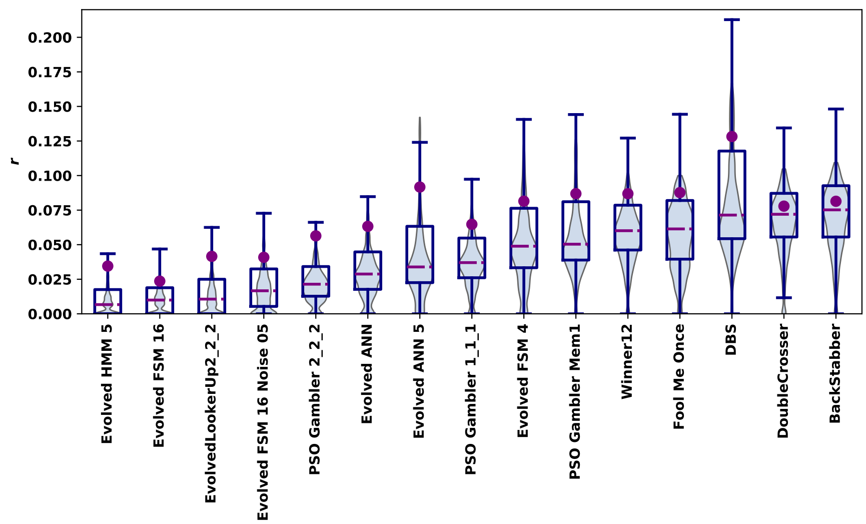



Figure 2: $r$ distributions of top 15 strategies in standard tournaments.

The top strategies in noisy tournaments are shown in Figure 3. These include deterministic strategies, such as Tit For 2 Tats [16], Slow Tit For Tats [4], Hard Tit For 2 Tats [59] and Cycler CCCCCD, and strategies which decide their actions based on the cooperations to defections ratio, such as ShortMem [23], Grumpy and $e$ [4]. The Retaliate and Limited Retaliate strategies are implemented in [4] by the same contributor. They are strategies designed to defect if the opponent has tricked them more often than $x\%$ of the times that they have done the same. Finally, in $4^{\text{th}}$ and $9^{\text{th}}$ place are Hunter strategies which trying to extort, equivalently, strategies that play cyclically and defectors.

From Figure 3, it is evident that the normalised rank distributions in noisy environments are more variant with higher medians compared to standard tournaments. The distributions are bimodal. This indicates that although the top ranked strategies mainly performed well, there are several tournaments that they ranked in the bottom half. To gain a better understanding of behaviour in noisy tournaments, the $r$ distribution over the noise probability $p_n$ for the top 6 strategies of Figure 3, are given in Figure 4.

For $p_n$ strictly lower than 0.5, Grumpy, Tit For 2 Tats and Slow Tit For Two Tat have a moderate performing, whereas $e$, Cycle Hunter and Ricky QLearner are behaving poorly. At $p_n = 0.5$, all the distributions are bimodal because with a 0.5 probability of noise any strategies corresponds to a random player. Interestedly, for a $p_n$ larger than 0.5 all of the 6 strategies become successful. Note that a value $p_n = 1$ corresponds to a strategy playing the exact opposite from what they intended. Thus, the successful strategies in noisy tournaments presented here, are effective when they are not playing as themselves. If $p_n$ was strictly less 0.5 then the top ranked strategies are different, Table 4. The top spots are mainly overtaken by the Meta strategies which are based on teams.

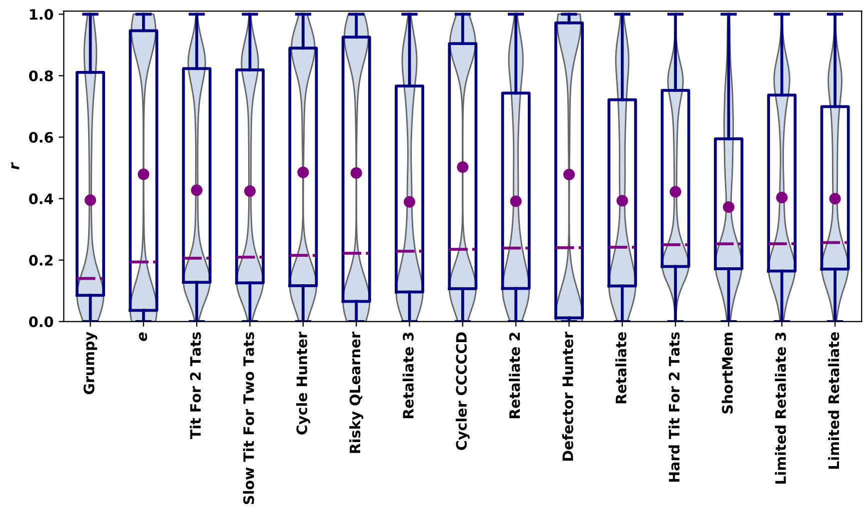



Figure 3: $r$ distributions for best performed strategies in noisy tournaments.

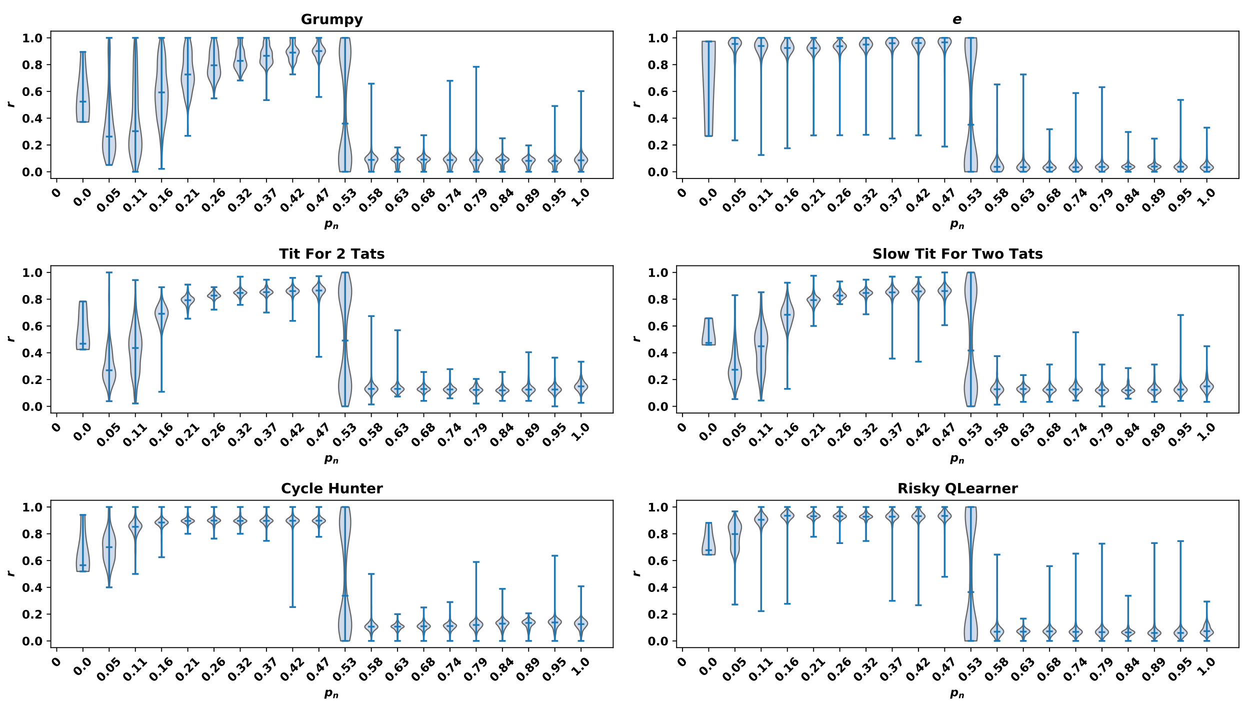



Figure 4: $r$ distributions for top 6 strategies in noisy tournaments over the probability of noisy ($p_n$).

The 15 top ranked strategies in probabilistic ending tournaments include Fortress 3, Fortress 4 (both introduced in [11]), Raider [12] and Solution B1 [12], which are strategies based on finite state automata

| Name | $\bar{r}$ |
|---|---|
| MEM2 | 0.06135 |
| Spiteful Tit For Tat | 0.06344 |
| Nice Meta Winner | 0.06620 |
| Grudger | 0.06667 |
| Meta Winner Long Memory | 0.07339 |
| Forgiver | 0.07362 |
| Fool Me Once | 0.07362 |
| Meta Winner | 0.07487 |
| Meta Winner Memory One | 0.07621 |
| Meta Winner Finite Memory | 0.07692 |
| Meta Winner Deterministic | 0.07792 |
| NMWE Deterministic | 0.08696 |
| NMWE Long Memory | 0.08696 |
| CollectiveStrategy | 0.08696 |
| Defector | 0.08889 |

Table 4: Top performances in noisy tournaments where $p_n < 0.5$.

introduced by Daniel and Wendy Ashlock. These strategies have been evolved using reinforcement learning, however, there were trained to maximise their payoffs in tournaments with fixed turns (150 specifically) and not in probabilistic ending ones. In probabilistic ending tournaments it appears that the top ranks are mostly occupied by defecting strategies. These include Better and Better, Gradual Killer, Hard Prober (all from [1]), Bully (Reverse Tit For Tat) [49] and Defector. Thus, it's surprisingly that EasyGo and Fool Me Forever which are strategies that will defect until their opponent defect, then they will cooperate until the end, ranked 14$^{\text{th}}$ and 15$^{\text{th}}$. Upon inspection, it was concluded that they are actually the same strategy. This was not known to the authors at the time of data collection. Figure 5 verifies that their perfomance is the same. Both strategies have repeatedly ranked highly and there are cases for which they were the winners of the tournament.

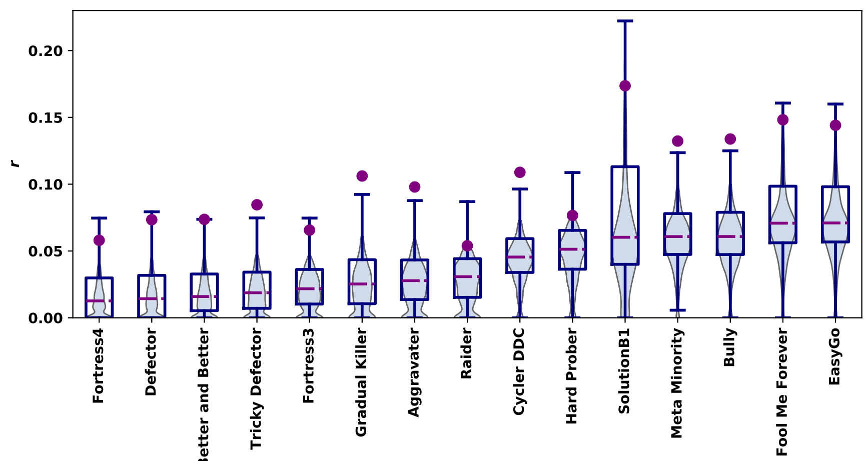



Figure 5: $r$ distributions for best performed strategies in probabilistic ending tournaments.

The distributions of the normalised rank in probabilistic ending tournaments, shown in Figure 5, are less variant than those of noisy tournaments. The medians of the top 15 strategies are lower than 0.1 and the distributions are skewed towards 0. Though the large difference between the means and the medians indicates some outliers, the strategies have overall performed well in the probabilistic ending tournaments that they participated.

The distributions of $r$ over $p_e$ for the top 6 strategies are also given by Figure 6. It is shown that the rank of the strategies is decreasing as the probability of the game ending increases and at the point of $p_e = 0.1$ the strategies become dominant. All the top ranked strategies in this setting are defecting strategies, and what is exhibited is that they do better as the probability of the game ending in the next turn increases, which is inline with the Folk Theorem [31]. Consider tournaments where the probability of the game ending was less than 0.1, the top ranked strategies based on $\bar{r}$ are given by Table 5. The top ranked strategies include strategies based on teams, trained strategies, Grudger and Spiteful Tit for Tat.

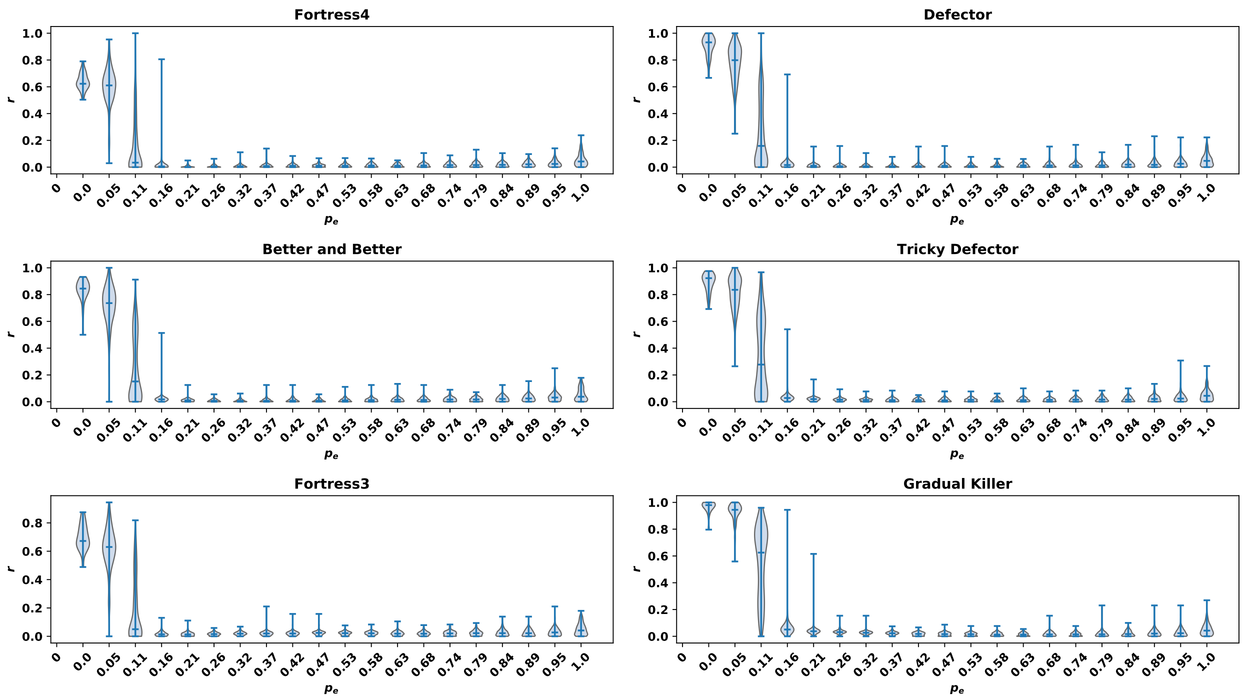



Figure 6: $r$ distributions for top 6 strategies in probabilistic ending tournaments over $p_e$.

| Name | $\bar{r}$ |
|---|---|
| Evolved FSM 16 | 0.00000 |
| Evolved FSM 16 Noise 05 | 0.01266 |
| MEM2 | 0.02715 |
| Evolved HMM 5 | 0.04423 |
| EvolvedLookerUp2 2 2 | 0.04870 |
| Spiteful Tit For Tat | 0.05958 |
| Nice Meta Winner | 0.06842 |
| NMWE Finite Memory | 0.06923 |
| Grudger | 0.06985 |
| NMWE Deterministic | 0.07018 |
| NMWE Long Memory | 0.07407 |
| Nice Meta Winner Ensemble | 0.07595 |
| EvolvedLookerUp1 1 1 | 0.07692 |
| NMWE Memory One | 0.08000 |
| NMWE Stochastic | 0.08475 |

Table 5: Top performances in probabilistic ending tournaments with $p_e < 0.1$

In tournaments with both noise and an unspecified number of turns several of the top ranked strategies are strategies that were highly ranked in noisy tournaments. This demonstrates that, $e$, $\pi$, $\phi$ ($\pi$, $\phi$ are based on the same approach as $e$) and the Retaliate family are robust in noisy environments regardless of the number of turns. However, strategies from the top ranks in probabilistic ending tournaments did not rank highly here. The distributions of $r$ shown in Figure 7 have the largest median values compared to the top rank strategies of the other tournament types.

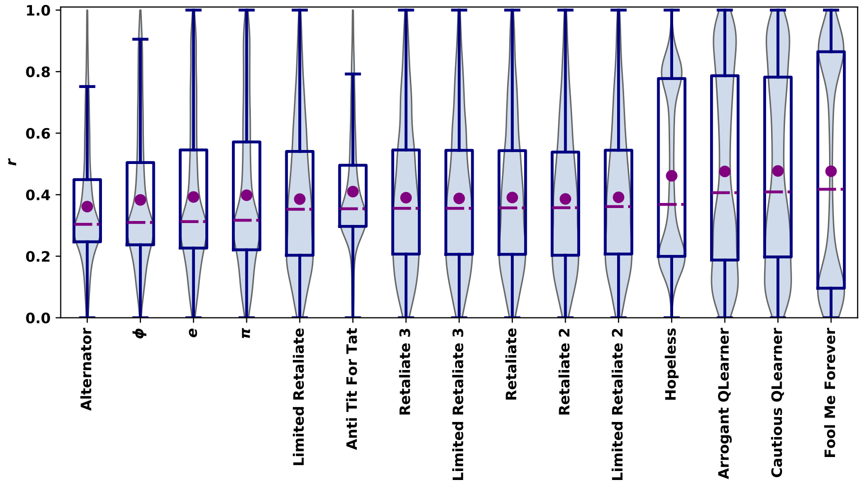



Figure 7: $r$ distributions for best performed strategies in noisy probabilistic ending tournaments.

The distributions of $r$ for the tournament types indicate that for probabilistic ending and standard tournaments successful strategies do exist. For these settings, the top 15 strategies have frequently ranked in the top spots with only a few exceptions. Contrarily, it appears that noise cause variation in the normalised ranks, and the strategies can always guarantee a spot in the top ranks.

Up till now, the performances of the 195 strategies have been evaluated for individual tournament types. The data set considered in this work, described in Section 2, contains a total of 45686 tournament results. For this part of the manuscript the strategies are ranked based on the median normalised rank they achieved over the entire data set. The top 15 strategies are given in Table 6 and their normalised rank distributions are given in Figure 8.

| Name | Normalized_Rank |
|---|---|
| Limited Retaliate 3 | 0.28609 |
| Retaliate 3 | 0.29630 |
| Retaliate 2 | 0.30250 |
| Limited Retaliate 2 | 0.30328 |
| Limited Retaliate | 0.31000 |
| Retaliate | 0.31707 |
| BackStabber | 0.32381 |
| DoubleCrosser | 0.33136 |
| Nice Meta Winner | 0.34921 |
| PSO Gambler 2_2_2 Noise 05 | 0.35146 |
| Grudger | 0.35156 |
| Evolved HMM 5 | 0.35714 |
| NMWE Memory One | 0.35714 |
| Nice Meta Winner Ensemble | 0.35870 |
| Forgetful Fool Me Once | 0.35884 |

Table 6: Top performances over all the tournaments

The top ranks include strategies that have been previously mentioned. The set of Retaliate strategies occupy the top spots followed by BackStabber and DoubleCrosser. Figure 8 gives the normalised rank distributions of these strategies. The distributions of the Retaliate strategies have no statistical difference. Thus, in an

IPD tournament where the type is not specified, playing as any of the Retaliate strategies will have the result. DoubleCrosser performed well in standard tournaments and the strategy is just an extension of BackStabber. It should be noted that these strategies can be characterised as ”cheaters”. The source code of the strategies allows them to known the number of turns in a match (if they are specified). PSO Gambler and Evolved HMM 5 are trained strategies introduced in [34] and Nice Meta Winner and NMWE Memory One are strategies based on teams. Grudger is a strategy from Axelrod’s original tournament and Forgetful Fool Me Once is based on the same approach as Grudger. All the top 15 strategies are fundamentally different. Some are cheaters, some are complex, others are simple deterministic strategies and strategies based on teams. The results of 45686 tournaments used in this work imply the following: they is not a single type of strategy which can performance well in any IPD interaction.

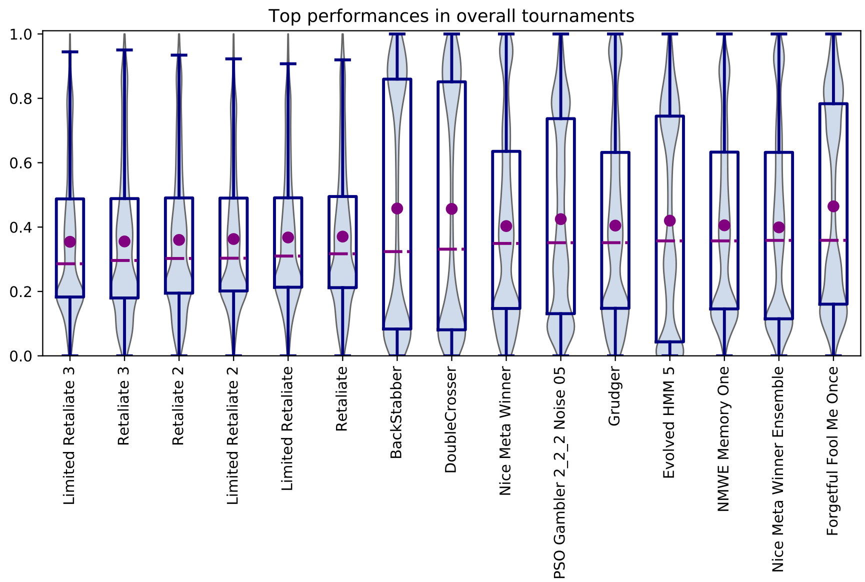



Figure 8: $r$ distributions for best performed strategies in the data set [33].

This section presented the winning strategies in a series of IPD tournaments. In standard tournaments the top spots were dominated by complex strategies that had been trained using reinforcement learning techniques. In noisy environments, whether the number of turns was fixed or not, the winning strategies were deterministic strategies designed to defect if the opponent tricked them more than a current amount of the times that they had tricked their opponent. In probabilistic ending tournaments most of the winning strategies were defecting strategies and trained finite state automata, designed by the same authors. Finally the performance of all 195 strategies over the 45686 tournaments in this manuscript was assessed on $\bar{r}$. The top ranked strategies were a mixture of behaviours that did well in standard tournaments and tournaments with noise, as well as a few strategies based on teams.

The results of this section imply that successful strategies for specific settings exist for an IPD tournament. The top ranked strategies in both standard tournaments and tournaments with probabilistic ending, managed to rank in the top 10% of the tournament most of the times. Strategies in noisy environments demonstrated that no strategy can be consistently successful. Overall, there has been not a single strategy that has shown to perform well in more than one setting. The aim of the next section is to understand which are the factors that made these strategies successful, in each setting separately but also overall.

# 4 Evaluation of performance

The aim of this section is to explore the factors that contribute to a strategy's successful performance. The factors explored are measures regarding a strategy's behaviour, along with measures regarding the tournaments the strategies competed in. These are given in Table 7.

| measure | measure explanation | source | value type | min value | max value |
|---|---|---|---|---|---|
| stochastic | If a strategy is stochastic | strategy classifier from [4] | boolean | Na | Na |
| makes use of game | If a strategy makes used of the game information | strategy classifier from [4] | boolean | Na | Na |
| makes use of length | If a strategy makes used of the number of turns | strategy classifier from [4] | boolean | Na | Na |
| memory usage | The memory size of a strategy divided by the number of turns | memory size from [4] | float | 0 | 1 |
| SSE | A measure of how far a strategy is from ZD behaviour | method described in [40] | float | 0 | 1 |
| max cooperating rate ($C_{\max}$) | The biggest cooperating rate in a given tournament | result summary | float | 0 | 1 |
| min cooperating rate ($C_{\min}$) | The smallest cooperating rate in a given tournament | result summary | float | 0 | 1 |
| median cooperating rate ($C_{\text{median}}$) | The median cooperating rate in a given tournament | result summary | float | 0 | 1 |
| mean cooperating rate ($C_{\text{mean}}$) | The mean cooperating rate in a given tournament | result summary | float | 0 | 1 |
| $C_r$ / $C_{\max}$ | A strategy's cooperating rate divided by the maximum | result summary | float | 0 | 1 |
| $C_r$ / $C_{\min}$ | A strategy's cooperating rate divided by the minimum | result summary | float | 0 | 1 |
| $C_r$ / $C_{\text{median}}$ | A strategy's cooperating rate divided by the median | result summary | float | 0 | 1 |
| $C_r$ / $C_{\text{mean}}$ | A strategy's cooperating rate divided by the mean | result summary | float | 0 | 1 |
| $C_r$ | The cooperating ratio of a strategy | result summary | float | 0 | 1 |
| $CC$ to $C$ rate | The probability a strategy will cooperate after a mutual cooperation | result summary | float | 0 | 1 |
| $CD$ to $C$ rate | The probability a strategy will cooperate after being betrayed by the opponent | result summary | float | 0 | 1 |
| $DC$ to $C$ rate | The probability a strategy will cooperate after betraying the opponent | result summary | float | 0 | 1 |
| $DD$ to $C$ rate | The probability a strategy will cooperate after a mutual defection | result summary | float | 0 | 1 |
| $p_n$ | The probability of a player's action being flip at each interaction | trial summary | float | 0 | 1 |
| $n$ | The number of turns | trial summary | integer | 1 | 200 |
| $p_e$ | The probability of a match ending in the next turn | trial summary | float | 0 | 1 |
| $N$ | The number of strategies in the tournament | trial summary | integer | 3 | 195 |
| $k$ | The number of repetitions of a given tournament | trial summary | integer | 10 | 100 |

Table 7: The measures which are included in the performance evaluation analysis.

Axelrod-Python makes use of classifiers to classify strategies according to various dimensions. These determine whether a strategy is stochastic or deterministic, whether it makes use of the number of turns or the game's payoffs. The memory usage measure is calculated as the memory size of strategy (which is specified in the strategies implementation in [4]) divide by the number of turns. For example, Evolved FSM 16 Noise 05 has a memory size of 16 and participated in a tournament where $n$ was 134. In the given tournament Evolved FSM 16 Noise 05 has a memory usage of 0.119. For tournaments with a probabilistic ending the number of turns was not collected, so the memory usage measure is not used for probabilistic ending tournaments. The SSE is a measure introduced in [40] which shows how close a strategy is to behaving as a ZDs, and subsequently, in an extortionate way. The method identifies the ZDs closest to a given strategy and calculates the algebraic distance between them, defined as SSE. A SSE value of 1 indicates no extortionate behaviour at all whereas a value of 0 indicates that a strategy is behaving a ZDs. The rest of the factors considered are the $CC$ to $C$, $CD$ to $C$, $DC$ to $C$, and $DD$ to $C$ rates as well as cooperating ratio of a strategy. The minimum, maximum, medium and median cooperating ratios of each tournament are also included, and finally the number of turns, the number of strategies, the number of repetitions and the probabilities of noise and the game ending are also included.

Table 8 shows the correlation coefficients between the measures of Table 7 the median score and the median normalised rank. Note that the correlation for the classifiers is not included because they are binary variables and they will be evaluated using a different method. The correlation coefficients for all the measures in Table 7 against themselves have also been calculated and a graphical representation can be found in the Appendix C.

In standard tournaments the measures $CC$ to $C$, $C_r$, $C_r/C_{\max}$ and the cooperating ratio compared to $C_{\text{median}}$ and $C_{\text{mean}}$ have a moderate negative effect on the normalised rank, and a moderate positive on the median score. The SSE error and the $DD$ to $C$ have the opposite effects. Thus, in standard tournaments behaving cooperatively corresponds to a more successful performance. Even though being nice pays off, that's not true against defective strategies. Cooperating after a mutual defection lowers a strategy's success. Figure 9 confirms that the winners of standard tournaments always cooperate after a mutual cooperation and almost

| | Standard | | Noisy | | Probabilistic ending | | Noisy probabilistic ending | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $r$ | median score | $r$ | median score | $r$ | median score | $r$ | median score | $r$ | median score |
| $CC$ to $C$ rate | -0.501 | 0.501 | 0.414 | -0.504 | 0.408 | -0.323 | 0.260 | 0.022 | -0.501 | 0.501 |
| $CD$ to $C$ rate | 0.226 | -0.199 | 0.456 | -0.330 | 0.320 | -0.017 | 0.205 | -0.220 | 0.226 | -0.199 |
| $C_r$ | -0.323 | 0.384 | 0.711 | -0.678 | 0.714 | -0.832 | 0.579 | -0.135 | -0.323 | 0.384 |
| $C_r$ / $C_{max}$ | -0.323 | 0.381 | 0.616 | -0.551 | 0.714 | -0.833 | 0.536 | -0.116 | -0.323 | 0.381 |
| $C_r$ / $C_{mean}$ | -0.331 | 0.358 | 0.731 | -0.740 | 0.721 | -0.861 | 0.649 | -0.621 | -0.331 | 0.358 |
| $C_r$ / $C_{median}$ | -0.331 | 0.353 | 0.652 | -0.669 | 0.712 | -0.852 | 0.330 | -0.466 | -0.331 | 0.353 |
| $C_r$ / $C_{min}$ | 0.109 | -0.080 | -0.358 | 0.250 | -0.134 | 0.150 | -0.368 | 0.113 | 0.109 | -0.080 |
| $C_{max}$ | -0.000 | 0.049 | 0.000 | 0.023 | -0.000 | 0.046 | 0.000 | -0.004 | -0.000 | 0.049 |
| $C_{mean}$ | -0.000 | 0.229 | -0.000 | 0.271 | 0.000 | 0.200 | 0.000 | 0.690 | -0.000 | 0.229 |
| $C_{median}$ | 0.000 | 0.209 | -0.000 | 0.240 | -0.000 | 0.187 | -0.000 | 0.673 | 0.000 | 0.209 |
| $C_{min}$ | 0.000 | 0.084 | 0.000 | -0.017 | -0.000 | 0.007 | -0.000 | 0.041 | 0.000 | 0.084 |
| $DC$ to $C$ rate | 0.127 | -0.100 | 0.509 | -0.504 | -0.018 | 0.033 | 0.341 | -0.016 | 0.127 | -0.100 |
| $DD$ to $C$ rate | 0.412 | -0.396 | 0.533 | -0.436 | -0.103 | 0.176 | 0.378 | -0.263 | 0.412 | -0.396 |
| $N$ | 0.000 | -0.009 | -0.000 | 0.002 | -0.000 | 0.003 | -0.000 | 0.001 | 0.000 | -0.009 |
| $k$ | 0.000 | -0.002 | -0.000 | 0.003 | -0.000 | 0.001 | -0.000 | -0.008 | 0.000 | -0.002 |
| $n$ | 0.000 | -0.125 | -0.000 | -0.024 | - | - | - | - | 0.000 | -0.125 |
| $p_e$ | - | - | - | - | 0.000 | 0.165 | 0.000 | -0.058 | -0.001 | 0.001 |
| $p_n$ | - | - | -0.000 | 0.207 | - | - | -0.000 | -0.650 | 0.002 | -0.000 |
| Make use of game | -0.003 | -0.022 | 0.025 | -0.082 | -0.053 | -0.108 | 0.013 | -0.016 | -0.003 | -0.022 |
| Make use of length | -0.158 | 0.124 | 0.005 | -0.123 | -0.025 | -0.090 | 0.014 | -0.016 | -0.154 | 0.117 |
| SSE | 0.473 | -0.452 | 0.463 | -0.337 | -0.156 | 0.223 | 0.305 | -0.259 | 0.473 | -0.452 |
| memory usage | -0.082 | 0.095 | -0.007 | -0.017 | - | - | - | - | -0.084 | 0.095 |
| stochastic | 0.006 | -0.024 | 0.022 | -0.026 | 0.002 | -0.130 | 0.021 | -0.013 | 0.006 | -0.024 |

Table 8: Correlations table between the measures of Table 7 the normalised rank and the median score.

always defects after a mutual defection.

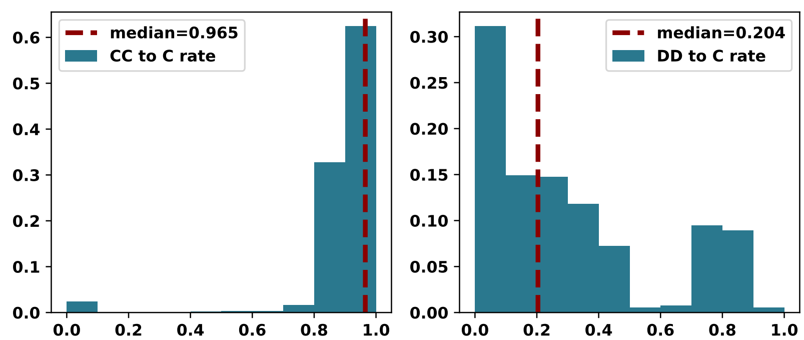



Figure 9: Distributions of $CC$ to $C$ and $DD$ to $C$ for the winners in standard tournaments.

Compared to standard tournaments, in both noisy and in probabilistic ending tournaments the higher the rates of cooperation the lower a strategy's success and median score. A strategy would want to cooperate less than both the mean and median cooperator in such settings. In probabilistic ending tournaments the correlations coefficients have a larger values, indicating a stronger effect. Thus a strategy will be punished more by it's cooperative behaviour in probabilistic ending environments, this was seen in Section 4 as well. The distributions of the $C_r$ of the winners in both tournaments is given by Figure 10. It confirms that the winners in noisy tournaments cooperated less than 35% of the times and in probabilistic ending tournaments less than 10%. In noisy probabilistic ending tournaments and in over all the tournaments' results, the only measures that had a moderate affect are $C_r/C_{\text{mean}}, C_r/C_{\text{max}}$ and $C_r$. In such environments cooperative behaviour appears to be punished by not as much as in noisy and probabilistic ending tournaments.

The performances are clustered in two clusters based on the nornalised rank. More specifically, there are clustered based on whether the normalised rank was in the top 5%, the 25% and the 50%. A random forest

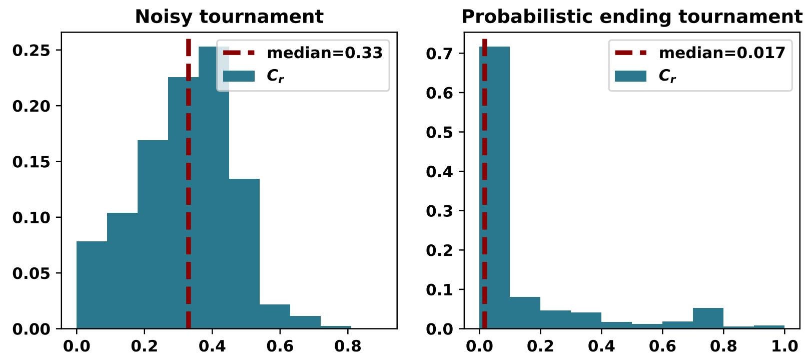



Figure 10: $C_r$ distributions of the winners in noisy and in probabilistic ending tournaments.

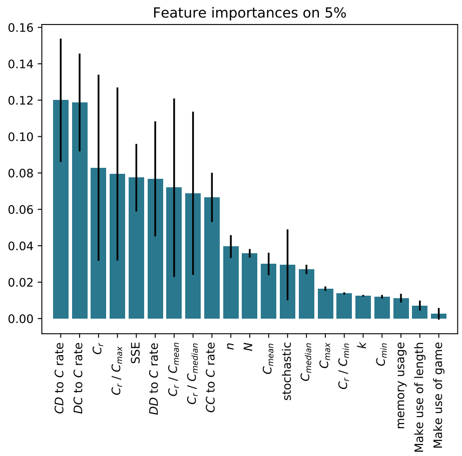
approach [22] is applied to the data to predict the cluster to which a strategy's performance has been assigned to. The random forest method constructs many individual decision trees and the predictions from all trees are pooled to make the final prediction. The random forest models are trained on a training set of 70% of the tournaments results. The accuracy of each model based on $R^2$ are given by Table 9. The out of the bag error [35] has also been calculated. The models fit well, and a high value of both the accuracy measure on the test data and the OOB error indicate that the model is not over fitting.

The performances have also been clustered based on their normalised rank and their median score by a $k-$means algorithm [8]. The number of clusters is not deterministically chosen but it is based on the silhouette coefficients [56]. The chosen cluster for each tournament type, as well as the accuracy for random forest models, are given in Table 9.

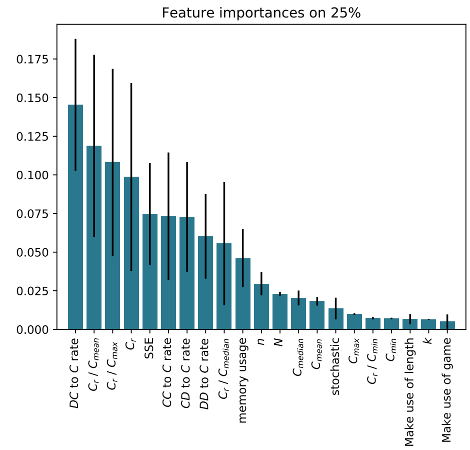
| Tournament type | Clustering on | Number of clusters | $R^2$ training data | $R^2$ test data | $R^2$ OOB score |
|---|---|---|---|---|---|
| standard | top 5% $r$ | 2 | 0.998831 | 0.987041 | 0.983708 |
| | top 25% $r$ | 2 | 0.998643 | 0.978626 | 0.969202 |
| | top 50% $r$ | 2 | 0.998417 | 0.985217 | 0.976538 |
| | $r$ & normalised score | 2 | 0.998794 | 0.990677 | 0.982959 |
| noisy | top 5% $r$ | 2 | 0.996677 | 0.950572 | 0.935383 |
| | top 25% $r$ | 2 | 0.996677 | 0.950572 | 0.935383 |
| | top 50% $r$ | 2 | 0.996677 | 0.950572 | 0.935383 |
| | $r$ & normalised score | 3 | 0.996677 | 0.950572 | 0.935383 |
| probabilistic ending | top 5% $r$ | 2 | 0.999592 | 0.995128 | 0.992819 |
| | top 25% $r$ | 2 | 0.999592 | 0.995128 | 0.992819 |
| | top 50% $r$ | 2 | 0.999592 | 0.995128 | 0.992819 |
| | $r$ & normalised score | 2 | 0.999592 | 0.995128 | 0.992819 |
| noisy probabilistic ending | top 5% $r$ | 2 | 0.990490 | 0.813905 | 0.791418 |
| | top 25% $r$ | 2 | 0.990490 | 0.813905 | 0.791418 |
| | top 50% $r$ | 2 | 0.990490 | 0.813905 | 0.791418 |
| | $r$ & normalised score | 4 | 0.990490 | 0.813905 | 0.791418 |
| over 45686 tournaments | top 5% $r$ | 2 | 0.993396 | 0.913409 | 0.898059 |
| | top 25% $r$ | 2 | 0.993396 | 0.913409 | 0.898059 |
| | top 50% $r$ | 2 | 0.993396 | 0.913409 | 0.898059 |
| | $r$ & normalised score | 3 | 0.993396 | 0.913409 | 0.898059 |

Table 9: Accuracy metrics for random forest models.

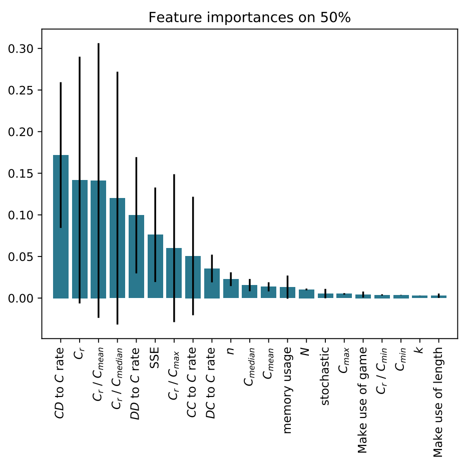
The importance that the measures of Table 7 had on the classification tasks; to which cluster a performance was assigned to, have been calculated and are given by Figures 11, 12, 13, 14 and 15. These show that the classifiers stochastic, make use of game and make use of length have no significant effect, and several of the measures that are highted by the importance are inline with the correlation results. The most important measures based on the random forest analysis were $C_r/C_{median}$ and $C_r/C_{mean}$.



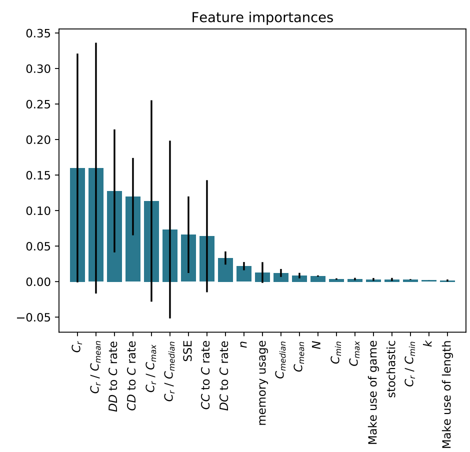

(a) Importance of features for clusters on 5% performance.




(b) Importance of features for clusters on 25% performance.



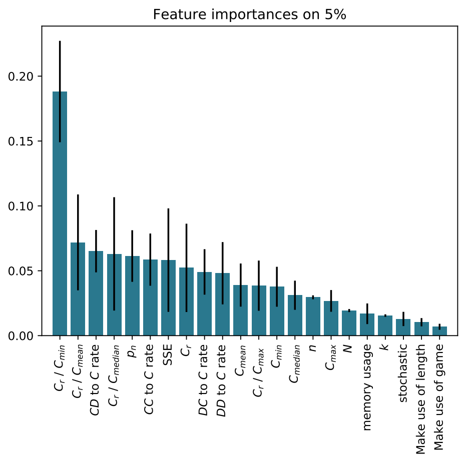

(c) Importance of features for clusters on 50% performance.

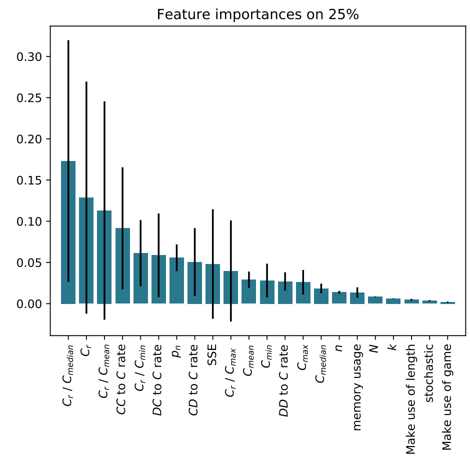



(d) Importance of features for clusters based on $k$means algorithm.

Figure 11: Importance of features in standard tournaments for different clustering methods.

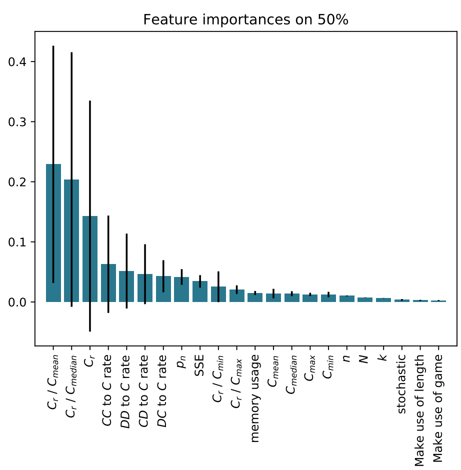
The effect of both these measures can be further explored. In Figure 16 the distributions of $C_/C_{\text{mean}}$ and $C_/C_{\text{median}}$ are given for the winners. A value of $C_/C_{\text{mean}} = 1$ imply that the cooperating ratio of the winner was the same as the mean / median cooperating ratio. In standard tournaments, the mean for both ratios is 1. Therefore, an effective strategy in standard tournaments was the mean / median cooperator of its respective tournament. In comparison, Figure 17 shows the distributions of the measure for the winners in noisy tournaments. The mean is at 0.67, thereupon the winners cooperated 67% of the times the mean / median cooperator did. This analysis is applied to the rest of the tournaments and the distributions are given by Figures 18, 19 and 20. In a tournament with noisy and a probabilistic ending the winners cooperated 60%, whereas in settings that the type of the tournament can vary between the types considered in this work the winners cooperated 67% of the times the mean or median cooperator did. Finally, in probabilistic ending tournament it has already been mentioned that defecting strategies prevail and this result is once

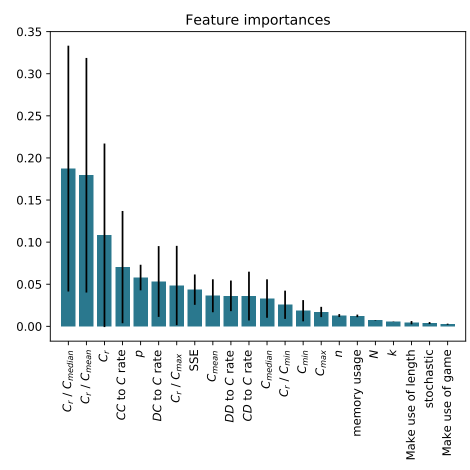



(a) Importance of features for clusters on 5% performance.

(b) Importance of features for clusters on 25% performance.

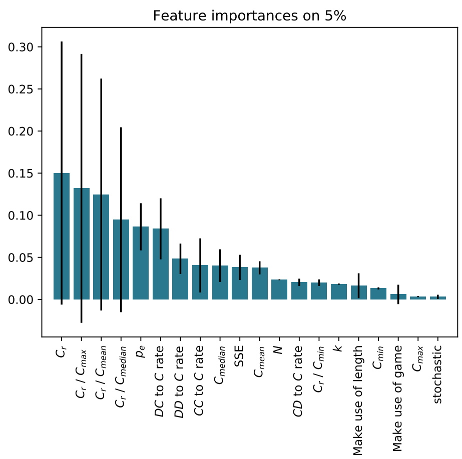


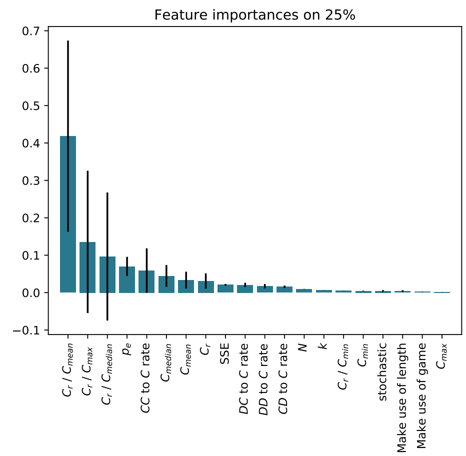

(c) Importance of features for clusters on 50% performance.

(d) Importance of features for clusters based on $k$means algorithm.

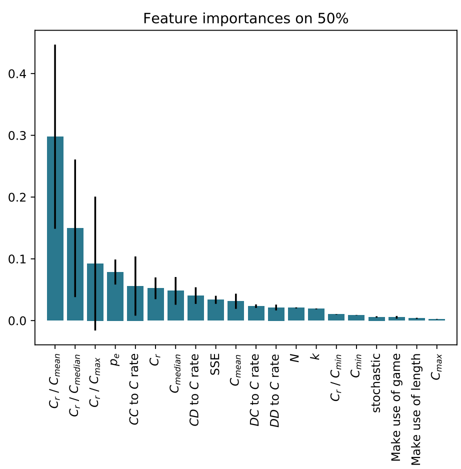
Figure 12: Importance of features in noisy tournaments for different clustering methods.



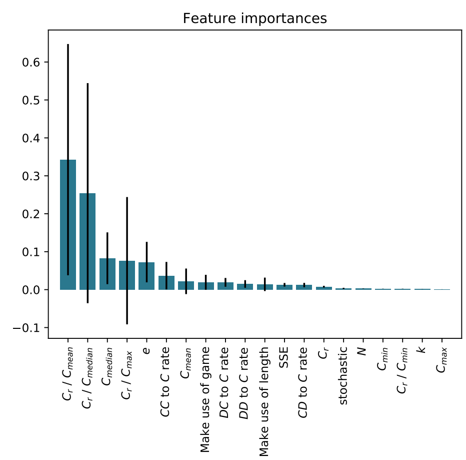

(a) Importance of features for clusters on 5% performance.




(b) Importance of features for clusters on 25% performance.

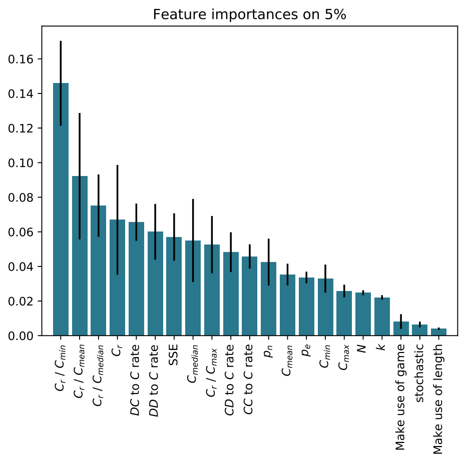



(c) Importance of features for clusters on 50% performance.

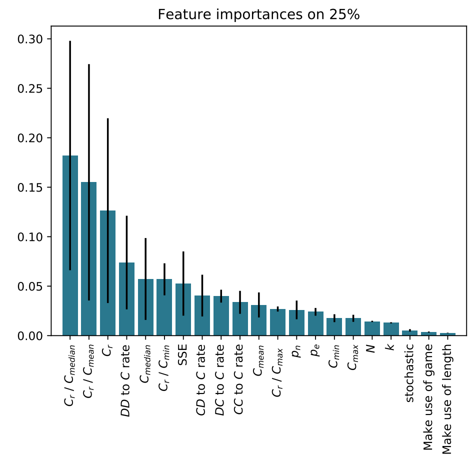



(d) Importance of features for clusters based on $k$means algorithm.

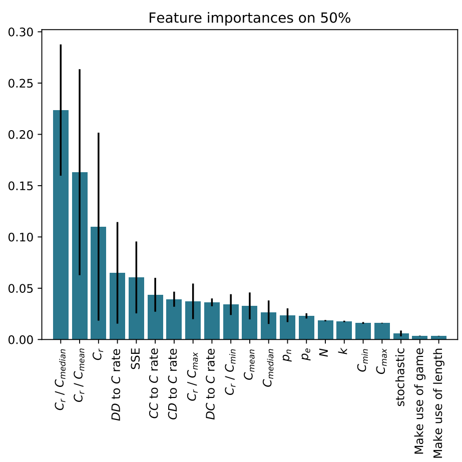
Figure 13: Importance of features in probabilistic ending tournaments for different clustering methods.



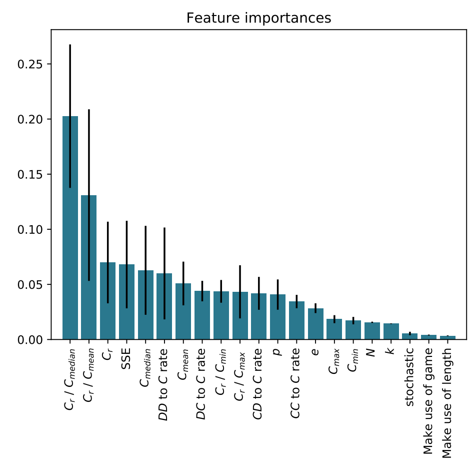

(a) Importance of features for clusters on 5% performance.




(b) Importance of features for clusters on 25% performance.

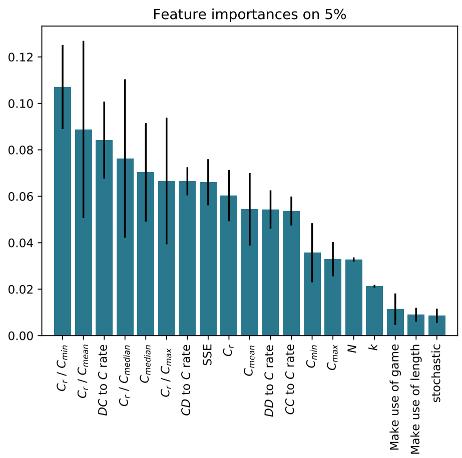



(c) Importance of features for clusters on 50% performance.

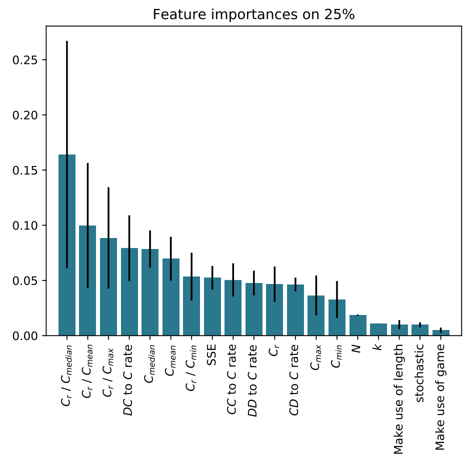



(d) Importance of features for clusters based on $k$means algorithm.

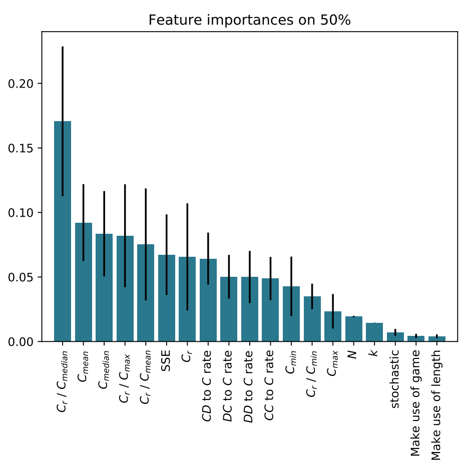
Figure 14: Importance of features in noisy probabilistic ending tournaments for different clustering methods.



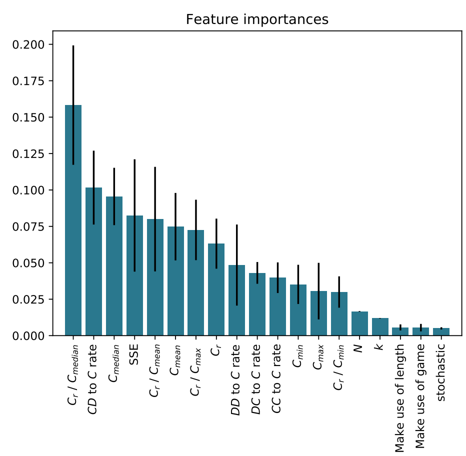

(a) Importance of features for clusters on 5% performance.




(b) Importance of features for clusters on 25% performance.




(c) Importance of features for clusters on 50% performance.




(d) Importance of features for clusters based on $k$means algorithm.

Figure 15: Importance of features over all the tournaments for different clustering methods.

again confirmed in this section.

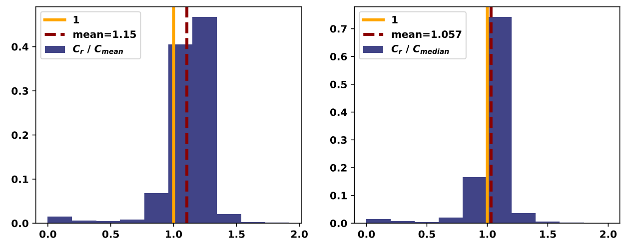



Figure 16: Distributions of $C_r/C_{\text{median}}$ and $C_r/C_{\text{median}}$ for winners of standard tournaments.

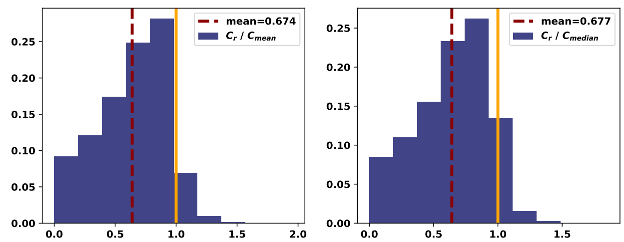



Figure 17: Distributions of $C_r/C_{\text{median}}$ and $C_r/C_{\text{median}}$ for winners of noisy tournaments.

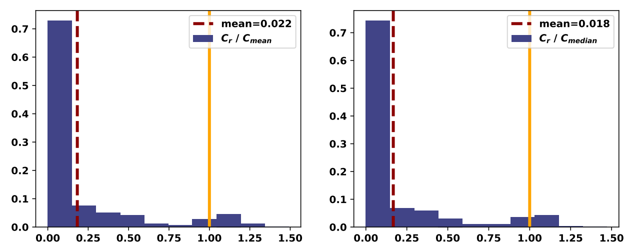



Figure 18: Distributions of $C_r/C_{\text{median}}$ and $C_r/C_{\text{median}}$ for winners of probabilistic ending tournaments.

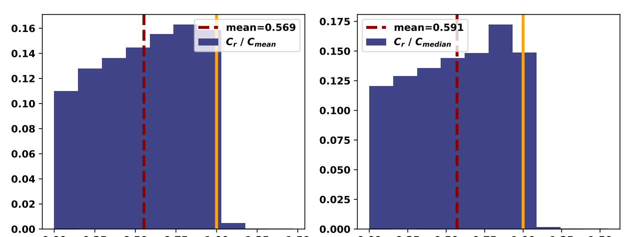



Figure 19: Distributions of $C_r/C_{\text{median}}$ and $C_r/C_{\text{median}}$ for winners of noisy probabilistic ending tournaments.

In this section the effect of several measures, regarding a strategy's behaviour and the tournament, on it's performance were presented. This was done using two approaches. Correlation coefficients and a random forest analysis. The results of these are discussed in the following section.

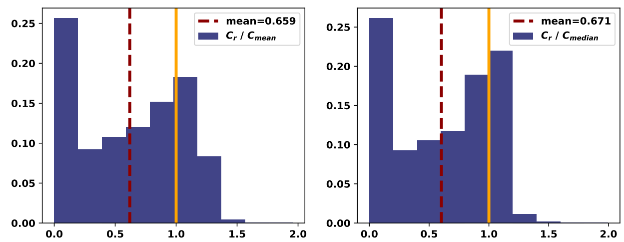



Figure 20: Distributions of $C_r/C_{\text{median}}$ and $C_r/C_{\text{median}}$ for winners of over all the tournaments.

# 5 Conclusion

This manuscript has explored the performance of 194 strategies of the Iterated Prisoner's Dilemma in a large number of computer tournaments. The results of the analysis demonstrated that, although for specific tournament type, such as standard, noisy and probabilistic ending tournaments, dominant strategies exist there is not a single dominant strategy if the environments vary. Moreover, a strategy with a theory of mind should aim to adapt its behaviour based on the mean and median cooperators.

The 194 strategies used in this manuscript have been mainly for the literature, and they have been accessible due to an open source software called Axelrod-Python. The software was used to generate a total of 45686 computer tournaments results with different number of strategies and different participants each time. The data collection was described in Section 2. In Section 3, the tournaments results were used to present the top performances. The data set contained results from four different settings, and these were also studied individually. In standard tournaments complex strategies trained using reinforcement learning ranked in the top places. In probabilistic ending tournaments, several trained strategies based on finite state automata also performed well. The rest top strategies, in this setting, were defecting strategies. Finally, in tournaments with noise, the Retaliate set of strategies demonstrated their robustness in tournaments with probabilistic ending and not.

Section 4, covered an analysis of performance based on several measures associated with a strategy and with the environments it was competing. The results of this analysis showed that a strategy's characteristics such as whether or not it's stochastic, and the information it used regarding the game had no effect on the strategy's success. The most important factors have been those that compared the strategy's behaviour to it's environment. The cooperating ratio of the strategy compared to the mean and median cooperator was highlighted as the most important feature in the analysis. More specifically, if a strategy were to enter a tournament with a theory of mind of it's environment it would choose to be the median cooperator in standard tournaments, the defector in probabilistic ending tournaments and to cooperate 60% of the times the median cooperator did in noisy and noisy probabilistic tournaments. Lastly, if a strategy was aware of the opponents but not of the setting on the tournament, a strategy would be more likely to be successful if it were to identify the median cooperator and cooperated 67% of the times that they did.

Further data mining could be applied to the data set of this work, available at [33].

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## 6 Acknowledgements

A variety of software have been used in this work:

- The Axelrod library for IPD simulations [4].
- The Matplotlib library for visualisation [37].
- The Numpy library for data manipulation [63].
- The scikit-learn library for data analysis [52].

## A A summary of parameters

## B List of strategies

The strategies used in this study which are from Axelrod version 3.0.0 [4].

1. $\phi$ [4]
2. $\pi$ [4]
3. $e$ [4]
4. ALLCorALLD [4]
5. Adaptive [43]
6. Adaptive Pavlov 2006 [39]
7. Adaptive Pavlov 2011 [43]
8. Adaptive Tit For Tat: 0.5 [60]
9. Aggravater [4]
10. Alexei [3]
11. Alternator [17, 47]
12. Alternator Hunter [4]
13. Anti Tit For Tat [36]
14. AntiCycler [4]
15. Appeaser [4]
16. Arrogant QLearner [4]
17. Average Copier [4]
18. Backstabber [4]
19. Better and Better [1]
20. Bully [49]
21. Calculator [1]
22. Cautious QLearner [4]
23. Champion [16]
24. CollectiveStrategy [2]
25. Contrite Tit For Tat [64]
26. Cooperator [17, 47, 53]
27. Cooperator Hunter [4]
28. Cycle Hunter [4]
29. Cycler CCCCCD [4]

| measure | measure explanation |
|---|---|
| stochastic | If a strategy is stochastic |
| makes use of game | If a strategy makes used of the game information |
| makes use of length | If a strategy makes used of the number of turns |
| memory usage | The memory size of a strategy divided by the number of turns |
| SSE | A measure of how far a strategy is from extortionate behaviour |
| $C_{\max}$ | The biggest cooperating rate in the tournament |
| $C_{\min}$ | The smallest cooperating rate in the tournament |
| $C_{\text{median}}$ | The median cooperating rate in the tournament |
| $C_{\text{mean}}$ | The mean cooperating rate in the tournament |
| $C_r$ / $C_{\max}$ | A strategy's cooperating rate divided by the maximum |
| $C_r$ / $C_{\min}$ | A strategy's cooperating rate divided by the minimum |
| $C_r$ / $C_{\text{median}}$ | A strategy's cooperating rate divided by the median |
| $C_r$ / $C_{\text{mean}}$ | A strategy's cooperating rate divided by the mean |
| $C_r$ | The cooperating ratio of a strategy |
| $CC$ to $C$ rate | The probability a strategy will cooperate after a mutual cooperation |
| $CD$ to $C$ rate | The probability a strategy will cooperate after being betrayed by the opponent |
| $DC$ to $C$ rate | The probability a strategy will cooperate after betraying the opponent |
| $DD$ to $C$ rate | The probability a strategy will cooperate after a mutual defection |
| $p_n$ | The probability of a player's action being flip at each interaction |
| $n$ | The number of turns |
| $p_e$ | The probability of a match ending in the next turn |
| $N$ | The number of strategies in the tournament |
| $k$ | The number that a given tournament is repeated |

Table 10: The measures which are included in the performance evaluation analysis.

30. Cycler CCCD [4]
31. Cycler CCCDCD [4]
32. Cycler CCD [47]
33. Cycler DC [4]
34. Cycler DDC [47]
35. DBS [13]
36. Davis [15]
37. Defector [17, 47, 53]
38. Defector Hunter [4]
39. Double Crosser [4]
40. Desperate [62]
41. DoubleResurrection [7]
42. Doubler [1]
43. Dynamic Two Tits For Tat [4]
44. EasyGo [43, 1]
45. Eatherley [16]
46. Eventual Cycle Hunter [4]
47. Evolved ANN [4]
48. Evolved ANN 5 [4]
49. Evolved ANN 5 Noise 05 [4]
50. Evolved FSM 16 [4]
51. Evolved FSM 16 Noise 05 [4]
52. Evolved FSM 4 [4]
53. Evolved HMM 5 [4]
54. EvolvedLookerUp1 1 1 [4]
55. EvolvedLookerUp2 2 2 [4]
56. Eugine Nier [3]
57. Feld [15]
58. Firm But Fair [30]
59. Fool Me Forever [4]
60. Fool Me Once [4]
61. Forgetful Fool Me Once [4]
62. Forgetful Grudger [4]
63. Forgiver [4]
64. Forgiving Tit For Tat [4]
65. Fortress3 [11]
66. Fortress4 [11]
67. GTFT [32, 50]
68. General Soft Grudger [4]
69. Gradual [19]
70. Gradual Killer [1]
71. Grofman[15]
72. Grudger [15, 18, 19, 62, 43]
73. GrudgerAlternator [1]
74. Grumpy [4]
75. Handshake [54]
76. Hard Go By Majority [47]
77. Hard Go By Majority: 10 [4]
78. Hard Go By Majority: 20 [4]
79. Hard Go By Majority: 40 [4]
80. Hard Go By Majority: 5 [4]
81. Hard Prober [1]
82. Hard Tit For 2 Tats [59]

83. Hard Tit For Tat [61]
84. Hesitant QLearner[4]
85. Hopeless [62]
86. Inverse [4]
87. Inverse Punisher [4]
88. Joss [15, 59]
89. Knowledgeable Worse and Worse [4]
90. Level Punisher [7]
91. Limited Retaliate 2 [4]
92. Limited Retaliate 3 [4]
93. Limited Retaliate [4]
94. MEM2 [44]
95. Math Constant Hunter [4]
96. Meta Hunter Aggressive [4]
97. Meta Hunter [4]
98. Meta Majority [4]
99. Meta Majority Finite Memory [4]
100. Meta Majority Long Memory [4]
101. Meta Majority Memory One [4]
102. Meta Minority [4]
103. Meta Mixer [4]
104. Meta Winner [4]
105. Meta Winner Deterministic [4]
106. Meta Winner Ensemble [4]
107. Meta Winner Finite Memory [4]
108. Meta Winner Long Memory [4]
109. Meta Winner Memory One [4]
110. Meta Winner Stochastic [4]
111. NMWE Deterministic [4]
112. NMWE Finite Memory [4]
113. NMWE Long Memory [4]
114. NMWE Memory One [4]
115. NMWE Stochastic [4]
116. Naive Prober [43]
117. Negation [61]
118. Nice Average Copier [4]
119. Nice Meta Winner [4]
120. Nice Meta Winner Ensemble [4]
121. Nydegger [15]
122. Omega TFT [39]
123. Once Bitten [4]
124. Opposite Grudger [4]
125. PSO Gambler 1 1 1 [4]
126. PSO Gambler 2 2 2 [4]
127. PSO Gambler 2 2 2 Noise 05 [4]
128. PSO Gambler Mem1 [4]
129. Predator [11]
130. Prober [43]
131. Prober 2 [1]
132. Prober 3 [1]
133. Prober 4 [1]
134. Pun1 [11]
135. Punisher [4]
136. Raider [12]
137. Random Hunter [4]
138. Random: 0.5 [15, 60]
139. Remorseful Prober [43]
140. Resurrection [7]
141. Retaliate 2 [4]
142. Retaliate 3 [4]
143. Retaliate [4]
144. Revised Downing [15]
145. Ripoff [10]
146. Risky QLearner [4]
147. SelfSteem [24]
148. ShortMem [24]
149. Shubik [15]
150. Slow Tit For Two Tats [4]
151. Slow Tit For Two Tats 2 [1]
152. Sneaky Tit For Tat [4]
153. Soft Go By Majority [17, 47]
154. Soft Go By Majority 10 [4]
155. Soft Go By Majority 20 [4]
156. Soft Go By Majority 40 [4]
157. Soft Go By Majority 5 [4]
158. Soft Grudger [43]
159. Soft Joss [1]
160. SolutionB1 [9]
161. SolutionB5 [9]
162. Spiteful Tit For Tat [1]
163. Stalker [23]
164. Stein and Rapoport [15]
165. Stochastic Cooperator [6]
166. Stochastic WSLS [4]
167. Suspicious Tit For Tat [19, 36]
168. TF1 [4]
169. TF2 [4]
170. TF3 [4]
171. Tester [16]
172. ThueMorse [4]

173. ThueMorseInverse [4]
174. Thumper [10]
175. Tit For 2 Tats (**Tf2T**) [17]
176. Tit For Tat (**TfT**) [15]
177. Tricky Cooperator [4]
178. Tricky Defector [4]
179. Tullock [15]
180. Two Tits For Tat (**2TfT**) [17]
181. VeryBad [24]
182. Willing [62]
183. Win-Shift Lose-Stay (**WShLSt**) [43]
184. Win-Stay Lose-Shift (**WSLS**) [41, 50, 59]
185. Winner12 [45]
186. Winner21 [45]
187. Worse and Worse[1]
188. Worse and Worse 2[1]
189. Worse and Worse 3[1]
190. ZD-Extort-2 v2 [42]
191. ZD-Extort-2 [59]
192. ZD-Extort-4 [4]
193. ZD-GEN-2 [42]
194. ZD-GTFT-2 [59]
195. ZD-SET-2 [42]

# C Correlation coefficients

A graphical representation of the correlation coefficients for the measures in Table 7.

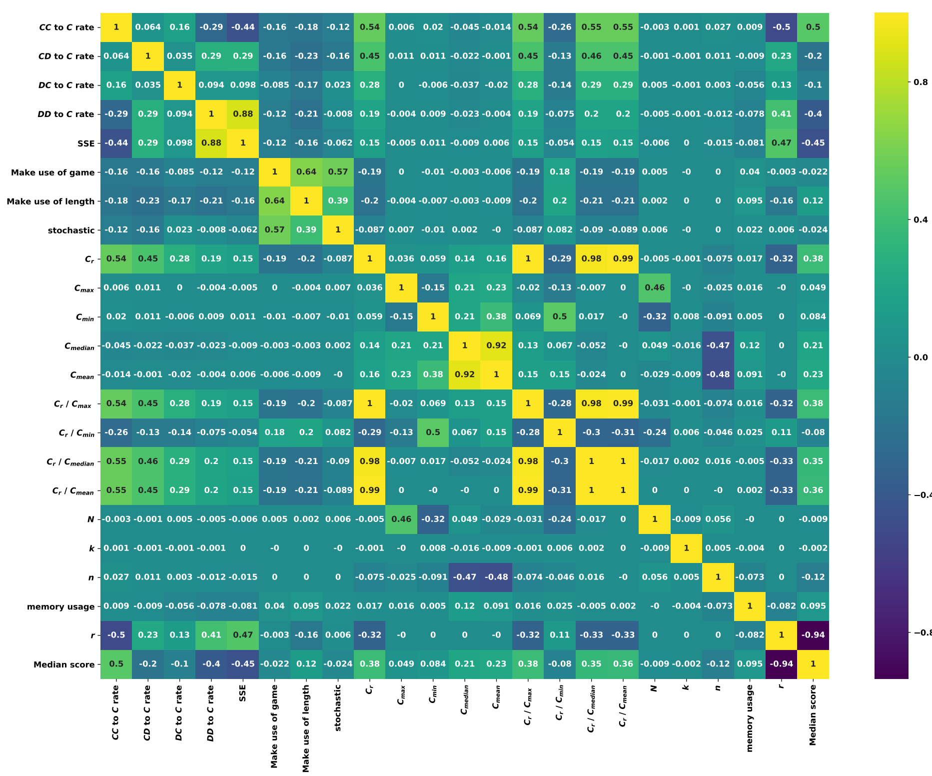


Figure 21: Correlation coefficients of measures in Table 7 for standard tournaments

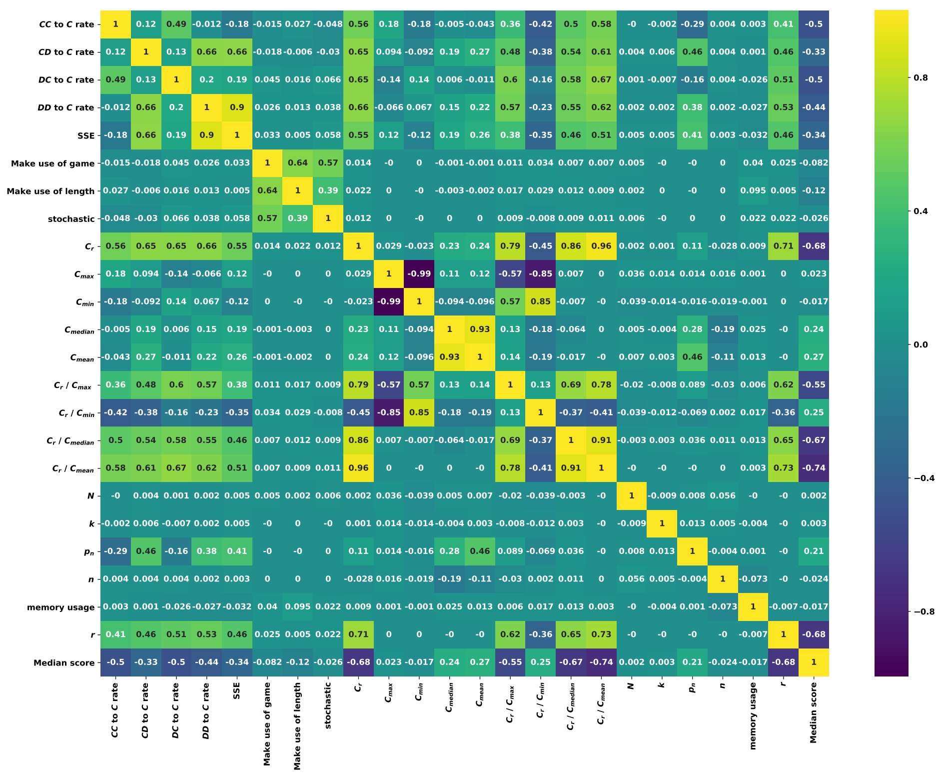

Figure 22: Correlation coefficients of measures in Table 7 for noisy tournaments

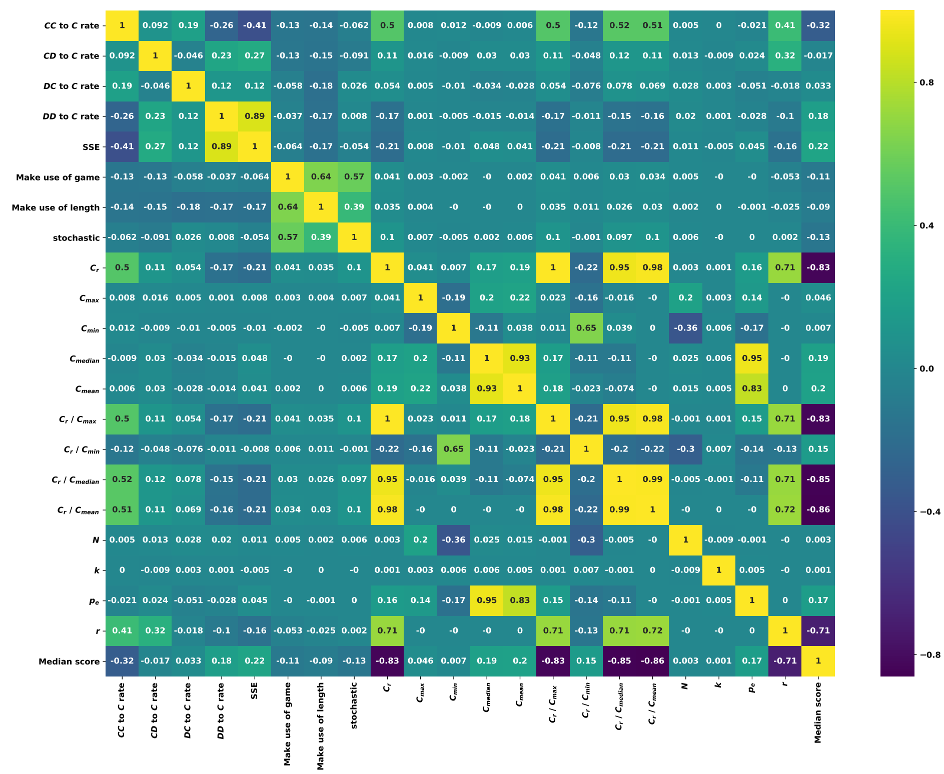


Figure 23: Correlation coefficients of measures in Table 7 for probabilistic ending tournaments

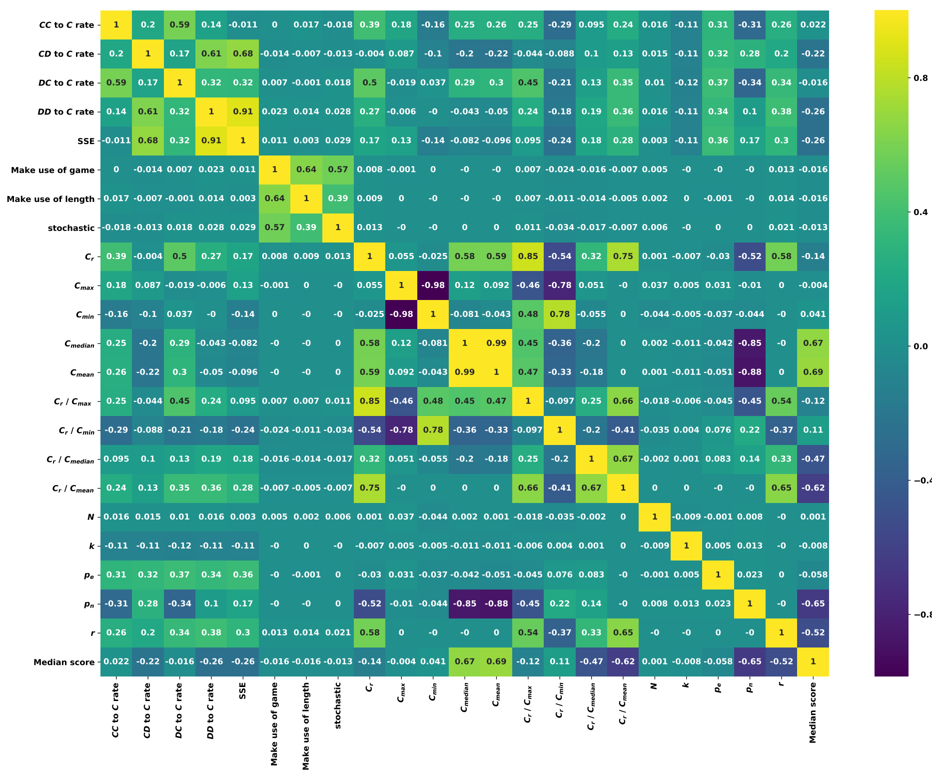

Figure 24: Correlation coefficients of measures in Table 7 for noisy probabilistic ending tournaments

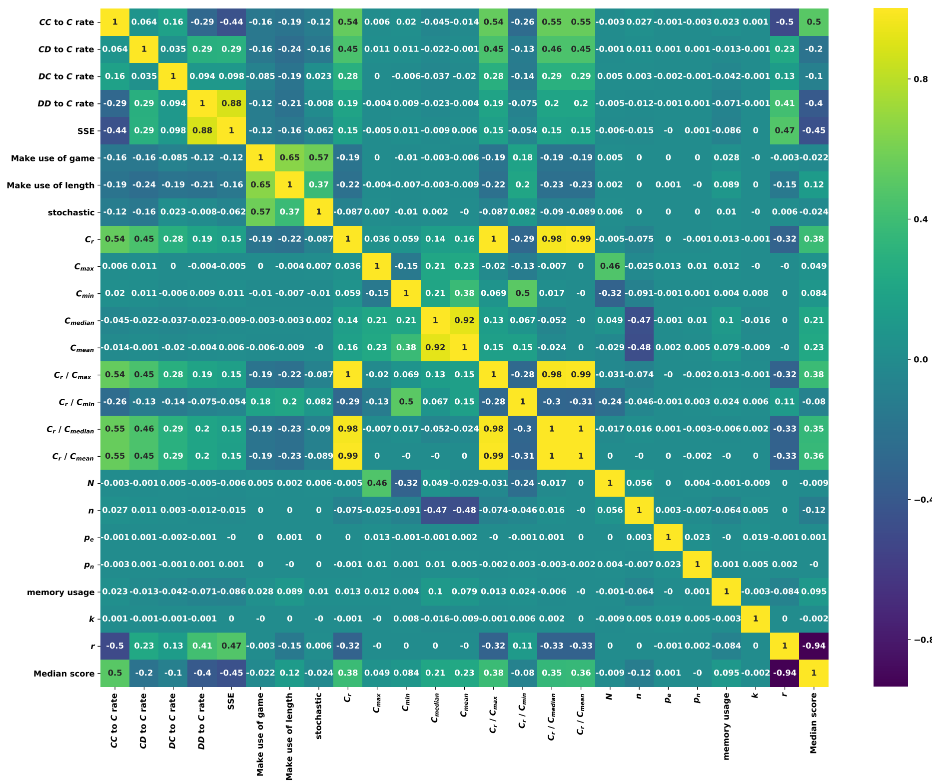

Figure 25: Correlation coefficients of measures in Table 7 for data set