

A Socio-Psychological Approach to the Iterated Prisoner's Dilemma

by

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Abstract

Affect Control Theory (ACT), as a model of human interaction, attempts to capture a part of the human psyche that tends to go overlooked in the study of Artificial Intelligence: the role of emotion in decision making. It provides an empirically derived mathematical framework for the otherwise ethereal “feeling” that guide our every action, even in ways that may appear irrational. In this work, we apply BayesACT, a variant on classical ACT, to the much-studied Iterated Prisoner’s Dilemma, showing that it appears to human players to approach the game more like a human than other computerized agents. Additionally, we expand into the networked version of this game, showing that the observed human behaviours of decision hysteresis, network structure invariance, and anti-correlation of cooperation and reward, are all emergent properties of the networked BayesACT agents.

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Chapter 1

Introduction

A social dilemma may be defined as a “situation[] in which individual rationality leads to collective irrationality” [33], which is to say that agents acting out of purely rational self-interest will decrease the total reward received by all agents. Such situations are ubiquitous in modern society: cutting off a fellow driver, jumping a queue, and accepting under-the-table payment are minor, if not quite innocuous, examples. Of course, not all such conflicts need be small. For instance, the annexation of a territory could be viewed as a social dilemma of sorts. Solutions to social dilemmas can therefore have broad application, and have seen much study by psychologists, sociologists, and more recently, computer scientists.

As a means of abstraction, social dilemmas are frequently cast as normal-form games. In the simplest case, these games involve two players who must simultaneously choose an action to perform. The unique combination of their choices is then used to assign each a payoff from a pre-defined reward matrix. In general, the players’ matrices need not be identical (i.e. they may be rewarded under different circumstances), but must be known by both parties before choosing their actions.

Over decades of research, several canonical dilemmas/games have emerged, each framing an otherwise sterile reward matrix within a relatable story. Examples include Assurance, Chicken, Public Goods, and the Tragedy of the Commons. None, however, is better studied than the Prisoner’s Dilemma, a game which has produced thousands of studies [33] and at least a few television game shows. In its case, one version of the canonical story may be told as follows.

The police are holding two partners-in-crime in separate rooms with no way for them to communicate with each other. During their interrogations, each has the option to either defect and snitch on the other, or cooperate with their partner and remain silent. Their choices produce one of the following results.

- If both partners cooperate, the prosecution fails to make a strong case, and each receives a 2 year sentence reduction.
- If only one partner defects, he receives a 3 year sentence reduction, and the

	C	D		C	D
C	R,R	S,T	C	2,2	0,3
D	T,S	P,P	D	3,0	1,1

Table 1.1: The general reward matrix and an example reward matrix for the Prisoner’s Dilemma. For all pairs, the row player’s reward is shown first, and the column player’s second.

other gets no reduction.

- If both partners defect, each receives only a 1 year sentence reduction.

The reward structure of this game is summarized in Table 1.1, where cooperation and defection are represented by C and D respectively, R is the reward for cooperation, S is the sucker’s payoff for being duped, T is the temptation payoff, and P is the punishment payoff. For a game to be considered a true Prisoner’s Dilemma, the following inequality must be obeyed [33] ¹.

$$T > R > P > S \tag{1.1}$$

As a direct result, for a single play of this game (or any finite number of repeated games between two players) defection is a dominant strategy and there is a Nash equilibrium for pure defection [34]. In other words, regardless of the choice the other makes, a player is rewarded more for defection than cooperation. However, it has repeatedly been shown that, in spite of this, human players do not adhere to an all-defect strategy [13, 12, 20].

Humans, it would seem, are not strictly rational creatures. This allows us to pursue a goal that could be viewed as non-traditional within the scope of Artificial Intelligence: rather than attempting to find the “best” strategy that collects the highest reward, we instead look for one that appears to best model the (frequently erratic) play of actual people. To that end, we have created several “bots”, or computerized agents, that each play different strategies in the Prisoner’s Dilemma. In particular, this work examines the effectiveness of our BayesACT bot, which plays in accordance with a modified version of Affect Control Theory (ACT) [29].

Standard ACT, as first formalized by David Heise [26] in 1977, begins by positing that every idea carries with it a culturally shared emotional sentiment [38]. That is to say, two individuals within a society will tend to make similar intuitive evaluations of a given thing (car, dog, hospital, etc.), action (hug, kick, kill, etc.), or person (banker, child, senior, etc.). Further, ACT posits that this identity can be measured with three numerical values $\in [-4.3, 4.3]$ [26] ²:

- Evaluation (E) - roughly good vs. bad

¹Note that other permutations of this inequality may produce other social dilemmas (eg. the Assurance Game is characterized by $R > T > P > S$) or no dilemma at all (eg. $R > S > T > P$, where cooperation dominates).

²This range is employed by David Heise’s Interact tool [24], effectively standardizing it.

- Potency (P) - roughly strong vs. weak
- Activity (A) - roughly fast or loud vs. slow or quiet

Combined, Evaluation, Potency, and Activity form the EPA triple, which encapsulates a sentiment in ACT. Such values have been gathered for many common words by conducting large, cross-cultural studies [27, 40]. As such, they represent the fundamental (or out-of-context) sentiments held by the particular group surveyed.

However, an individual’s feelings about a person/thing/action may change temporarily upon encountering unusual circumstances [26]. To formalize this idea, ACT defines transient sentiments to be EPA values that have been altered by context. In this case, context entails an Actor-Behaviour-Object (ABO) interaction, in which an Actor (A) performs a Behaviour (B) on an Object (O). We will examine the mathematics of such interactions in section 2.2, but intuitively, it is fair to say that the difference between fundamental and transient sentiments increases with the unexpectedness of the interaction. This difference is called the deflection, and is best demonstrated through example.

Suppose that a babysitter (EPA [1.01, 0.80, 0.11]) is acting on a baby (EPA [1.63, -1.64, 0.30]). If the behaviour performed is “feed something to” (EPA [1.01, 0.98, 2.2]), then the resulting deflection is just 0.9. This indicates that a babysitter feeding a baby would be an affectively expected action. Similarly, “comfort” (EPA [1.50, 1.70, -0.62]) produces a deflection of only 2.2. However, “beat up” (EPA [-1.92, 1.00, 1.62]), an unexpectedly aggressive action, gives a high deflection of 11.0, while “suck up to” (EPA [-1.23, -1.36, -0.50]), an action which is less negative but disrespects the power dynamic, produces a deflection of 8.6.³

It is from the deflection that ACT draws its predictive power as a model of human behaviour; it states that people naturally act in a way that minimizes the deflection they create [26]. That is, one’s default action is that which aligns best with society’s expectations. Certainly, one may choose to act in a different way, but then must incur the penalties of deflection. This may entail feelings of being disingenuous to one’s true self (discomfort, guilt, etc.), as well as receiving an EPA re-estimation in the eyes of any observers. Given an Actor and an Object, it is therefore possible to predict a Behaviour by choosing for it an EPA profile that minimizes the deflection.

BayesACT, the version of ACT used in this work, augments conventional ACT with Bayesian mathematics [29]. We discuss its workings further in section 2.2.2.

Our goal in this work is to show that an application of symbolic interactionist principles (i.e. BayesACT) produces more human-like agents in simple games than approaches typical to the field of Artificial Intelligence. The motivation for this is twofold: we wish to produce an agent that can act as a human analogue in the context of games or game-like situations, and we would like it to determine its actions in a way that is as consistent with human cognition as is possible. Meeting the first condition grants enormous predictive

³These values were found via Interact, an ACT tool provided by David Heise [24] using the Indiana 2002-4 dataset [14].

power, as very many important activities may be cast as games, (with auctions and elections being canonical examples). While Game Theory provides us tools for predicting the actions of self-interested agents, it generally ignores the emotional impact of actions taken. In situations where emotion takes a considerable toll (as, we will argue, is the case for the Prisoner's Dilemma), a robust model of human behaviour must take it into consideration.

Meeting our second condition is desirable for its implications to our understanding of the human mind. While any model that produces human-like behaviour can tell us how a person might act, one that does so through a process that could plausibly be ascribed to humans gives us insight as to why. To show that BayesACT is such a model gives evidence of its validity as a general explanation of human behaviour and its usefulness as tool for social scientists.

Chapter 2

Related Work

This chapter reviews publications that fall into one of two broad categories: work involving the Prisoner’s Dilemma (and a few other social dilemmas), or work related to Affect Control Theory.

2.1 The Prisoner’s Dilemma

The very first example of a Prisoner’s Dilemma is credited to Merrill Flood in collaboration with Melvin Dresher [13]. Inspired by von Neumann and Morgenstern’s *Theory of Games and Economic Behaviour*, which formalized many normal-form games [53], Flood created and tested several experimental games with human participants. Among these was “A Non-Cooperative Pair”, a game which satisfied the $T > R > P > S$ requirement, as can be observed from Table 2.1. It would later be associated with the canonical Prisoner’s Dilemma story by Albert W. Tucker.

Flood conducted a single trial of the iterated version of this game, using two of his colleagues at the RAND Corporation as players. Unfortunately, Flood’s collection of experiments were conducted in 1952 and not published until 1958, by which time records of the actual experiments had been lost. However, Flood was able to recall that the subjects of that one trial had converged towards a “split-the-difference” (cooperative) strategy, thereby beginning the trend of human players cooperating in a game that actively encourages defection.

	<i>C</i>	<i>D</i>
<i>C</i>	0.5,1	-1,2
<i>D</i>	1,-1	0,0.5

Table 2.1: Reward matrix for Flood and Dresher’s “A Non-Cooperative Pair”. Though not symmetric as has come to be expected from Prisoner’s Dilemma rewards, this structure satisfies the $T > R > P > S$ requirement.

2.1.1 Rational Strategies

For a single play of the Prisoner’s Dilemma game, in which each player makes their choice, collects their reward, and then walks away, it can be immediately seen that defection is a dominant strategy and that there is a Nash equilibrium for defect-defect. This is a result of the fact that defection always gives a higher payout, regardless of the what the other player chooses. A rational agent will therefore always choose to defect.

For the finitely repeated Prisoner’s Dilemma, in which the number of iterations, I , is known to both players in advance, we get a similar result of pure defection for two rational agents as a unique subgame perfect Nash equilibrium. Summarizing from Kreps et al. [34], this can be shown by the following argument.

In the final iteration, a rational agent must seek to immediately maximize its score, as its choice can have no impact on the future. This last iteration is therefore equivalent to the single-play Prisoner’s Dilemma, for which defection must be chosen by a rational agent. As both players are rational, the final round therefore be defect-defect.

In any round for which all future rounds have already been determined, a rational agent must immediately maximize its score, as its choice can have no impact on the future. Then, by the same logic applied to the final iteration, this round must be defect-defect.

So, by induction proceeding backwards from the last round to the first, all rounds must result in defect-defect between two rational agents.

It is still possible for a rational agent to cooperate if it is assumed that the other player is not rational. Such cases will be discussed in section 2.1.3.

Alternatively, we may instead look to versions of the game in which players do not know the number of rounds. In the extreme case, this is because $I = \infty$. Unfortunately, this causes rewards to go to infinity regardless of strategy. We must therefore slightly modify the rules of the game.

One potential modification is to apply a discounting factor, δ , to the players’ payouts with the reasoning that a reward now is considered to be worth more than a reward in the future. This may be represented as:

$$Q_a(\vec{a}) = (1 - \delta) \sum_{i=0}^{\infty} \delta^i q_a(a_a^i, a_o^i) \tag{2.1}$$

where Q_a is the agent’s total payout for the full action set \vec{a} , q_a is the agent’s payout for a pair of actions, a_a^i is the agent’s action at iteration i , and a_o^i is the opponent’s action at iteration i .

In this case, it can be shown that there may be cooperative equilibrium strategies when δ exceeds some combination of the reward matrix values R , T , S , and P [15]. For example, a grim trigger strategy (cooperate until the opponent defects, then defect thereafter) is

equilibrium when $\delta > 1 - R/T$, and Tit-for-tat (cooperate first, and thereafter emulate the opponent's last choice) is equilibrium when $\delta > (T - R)/(T - P)$ and $\delta > (T - R)/(R - S)$. However, this is somewhat unsatisfactory as a model for human behaviour. It requires knowledge of the opponent's strategy, predicts sharp changes in behaviour when reward values are slightly altered, and requires that the number of iterations be actually infinite, which no study has yet achieved.

We might therefore choose to alter the game in a different way, at least nominally. Rather than applying a discount factor, we instead give the game some probability, q , of continuing after every round, as in the work of Nowak [37]. This results in identical mathematics to those above, but replacing δ with q . Of course, though no longer (practically) infinite, this line of reasoning shares the other shortcomings of discounting and additionally requires changing the rules of the game as presented to the players.

2.1.2 Humans and the Prisoner's Dilemma

Fundamentally, social dilemmas are designed to produce conflict in human players, and have existed for much longer than computerized agents have been a possibility. As such, the earliest studies conducted in this field involved only human players under different experimental conditions. Though there are now also many studies involving human-bot or bot-bot interactions, human-human experiments remain a staple topic of social psychology journals.

Among the earliest of such studies is Martin Deutsch's 1958 work [12], in which the Prisoner's Dilemma is employed as a means of gauging trust between individuals. This study set college students against each other in several variations of the classic normal-form game. One group was assigned to the single-trial version, and then subdivided into games played:

- with no communication allowed,
- with communication allowed via written notes,
- with communication and the possibility of reversing one's decision,
- with communication, reversibility, and with players taking turns rather than playing simultaneously.

Each group was then subdivided further by the manner in which the players were influenced before the game, where some were encouraged to be:

- cooperative by an appeal to empathy for the other player,
- individualistic by emphasizing self-interest,
- competitive by suggesting a goal of defeating the other player.

Note that none of these influencing factors actually changed the reward matrix or the rules of the game in any way; they were purely a means of affecting a desired state of mind.

The results of these tests can be summarized as follows. Compared to the non-communicative case, cooperation generally increases when communication is allowed, increases further when reversing one's decision is allowed, and decreases somewhat when plays are non-simultaneous. Additionally, the influenced orientation of the subjects had very large effects, with cooperation rates decreasing from cooperative to individualistic, and again from individualistic to competitive. For example, in the case of no communication, cooperation rates were 89.1%, 35.9%, and 12.5% respectively. Note that even 12.5% is not the 0% predicted by rationality.

Similar results were observed for a second group of subjects assigned to a ten-trial finitely repeated game with communication disallowed. Cooperation rates were approximately 70%, 35%, and 25% for each of the cooperative, individualistic, and competitive groups. Of particular note was that cooperation dropped sharply among the individualistic and competitive in the final few trials, but remained fairly constant for the cooperative. This strongly hints at the existence of emotional factors affecting play.

While it is the results where communication was banned that are the most directly applicable to our work, Deutsch nevertheless makes observations about communication that are worth noting. Firstly, it greatly increased cooperation among individualistically influenced players (i.e. those representing the most pure form of the game) from 35.9% to 70.6% in the single-trial case. Additionally, Deutsch identifies several features of the dialogue used by the most successful cooperators, namely:

- expectation (i.e. I want you to cooperate)
- intention (i.e. I will cooperate)
- retaliation (i.e. I will defect if you defect)
- forgiveness (i.e. I will cooperate if you return to cooperation)

These features strongly foreshadow those advocated by Axelrod for use in Prisoner's Dilemma bots [8], to be discussed in section 2.1.3.

As another example of a human-human iterated Prisoner's Dilemma study, we refer to Andreoni and Miller [3], who conducted their study as a follow up to the proof of all-defect as the only rational strategy in the finitely repeated Prisoner's Dilemma by Kreps et al. Four tests were conducted with the intent to show that anomalously high cooperation rates could be attributed to some form of altruism. The test conditions were as follows (with each using computer terminals to provide anonymity):

1. pair participants with each other for ten rounds, and then switch partners
2. switch the pairings every round

3. same as (1), but tell the participants that there is a 50% chance of being paired with a Tit-for-tat bot
4. same as (3), but reduce the chance to 0.1%

By cooperation rate, the conditions ranked as $3 > 1 > 4 > 2$. This ordering contains two important pieces of information. First, partnering for ten rounds produced more cooperation than switching partners every round, which indicates a tendency towards reputation building in the hopes of reciprocal altruism. That is to say, in the early rounds, players found it worthwhile to establish themselves as trustworthy to encourage later cooperation from their partners. In the case where partners were exchanged every round, reputation building was clearly not possible, and so the cooperation rate was predictably lower.

The second major observation is that a (supposed) 50% rate of occurrence for Tit-for-tat engendered more cooperation than a 0.1% rate, which incorporates altruism in another fashion. It was known that a rational agent would subscribe to an all-defect strategy if playing against another rational agent. However, if there were some probability that the opponent were irrational, then even a rational agent might choose to cooperate. In this case, Tit-for-tat, which always begins by cooperating, can be viewed as an irrational altruist. As such, a higher rate of cooperation amidst a more altruistic population supports the rationality argument.

In addition to their two major points, Andreoni and Miller also note that among their subjects were some number of true altruists, which they infer from cooperation patterns over 10-round sets not deteriorating in the sets near the end of the experiment. That being the case, rationality can clearly not be ascribed to all participants.

This is an interesting development, as altruism in a competitive environment requires its own explanation. After all, if early humans truly sacrificed their own well-being to aid their confederates, surely they would have been out-competed by less well-intentioned individuals. It stands to reason, then, that if altruists do in fact exist, there must have been conditions under which altruism was evolutionarily favoured. Nowak [37] shows this for five versions of altruism as applied to the Prisoner's Dilemma.

The first of these is kin selection, which posits that if the coefficient of relatedness (the probability of a particular gene being shared) between partners exceeds the cost-to-benefit ratio ($1 - R/T$) of the altruistic act (cooperation), then altruism is favoured. Of course, given that the individuals must be related, kin selection is of limited applicability. Fortunately, Nowak goes on to argue that direct reciprocity (i.e. reciprocal altruism) and indirect reciprocity (altruism within a group, based on reputation) are also evolutionarily stable if the chance of meeting someone again or knowing their reputation exceeds the cost-to-benefit ratio.

He additionally proposes two mechanisms for Prisoner's Dilemma games with altered rule sets. Group selection applies when evolutionary cohorts stay together within groups that only split upon reaching a size threshold. Among the works we survey, this scenario is

unique to Nowak's, and so we omit the details here. However, Nowak's take on network reciprocity is worth noting, particularly with an eye to Section 2.1.5. This mechanism applies to a Prisoner's Dilemma game on a network, in which an agent has a fixed number of neighbours that all benefit if that agent chooses to act altruistically (cooperate). Ultimately, it is found that such altruism is favoured if the benefit-to-cost ratio ($T/(T - R)$) is greater than the average degree of the network.

Here, we have boiled down altruism to an act that is (paradoxically) actually self-serving. Note, however, that this interpretation of altruism is most useful on an evolutionary scale, and is not mutually exclusive with altruism as the product of an emotional response. Trivers [51], for example, argues that emotions exist because evolution needed a mechanism by which to encourage altruism.

Trivers first establishes that some degree of altruism would almost certainly have been an advantageous trait for early groups of humans to have, citing cases that come at a small cost to the giver, but result in a large benefit for the receiver. Examples include sharing food and tools, helping the wounded, sick, or very young, and sharing knowledge. Further, small, stable groups would have provided ample opportunity for acts of altruism to be applied to kin, or to be reciprocated by the receiver in the future. As a means of encouraging such acts, Trivers proposes the development (or at least co-option) of emotion. Sympathy is an impetus to help those in need. Gratitude promotes returning the favour. Guilt dissuades from cheating others in the group.

This is all to say that a person playing the Prisoner's Dilemma might choose not to defect out of guilt, which, to that person, is simply an immediate emotional response. However, that guilt exists as a means of promoting altruism through a long evolutionary process.

2.1.3 Bots and the Prisoner's Dilemma

When writing a bot to play the iterated Prisoner's Dilemma game (the single-shot version being too limiting to be very interesting), a logical goal to pursue is the one presented by the game itself: maximizing the reward received. While this is not the goal that we pursue in this work, it has nevertheless been the focus of much research since Axelrod's famous bot tournaments of 1980.

The first of these tournaments [6] was entered by fourteen academics from computer science, economics, psychology, and various other disciplines. Each submitted a bot to take part in an automated round-robin tournament. Surprisingly, it was Tit-for-tat, the simplest of the bots, that ultimately won with an average of score of 504 out of a possible 1000. (For reference, the next closest bot scored 500, and the worst scored 276).

Following this result, Axelrod held a second tournament [7] and this time received entries from 63 participants, each of whom knew that Tit-for-tat had won previously. Despite this, Tit-for-tat triumphed yet again, with an average score of 434.73 (compared to the runner-up with 433.88 and the worst bot with 220.50). These results led Axelrod to make several observations about the most successful bots [8]. In general, they were:

- nice, meaning that they always opened with cooperation and would not be the first to defect,
- provokable, meaning that they would respond to defectors with defection of their own,
- not envious, meaning that they sought only to maximize their own reward and not necessarily do better than any particular opponent,
- clear, meaning that they did not try to hide their strategy from their opponents or attempt anything too “tricky”.

Notably, Tit-for-tat fulfilled all of these requirements and, at just five lines of code, was the simplest bot to do so. This extraordinary success led to its further analysis by Hamilton and Axelrod in an evolutionary setting [23]. Three key characteristics that a cooperator must exhibit in order to succeed and proliferate are identified:

1. Robustness - the ability to thrive in an environment of many different, varied strategies,
2. Stability - the ability for a population using one strategy to resist invasion by a rare mutant employing a different strategy,
3. Initial viability - the ability to grow from a small initial group to a position of dominance within a population that is primarily non-cooperative.

Axelrod’s tournaments are cited as proof that Tit-for-tat is robust. Of course, having the best performance in two tournaments does not imply that it is the optimal strategy, especially since the concept of optimality here depends on which strategies comprise the rest of the population. However, robustness requires only that a strategy do well, not that it necessarily be the best possible, and it is undeniable that Tit-for-tat did well.

To show stability, it is argued that Tit-for-tat will never be the first to defect, and so if any defection is to occur, it must be initiated by the invading strategy. An invader who does not initiate defection will only ever cooperate with Tit-for-tat, doing neither better nor worse, and thereby failing in its invasion. On the other hand, an invader willing to defect will fail if the chance of two agents meeting again exceeds both $(T - R)/(T - P)$ and $(T - R)/(R - S)$, which is the same condition found by Nowak and others [15, 37].

The initial viability of Tit-for-tat is presented in a more speculative fashion. It is argued that, in an environment of defectors, Tit-for-tat could potentially invade by changing the rules slightly. For example, if the reward function were altered such that kinship were considered (i.e. give each agent a stake in the well-being of like agents), then Tit-for-tat would naturally have an advantage because it is cooperative with itself. Alternatively, a

group of Tit-for-tat agents could enter the population as a cluster and interact primarily with each other, leading to higher fitness when compared to their non-cooperative neighbours.¹

Outside of an evolutionary or tournament setting, it is not hard to produce a bot that always does at least as well as any particular opponent. The simplest example of such a strategy is all-defect, which on every turn guarantees a score of either T or P for the agent and a score of S or P for the opponent, and is therefore impossible to defeat one-on-one. However, all-defect makes no attempt to maximize its own score in the process.

Press and Dyson, on the other hand, present a bot that can both dominate its opponent and decide by how much [42]. This zero-determinant strategy (so named because it exploits the mathematics of the Prisoner's Dilemma by setting the determinant of a matrix of parameters to zero) is defined by four probabilities, corresponding to the probability of cooperation after each of the four possible outcomes of the previous round (cooperate-cooperate, cooperate-defect, defect-cooperate, and defect-defect). It is the choice of these probabilities that allows the zero-determinant bot to unilaterally set the ratio of its score to its opponent's score in the case where the opponent does as well as is allowed.

Additionally, if played against evolutionary opponents (that is, strategies that are updated in generations to maximize score), the zero-determinant bot can set the evolutionary landscape to anything it wants, with the obvious choice being to demand an increasingly extortionate share every few generations.

While a zero-determinant strategy cannot be beaten in the long term, it is possible for another bot to fight against the extortion, but it requires that bot to have a theory of mind. That is, if the opponent is aware that it is being offered an unfair division of reward, then it can refuse that share (i.e. all-defect) until the zero-determinant bot increases it to an acceptable level. This reduces the Prisoner's Dilemma to an ultimatum game, in which resources are divided unilaterally by one player (here, the zero-determinant bot), but the other may choose to veto. Of course, by this argument, we are ascribing a relatively high level of sophistication to both the zero-determinant bot and its opponent, neither of which is guaranteed to exhibit such qualities.

Entered into a larger population, zero-determinant strategies have been shown to perform poorly [1]. This is largely a result of two factors: they do not benefit from playing against each other, and (in an evolutionary setting) their mutants no longer possess the finely-tuned constants that makes them zero-determinant. As a result, they are not evolutionarily stable.

¹It is worth noting that all-defect, like Tit-for-tat, is evolutionarily stable. Arguing that Tit-for-tat could invade it in any case calls into question the value (and even definition) of stability. However, these concerns are not addressed.

2.1.4 Human-Bot Interaction

We have now seen how humans and bots each play the Prisoner’s Dilemma game amongst themselves, but the question remains: how do they interact with each other? In particular, do human players react differently to artificial agents than they do to other people in the context of a game? Kiesler et al. [32] demonstrate that, in fact, they do, and that these differences can be quite large.

In their experiment, a group of undergraduates played the single-shot Prisoner’s Dilemma against:

- another person (an associate of the experimenter playing from a script),
- a bot with an animated rendering of a woman’s face and a voice,
- a bot with a voice only,
- a bot with a text interface only,

each of which chose cooperation against one group of participants and defection against another. These conditions were further divided into those that allowed communication and those that did not, where communication was used to try to make participants verbally commit to cooperation.

Among the various bots, the one presenting a face was found to be the most human-like by a questionnaire, with the other two receiving fairly similar ratings. Despite this, the face-bot was actually betrayed the most of all the bots, with 43% of participants actually cooperating after committing to do so, compared to 51% for each of the other bots. It is not clear, however, if this was simply a result of small sample size (around 50 participants per bot). When playing another person, a more clear difference emerges. After committing to cooperation, 87% of participants followed through, a far higher fraction than for any of the bots. With communication disallowed, only 32.5% chose cooperation with the human associate, while only 20% did so with the various bots.

From these results, we can make two important observations. First, people feel more strongly obliged to keep their promises when those promises are made to real people. As a result, when attempting to elicit genuine reactions to the play of a bot, the artificial nature of that bot must remain hidden. Second, even though the effect is not as strong, a bot may still encourage cooperation by appealing to human emotions (in this case, honour).

The latter result is also supported by de Melo et al. [11], who found that people could be manipulated by emotions shown by an artificial agent. In their study, participants played a price negotiation game with a bot set to show emotion either verbally (in this case, via emotionally-charged on-screen text) or non-verbally (via a simulated man’s face capable of displaying neutral, happy, or angry expressions). In each case, the difference in price the participants were willing to offer was observed. In general, the emotions of the verbal

Number of neighbouring cooperators					
	0	1	2	...	N-1
C	0	2	4	...	$2(N - 1)$
D	1	3	5	...	$2(N - 1) + 1$

Table 2.2: Reward matrix for a single agent in Yao and Darwen’s N-player iterated Prisoner’s Dilemma [55]

bot had a slightly larger effect (i.e. the difference between emotions was greater), but in both cases a happy bot elicited a significantly smaller average offer than a neutral bot, which in turn received less than an angry bot.

2.1.5 Networked Prisoner’s Dilemma Games

When generalizing the Prisoner’s Dilemma to include more than two players (i.e. the N-Person [Iterated] Prisoner’s Dilemma), we must choose how to expand the reward matrix to accommodate the additional agents. Perhaps the simplest option is the Broadcast model, in which an agent chooses to either cooperate or defect, and this choice is applied to all partners according to the same matrix we have used previously. It is this model we will adopt for the remainder of this work; however, another reward scheme exists, and it is worth mentioning briefly.

This second matrix (given in Table 2.2) was used by Yao and Darwen to show that cooperation decreases as N increases in the N-Person Iterated Prisoner’s Dilemma [55]. Under this reward structure, an agent benefits from each other player who cooperates, and gains nothing from cooperating itself. So far, this is identical to the Broadcast model. Where this scheme differs is in the result of defection. Here, an agent benefits only once from defecting, as opposed to N-1 times under Broadcast. This greatly reduces the direct effect an agent has upon its own score.

Yao and Darwen applied this structure to an evolutionary setting, letting agents adapt over up to 1000 generations. Ultimately, they found that the fraction of cooperators decreased seemingly monotonically as N increased, with 7/10 runs reaching 90% cooperation in the 2-player case, 3/10 runs reaching 80% cooperation in the 4-player case, and no runs reaching a significant level of cooperation in either the 8-player or 16-player case. This result conflicts with the results of actual human N-player experiments [20].

Returning now to the Broadcast model, we must further choose with whom a particular agent will interact. That is, if we have very many agents and do not wish for each to interact with every other (which would result in N^2 interactions, quickly becoming impractical as N increases), then how should we design the network of partnerships? Several human studies have been performed with slightly different answers to this question. For example:

- Grujić et al. [19] arranged 169 participants on a grid (digitally), with each playing

against their 8 neighbours. Testing was conducted in three stages. First neighbours remained constant between iterations. Second, neighbours were shuffled after every iteration. Third, neighbours remained constant, but were not the same as in the first stage.

It was observed that individual participants tended to fall into one of five categories: pure cooperators, pure defectors, mostly cooperators (*cooperated* $\sim 2/3$ of the time), mostly defectors (defected $\sim 2/3$ of the time), and moody conditional cooperators. Here, Moody Conditional Cooperation (MCC) is defined as a strategy in which the probability of an agent cooperating increases with the number of cooperating neighbours, but also has a hysteresis. That is, an agent who cooperated last turn is more likely to cooperate again than one who defected last turn, assuming the two have the same number of cooperating neighbours. This behaviour applied even in the second experimental stage, when neighbours were constantly shuffled.

Additionally, it was found that, regardless of the experimental stage, cooperation declined from the first iteration until approximately the 25th, at which point it remained fairly constant at around 20%.

- Grujić et al. [21] conducted a smaller version of their previous study, this time with grids of size 16, in which each participant was connected to 4 neighbours. Again, tests were conducted for both a fixed lattice and one that was randomized after every iteration, and no significant difference in behaviour was found between the two conditions. This confirmation is interesting, as it suggests that strategy is not necessarily the primary motivator when choosing between cooperation and defection.
- Rand et al. [43] conducted experiments with networks of approximately size 20 in which participants were not only allowed to choose cooperation or defection, but were additionally given the opportunity to create or destroy links in the network. These choices were offered stochastically, with some fraction of connections being reviewed after every iteration. Unsurprisingly, players generally sought to punish defectors by severing ties with them when possible, which resulted in cooperation increasing as the fraction of reviewed links increased. It was also observed that many defectors reformed after receiving such punishment.

Grujić et al. [20] examine several such studies and make five important observations regarding general player behaviour:

1. **Network Invariance** - Once the number of neighbours has exceeded two, the average degree and structure of the network cease to significantly affect cooperation rates.
2. **Declining Cooperation Over Time** - The global cooperation rate begins high, but asymptotically declines to a near constant, but non-zero value.
3. **Anti-Correlation of Earnings and Cooperation** - On average, cooperation yields a lower reward than defection.

4. **Moody Conditional Cooperation** - The largest fraction of players exhibit behaviour consistent with MCC.
5. **Player Type Stratification** - The remaining players are stratified into the other four groups identified by Grujić et al. [19] (Pure Cooperators, Mostly Cooperators, Mostly Defectors, and Pure Defectors).

We will return to these observations when evaluating the BayesACT bot as a human-like agent.

Imitation-based models have been employed as a means of explaining behaviour in these games, as was done by Vilone et al. [52]. In this work, every agent in a simulated network plays by the following strategy:

- With probability q , imitate the action of a randomly chosen neighbour.
- With probability $(1 - q)$, perform a strategic imitation. (Several different methods were tried, but the main one presented is Unconditional Imitation, in which the single best scoring neighbour (including self) is imitated.)

This model was tested over varying values of q , differing reward values, and different network types (in this case, Erdős-Rényi [random], and scale-free). Ultimately, it was found that, for particular values of the parameters, MCC and network-independence could be recreated, but notably, these values did not include the actual reward matrices used in any human experiments. Also of note is that other researchers have found that evidence for imitation strategies is lacking in general [20].

2.2 Affect Control Theory

Affect Control Theory (ACT) has its roots in Osgood’s pioneering *The Nature and Measurement of Meaning* [38], which sets out to identify and formalize the feelings that words implicitly represent.² This is accomplished by an adaptation of so-called “scaling techniques”, which were becoming popular at the time of Osgood’s work. Such techniques involved the surveying of hundreds of people, asking each to rank words on several scales. Haagen [22], for example, asked participants to assign seven-point values for each of synonymity, vividness, familiarity, and association value. Though potentially useful for understanding the links between words, such scales were inadequate to fully capture their meaning.

²Note that although it is with words and phrases that we are primarily interested, Osgood’s work is not limited to them. He wrote about “signs”, which include anything that conjures the original object to mind, but is not that object itself. For instance, the words “alarm clock”, the sound of a buzzer, and a video of an alarm clock ringing are all signs for an alarm clock.

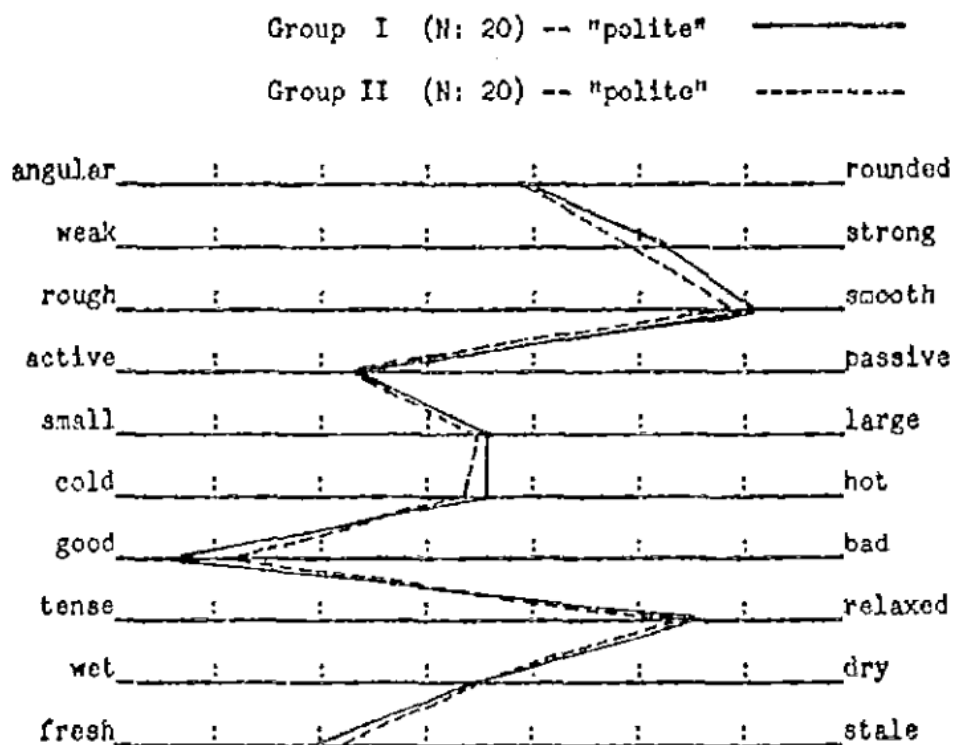


Figure 2.1: Results of Osgood’s semantic differential surveys for the word “polite” [38]. Notably, both groups, on average, gave very similar ratings on every scale.

To that end, Osgood proposes the use of *semantic differentials*, continuous sliding scales onto which a word may fall between two fundamentally opposite ideas. For instance, on a scale ranging between “kind” and “cruel”, we would expect “pacifist” to generally be rated as closer to “kind”. Osgood’s original results for “polite” rated on several semantic differentials are given by Figure 2.1.

Ultimately, it was not only found that words could be differentiated on the basis of these scales, but that additionally, similar groups of people tended to rate words in a very similar fashion. This lends credence to the idea that words have distinct, implicit, culturally-shared meanings.

Osgood finishes his seminal work by postulating that, if some subset of his semantic differentials could be proved sufficient to capture the meaning of any given word, then that subset could serve as a standard basis for meaning. By the time of writing his book, “The Measurement of Meaning” [39], a suitable subset had been found in evaluation, potency, and activity by factor analysis, with evaluation being the most descriptive of the three, and activity the least. Through the conduction of many more surveys, these results were found to hold across 21 different communities around the world [40], and thus the standard EPA scale was born.

Gollob [16, 18] and Heise [25] expand this work by showing (through yet more surveys) that, in an ABO interaction, an observer’s change in attitude can be predicted to a large

extent by the three fundamental EPA values involved. This altered altitude towards each of the actor, behaviour, and object is also measured in EPA-space, and was termed a “transient impression”.

The mathematics of transient impression formation were formalized by Heise [25] in the form of simple polynomial expressions, whose coefficients were found via regression. For example, the evaluation of each sentiment was found to change as: ³

$$T_{ae} = -0.15 + 0.37F_{ae} + 0.55F_{be} + 0.07F_{oe} + 0.25F_{be}F_{oe} \quad (2.2)$$

$$T_{be} = -0.24 + 0.23F_{ae} + 0.60F_{be} + 0.07F_{oe} + 0.25F_{be}F_{oe} \quad (2.3)$$

$$T_{oe} = -0.13 + 0.17F_{ae} + 0.40F_{be} + 0.36F_{oe} + 0.30F_{be}F_{oe} \quad (2.4)$$

with similar equations being found for the potency and activity. These equations would later be refined by Smith-Lovin [49] to the more accurate (and complicated) versions in use today. For example, the transient for the actor’s evaluation is given by:

$$\begin{aligned} T_{ae} = & -0.98 & +0.468F_{ae} & -0.15F_{aa} & +0.425F_{be} \\ & -0.069F_{bp} & -0.106F_{ba} & +0.055F_{oe} & -0.020F_{op} \\ & -0.001F_{oa} & +0.048F_{ae}F_{be} & +0.130F_{be}F_{oe} & +0.027F_{ap}F_{bp} \\ & +0.068F_{bp}F_{op} & +0.007F_{aa}F_{ba} & -0.038F_{ae}F_{bp} & -0.010F_{ae}F_{ba} \\ & +0.013F_{ap}F_{be} & -0.014F_{ap}F_{oa} & -0.058F_{be}F_{op} & -0.070F_{bp}F_{oe} \\ & -0.002F_{bp}F_{oa} & +0.010F_{ba}F_{oe} & +0.019F_{ba}F_{op} & +0.026F_{ae}F_{be}F_{oe} \\ & -0.006F_{ap}F_{bp}F_{op} & +0.031F_{aa}F_{ba}F_{oa} & +0.033F_{ae}F_{bp}F_{op} & +0.018F_{ap}F_{bp}F_{oa} \end{aligned} \quad (2.5)$$

with similar equations existing for each of the other components of the transient. It is worth noting here that although this version includes many more terms, some of which extend to third order, it is still fundamentally a polynomial combination of the fundamental sentiment components.

From calculable transients comes the deflection, and from the deflection comes finally the control principle. Heise [26] defines the deflection, D , as:

$$\begin{aligned} D = & (\vec{F} - \vec{T})^2 \\ = & (T_{ae} - F_{ae})^2 + (T_{ap} - F_{ap})^2 + (T_{aa} - F_{aa})^2 + (T_{be} - F_{be})^2 + (T_{bp} - F_{bp})^2 + \\ & (T_{be} - F_{be})^2 + (T_{oe} - F_{oe})^2 + (T_{op} - F_{op})^2 + (T_{oa} - F_{oa})^2 \end{aligned} \quad (2.6)$$

³In order to be consistent with notation, we do not use the same naming scheme as Heise. Instead, here and elsewhere, we adopt the notation of Hoey et al. [29], where $\vec{F} = [F_{ae}, F_{ap}, F_{aa}, F_{be}, F_{bp}, F_{ba}, F_{oe}, F_{op}, F_{oa}]$ is the fundamental sentiment and $\vec{T} = [T_{ae}, T_{ap}, T_{aa}, T_{be}, T_{bp}, T_{ba}, T_{oe}, T_{op}, T_{oa}]$ is the transient. Here, the first subscript designates by a, b, or o the actor, behaviour, or object respectively, and the second subscript denotes by e, p, or a the evaluation, potency, or activity components respectively.

and proposed that a person naturally follows the path of least deflection (i.e. the action that is expected by society). That is to say, the higher the deflection of an ABO interaction, the less likely that interaction is to occur. This principle is backed by psychological literature [9, 41] and empirical observations [17, 54, 45]. It follows that if we wish to know which of several options a person will most likely choose (say, cooperate or defect), due purely to affect, we have only to calculate the deflection of each and find the lowest value. Alternatively, if our options are not limited, then we can find the EPA of an “ideal” behaviour that minimizes the deflection. This action can be interpreted by mapping it onto a behaviour with a known, similar EPA.

2.2.1 Sentiment Modifications

Although we have now explored as much of classical ACT as is used in this work, there is another development worthy of note: the modification of EPA values due to emotion. Averett and Heise [5] define a modifier-identity hybrid EPA profile that can be used in place of a standard sentiment. This combination, $\vec{C} = [C_e, C_p, C_a]$, has elements of the form:

$$C_x = \alpha_1 + \alpha_2 f_e + \alpha_3 f_p + \alpha_4 f_a + \alpha_5 M_e + \alpha_6 M_p + \alpha_7 M_a \quad (2.7)$$

where x can be any of e, p, or a, \vec{f} refers to the three-dimensional fundamental identity being modified, \vec{M} is the EPA of the modification, and the α are constants determined by regression. The effect of this modification can be seen by example:

Recall that the baseline EPA of a babysitter is [1.01, 0.80, 0.11]. “Cheerful” has an EPA of [2.11, 1.43, 1.42]. A “cheerful babysitter” then has a modified EPA of [1.30, 1.11, 1.01]. For the sake of contrast, “furious” has an EPA of [-1.66, 0.06, 1.72], and a “furious babysitter” has [-1.32, 0.65, 1.15].⁴

As a corollary, if we have an ABO interaction, we can calculate an emotion (as applied to the actor, in this case) that minimizes the deflection, and may help us to explain why the actor behaved in an otherwise inconsistent way. This *characteristic* emotion is influenced roughly equally by the EPA of the transient and the size of the deflection [5].

We may similarly modify EPA values based on the location in which an interaction takes place. It is logical, for example, for “pushing” to cause less deflection at a hockey arena than at an opera house. For a full discussion of these mathematics, we refer the reader to Smith-Lovin [48].

The idea of sentiment modification is further explored by Heise [28] in an application to jury modelling. In this work, a virtual jury driven by ACT is compared to data from human mock juries recorded in the 1950s. As 32% of these jurors were female, a corresponding proportion of the virtual agents were assigned an EPA of [1.2, 0.7, 0.0] for

⁴These values were again found via Interact [24].

“female juror”, as opposed to the standard (male) EPA of [0.8, 1.6, -0.5] for “juror”.⁵

Actions of the mock juries were recorded as belonging to one of twelve Interaction Process Analysis (IPA) categories grouping similar behaviours. For example, the “shows solidarity” category includes “help”, “compliment”, and “gratify”. These behaviours are then mapped to EPA values whose average becomes the characteristic EPA for an IPA category. This mapping provides a means for comparing the output of the ACT agents to those of the human jurors.

This development leaves but one major question that must be answered before a complete model can be claimed: namely, who will be involved in an interaction? Classical ACT, after all, is only equipped to handle a single actor acting on a single object. To address this, Heise defines “personal tension” to be just the squared difference between an agent’s fundamental self-sentiment, and the transient self-sentiment resulting from the last interaction in which it participated. He then proposes that, in a group of agents, the one to act next will be the one with the highest personal tension, and it will act on the other agent that gives it the largest reduction in tension. This policy is then altered to only apply after an 80% chance for transposition (i.e. flip the actor and object of the last interaction) and a 40% chance for an address of the group as a whole.

With these modifications, Heise finds that his virtual jury acts more consistently like the mock juries than a random distribution of actions in several key ways:

- distribution of IPA categories chosen, on average,
- distribution of IPA categories by gender,
- number of actions taken, by gender (where females took disproportionately few actions),
- number of actions taken by as a distribution over the jurors (i.e. a few jurors took the majority of the actions).

Although it is perhaps unsatisfying to have a comparison only against purely random actions, the fact that seemingly accurate gender dynamics fall out of the model is certainly in the favour of ACT.

2.2.2 Bayesian Affect Control Theory

Bayesian Affect Control Theory, or BayesACT, is an extension of classical ACT that incorporates uncertainty using a Partially Observable Markov Decision Process (POMDP), as developed by Hoey et al. [29]. Rather than having one EPA triple to represent self-sentiment and another for the interacting partner, each has an associated distribution of

⁵One can argue as to whether “male juror” should have been the counterpart to “female juror”, but, given the time period in which the data was collected (1950s), it was deemed appropriate for “juror” to be thought of as a man.

possible EPA values weighted probabilistically. When choosing a deflection-minimizing action, then, it is with respect to these distributions rather than static values. Further, since it cannot be assumed that the partner’s EPA is known, it is instead inferred through a set of observables using Bayesian reasoning. Additionally, unlike in classical ACT, fundamental identities are allowed to drift over time. In general, this is assumed to be slow, but ultimately allows a BayesACT agent to develop a “feel” for its partner, as well as its own role.

The use of a POMDP also allows the inclusion of game elements normally outside the purview of ACT, such as a reward function for actions chosen. When choosing an action, then, there are potentially competing influences, as minimizing the deflection may not correspond with the highest reward. However, this is handled such that these forces do not compete directly. For discrete decision spaces (as in the case of the Prisoner’s Dilemma), a Partially Observable Monte-Carlo Planning (POMCP) [47] scheme is employed, in which nodes in a decision tree are expanded with probability inversely proportional to the deflection their respective action creates. That is to say, a desire to minimize the deflection guides the direction in which the tree expands, but the actual action taken is ultimately decided by maximization of the reward received. This is accomplished by repeated sampling of the state space distribution for as much time as is allowed, where a longer running time results in a more densely-filled tree, and therefore a more “scheming” agent.

This framework is applied to normal-form games (in this case, both the Prisoner’s Dilemma and Battle of the Sexes) by Asghar and Hoey [4]. This is not done with the explicit intention of appearing to be human, but instead compares the performance of BayesACT agents with varying POMCP timeout values. Interestingly, it is found that power dynamics frequently develop between agents, with the strong exploiting the weak, where strength generally correlates with longer timeouts.

Other recent applications of BayesACT include sentiment analysis of newspaper headlines [2], and the development of assistive technology for those coping with Alzheimer’s disease [35].

Chapter 3

Prisoner’s Dilemma Study

This chapter recounts the methodology and results of our study exploring the interaction between human players and BayesACT agents in the Iterated Prisoner’s Dilemma. ¹

3.1 Description of the Experiment

We recruited 70 students (55 male and 15 female) from an undergraduate class on artificial intelligence at the University of Waterloo to participate in our study. These participants were required to sign up online first, and were given an automatically generated username. As part of this process, they were briefed on both ACT, including how to assign EPA ratings, and on the Prisoner’s Dilemma.

Note that the latter was deliberately presented in a manner that made no mention of crooks, snitching, or any other traditional story elements. Instead, emphasis was placed on how each action either benefited the player herself, or the player’s partner instead. To that end, the usual options of cooperation or defection were semantically replaced with “give 2” or “take 1”. This scheme is sensible if one views the game, as defined by Table 3.1, as an allocation of resources from a communal pool. Cooperation corresponds to giving two units to the partner, while defection corresponds to taking a single unit for oneself. Though such a description may reduce a player’s emotional connection to the game, it was deemed necessary, as the telling of the Prisoner’s Dilemma story is not standardized and leaves much room for manipulation on the part of the experimenter.

In addition to this briefing, participants were given an information and consent form and chose with the option to either withhold or consent to the use of their data. All materials shown to participants (including those yet to be discussed), as approved by the University of Waterloo Office of Research Ethics, are given in the Appendix.

The participants were divided into four groups of size 12-20 by last name, with each group playing together for 40 minutes in a computer lab environment. Groups of this size were necessary to minimize the time taken in finding new opponents. In total, 360 games were

¹Portions of this chapter have been previously reported [31].

	C	D
C	2,2	0,3
D	3,0	1,1

Table 3.1: Reward matrix used in our Prisoner’s Dilemma study. It employs the smallest non-negative integers that satisfy the $T > R > P > S$ requirement.

played, where the length of each game was uniformly randomly chosen between 12 – 18 rounds (plays of cooperation or defection). For any given game, a participant played against one of four possible opponents:

1. another randomly chosen participant,
2. the BayesACT bot,
3. a Tit-for-tat bot,
4. Jerkbot, a bot that plays a fixed strategy of three moves of cooperation followed by pure defection thereafter, independent of the participant’s play.

Participants played through all opponent types on a rotation, which was randomized individually for each participant at the start of play. Notably, they were led to believe that all opponents were other participants. It was not revealed to them until after testing was complete that the majority of their games were played against bots.

Upon sign-up (i.e. before playing any games), and after each game (of between 12 – 18 rounds), participants were asked to rate each of the following terms on a sliding scale (semantic differential) for each dimension of EPA space (Evaluation, Potency and Activity):

- two options presented by the game (i.e. take 1 or give 2),
- themselves (their self identity),
- their opponent in the game they just played.

The BayesACT agent for the first session was initialized using the 48 ratings that were given during the advanced sign-up phase. Specifically, this entailed appropriating the participants’ ratings of self, other player, give, and take for use as the BayesACT bot’s corresponding sentiments. In the case of the self and other sentiments, the sets of individual ratings were sampled uniformly randomly with replacement up to populations of 2000, which would form BayesACT’s initial sentiment distributions for self and other. As BayesACT does not support similar distributions for the actions, give and take, we instead took an average of the given EPA ratings for their sentiments.

Figure 3.1 gives the distribution of ratings for the identities of self and other after all sign-ups were completed. The self is seen as more positive than the other player (means 1/0.25 for self/other), but about the same power (0.56/0.64) and activity (0.41/0.33).

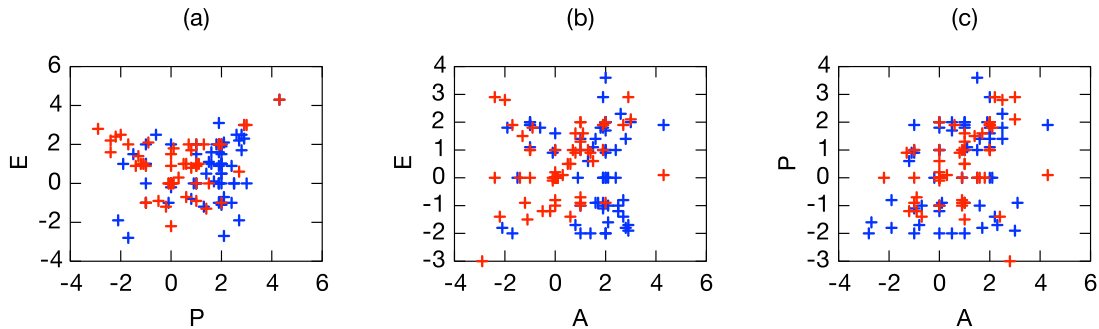


Figure 3.1: Out-of-context (sign-up) ratings of self (blue) and other (red).

Applying an ANOVA analysis along each dimension to check for a statistically significant difference (i.e. the observed differences were not the result of chance) reveals that the Evaluation dimension is almost certainly different (p-value < 0.01), while along the Potency and Activity dimensions, ratings are not distinguishable (p-values of 0.73 and 0.76, respectively). Intuitively, this makes sense, as it is easy to see the Prisoner’s Dilemma as adversarial in nature. If this view is taken, then the opponent must be aligned against the self, which manifests as a good vs. bad difference in the Evaluation dimension. It is much harder to say anything about the Potency or Activity of a general “other”, and so we see no significant difference along those axes.

For the second session, we reassigned sentiments to BayesACT in a similar fashion using the same method, but incorporated ratings given by the participants of the first session. This expanded pool contained 89 ratings.²

It must be noted here that an error was made with the BayesACT bot’s internal reward matrix. Rather than the one given by Table 3.1, it was playing by a matrix with values $R = 10, S = 0, T = 11, P = 1$. This corresponds to the actions “give 10” and “take 1”. While this mistake did not impact on the affective portion of BayesACT’s decision making process (deflection calculations do not consider the reward matrix), it may have affected choices produced by the POMCP. Resulting deviations in play are mitigated somewhat by the relatively short POMCP timeout of 1 second that was used for this study, however it is likely that the increased score for giving encouraged more cooperative play.³

3.2 Results

Before discussing specific results, we note here the process by which we cleaned our data. Data associated with 8 (out of 70) participants whose pattern of ratings indicated that they did not take the experiment seriously was eliminated. To make these determinations, we considered each participant’s proportion of extreme ratings, as well as their relative

²Technical difficulties encountered during the first session prevented this number from being greater.

³Indeed, as can be seen in Figure 3.2, BayesACT is a little too cooperative compared to humans. We therefore may have observed even better results had the correct reward matrix been used.

proportions of positive, neutral, and negative ratings. Specifically, a participant’s data was eliminated if that participated met at least two of the following conditions:

- The participant rated more than 50% of the questions in an extreme manner (between 4 and 4.3).
- The participant rated more than 50% of the questions in a neutral manner (between 0 and 0.3).
- The participant rated more than 65% of the questions in a single direction on the slider (either positive or negative).
- The participant rated more than 65% of the questions at exactly 0.

3.2.1 Game Play and Scores

Figure 3.2 gives the mean, standard deviation, and median reward gathered for each round of the game, by each of the opponents. The blue lines show the human play, while the red lines show the opponent (one of human, BayesACT, Tit-for-tat, or Jerkbot). (For the sake of visual consistency, we have split the human-human graph into blue and red, though there is no practical difference between the groups.) From these plots (and Tables 3.2 and 3.3), we make the following observations:

- When playing against each other (i.e. human-human games), participants maintained moderately high levels of cooperation until near the end of a game. This is logical from a reward-maximization perspective, as there is less opportunity for the opponent to punish defection late in the game.
- The BayesACT bot also tends to mostly cooperate, and does so at a slightly higher rate than its human opponents. As the end of the game approaches, human players begin to defect, but the BayesACT bot, which has not been programmed with knowledge of the game length, does not.
- Tit-for-tat cooperates at a very high level throughout the game and promotes similarly high cooperation from its human opponents. Interestingly, the human players are dissuaded from defection even near the end of a game.
- Jerkbot follows its script, eliciting from its opponent high cooperation followed by a sharp descent into pure defection.

Table 3.2 gives the cooperation rates of the agents and their human opponents averaged over all rounds of play. It also provides a statistical analysis (using ANOVA) comparing each case to human-human games. This reveals that there is a statistically significant difference in the play of Tit-for-tat and Jerkbot when compared to humans, and a similarly

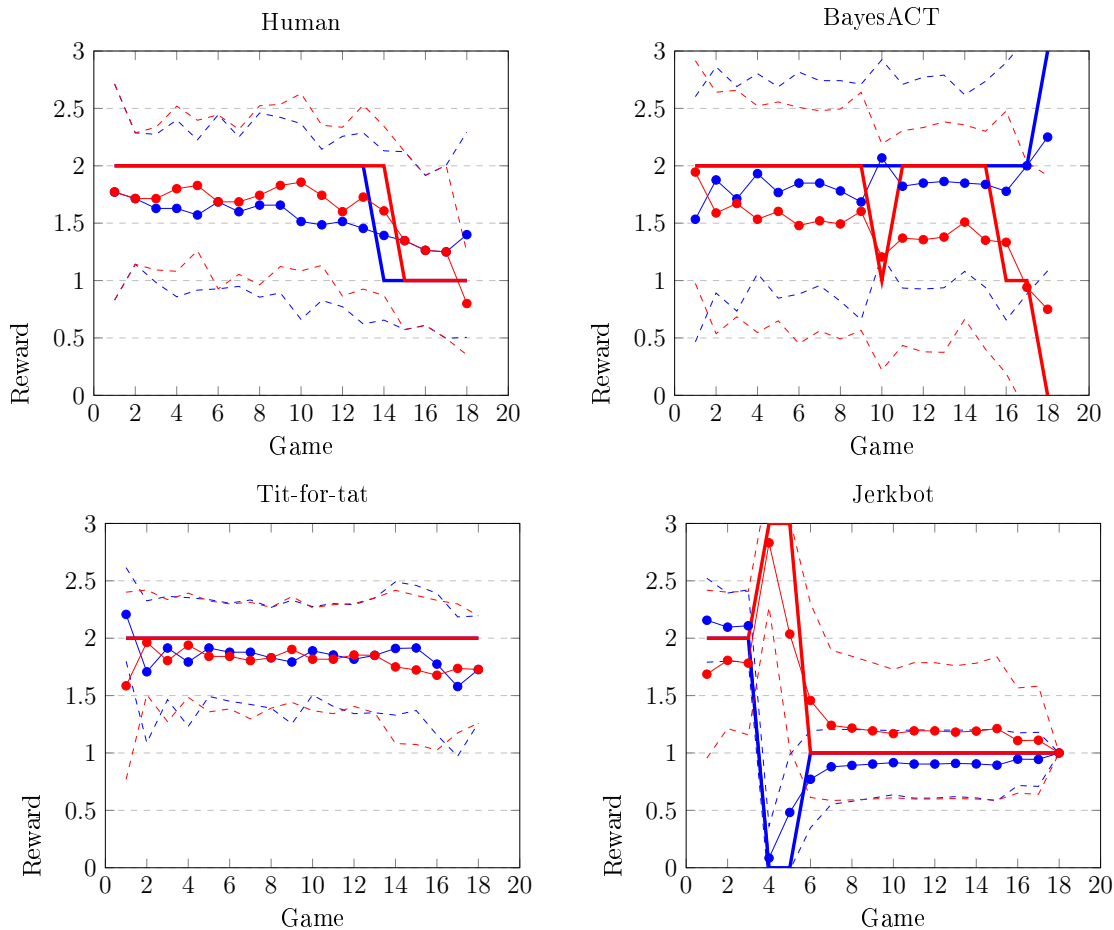


Figure 3.2: Scores per round obtained by the agents (human, BayesACT, Tit-for-tat, and Jerkbot) in red vs. human participants in blue. Solid lines with markers indicate the mean, thick solid lines indicate the median, and dashed lines give the standard deviation.

significant difference in the play that they elicit from their human opponents. BayesACT, on the other hand, does not produce a statistically significant difference in either case. Over the course of a whole game, then, BayesACT can be said to play more like a human than either of the other two bots.

To gain insight into the end-effects observed in Figure 3.2, we have performed the same analysis using only rounds 10 and later. These results are given by Table 3.3. Here, we again observe play that significantly deviates from that of humans by both Tit-for-tat and Jerkbot. (It is, in fact, even more significant for Tit-for-tat given the lower p-values.) For BayesACT, we now do observe a significant difference from human play (due to BayesACT’s ignorance of the end approaching, as previously mentioned), but it becomes even more difficult (higher p-value) to differentiate the plays of its human opponents from those playing other humans. That is to say, in the final rounds of a game, our participants treated BayesACT far more like another person than they did either of the other bots.

3.2.2 EPA Ratings

Table 3.4 gives all mean EPA ratings, collected either on sign-up (initial), or after playing one of the possible opponents. Of particular interest is the EPA of “other”, which is the most direct measurement possible of how the participants felt about each of their opponents. If we compare each of the bots as an opponent to human opponents, we find (as expected) that Tit-for-tat has noticeably higher Evaluation than humans, while Jerkbot is rated noticeably lower. Quantifying these differences with ANOVA, we find that Tit-for-tat differs significantly along each of Evaluation/Potency/Activity (p-values $<0.001/<0.001/0.001$), Jerkbot differs significantly in Evaluation (p-values $<0.001/0.198/0.231$), and BayesACT does not differ significantly in any dimension (p-values $0.843/0.721/0.131$). We therefore conclude, by direct rating, that BayesACT appeared to our participants to be the most human-like.

3.3 Discussion and Future Work

By all of our metrics, BayesACT appears more human than either of the other two bots tested. Of course, neither of them was designed with the purpose of modelling human players, but at a minimum, Tit-for-tat serves as a baseline for the way in which Prisoner’s Dilemma bots typically operate. We address this issue (albeit, in a somewhat different setting) in the coming chapter with our comparisons to imitation-based bots.

When designing this study, there were several places where we had a free choice over which direction to take. With an eye to future work, we now explore a few of the alternatives that were passed over. The easiest of these to identify are the various numerical parameters for which arbitrary values had to be chosen. These include the reward matrix values, the number of rounds per game and the amount of variance in that number, and the POMCP timeout of the BayesACT bot (1 second), among others. Due to the cost (in both dollars and time) of conducting a study with human participants, it was simply not possible to check more than one set of these values. In the network simulations of Chapter 4, which were run in much greater number, we test many more combinations.

It would additionally be interesting to expand the pool of bots. Tit-for-tat was selected for its ubiquity in Prisoner’s Dilemma literature, while Jerkbot was created with the express purpose of eliciting a strong reaction from the participants. Of course, these are not the only bots with the potential to produce interesting results, but including more brought the risk of spreading our data too thin. Were a follow-up to be performed, we would consider including:

- a pure-random bot (i.e. 50% chance to cooperate every turn), which is the most logical strategy to use as a baseline,
- the zero-determinant bot presented by Press and Dyson [42], which has the potential to rival Jerkbot as a highly negative partner,

- the imitator bot of Vilone et al. [52],
- BayesACT under the original settings described by Asghar and Hoey [4].

The manner in which information was presented to the participants also offers opportunities for variation. While we chose to deliberately strip the Prisoner’s Dilemma of its story elements, leaving them in would likely have produced more extreme EPA ratings. This is particularly true for the two actions, which instead of “give 2” and “take 1”, would have become the traditional “cooperate” and “defect”, or perhaps “keep quiet” and “snitch”.

Additionally, it could be interesting to keep hidden the approximate number of rounds per game, which would very likely reduce the magnitude of the end-effects we observed. Of course, this information can be deduced after only a few games, so participants would have to be rotated out much more frequently.

Looking to a further future, we recognize that BayesACT need not be limited to the Prisoner’s Dilemma. In principle, any problem that can be cast as a normal-form game can be played by the BayesACT bot, and by conducting a similar study, BayesACT can be tuned to act as a human analogue. This has the potential to be a useful predictor of actual human behaviour.

Agent	Num. Games	Agent C %	Agent-Human ANOVA p-value	Human C %	Human-Human ANOVA p-value
Human	35	63.9	–	63.9	–
BayesACT	73	71.5	0.180	60.8	0.664
Tit-for-tat	82	85.1	0.001	83.5	0.004
Jerkbot	83	20.3	< 0.001	34.5	< 0.001

Table 3.2: A comparison of cooperation rates among agents and their human partners averaged over all rounds. Two ANOVA p-values are provided, which indicate the statistical significance of the difference between two distributions, where we consider $p < 0.05$ to be significant. The Agent-Human analysis examines the difference between the agent’s cooperation rate and that of humans playing against other humans. The Human-Human analysis is instead for the difference in cooperation rate for a human playing the given agent, and a human playing other humans. Shaded rows indicate agents for which neither analysis could discern a significant difference from human-human play.

Agent	Num. Games	Agent C %	Agent-Human ANOVA p-value	Human C %	Human-Human ANOVA p-value
Human	35	55.4	–	55.4	–
BayesACT	73	71.1	0.028	53.3	0.796
Tit-for-tat	82	83.4	< 0.001	81.8	< 0.001
Jerkbot	83	0.0	< 0.001	8.9	< 0.001

Table 3.3: A comparison of cooperation rates among agents and their human partners averaged over rounds 10 and later. Columns are as described in the caption of Table 3.2.

opponent	give 2			take 1			self (human)			other (human/bot)		
	<i>E</i>	<i>P</i>	<i>A</i>	<i>E</i>	<i>P</i>	<i>A</i>	<i>E</i>	<i>P</i>	<i>A</i>	<i>E</i>	<i>P</i>	<i>A</i>
(initial)	1.4	0.1	0.2	−0.6	0.9	0.6	1.1	0.6	0.3	0.2	0.6	0.3
jerkbot	1.3	−0.3	−0.1	−1.3	0.8	0.7	1.3	−0.1	0.9	−1.9	0.4	0.5
bayesact	1.3	0.1	0.0	−0.9	1.1	1.0	0.7	1.4	1.2	0.4	−0.1	−0.3
human	1.7	0.7	0.3	−1.2	0.4	0.3	1.5	1.2	1.0	0.5	0.0	0.1
titfortat	2.3	1.2	1.1	−1.2	0.5	0.3	1.9	1.7	1.7	2.2	1.1	1.1

Table 3.4: Means of pre-game (initial) and post-game impressions for each opponent type.

Chapter 4

Networked Experiments

This chapter describes our experimental application of BayesACT to the Networked Iterated Prisoner’s Dilemma (NIPD).

4.1 Description of the Experiment

For each test, 169 bots of one type (where 169 was chosen to correspond with a 13 by 13 grid) were arranged on a static network to play the Iterated Prisoner’s Dilemma with their neighbours. These games each lasted for 60 individual rounds, a number comparable to those of the largest human studies [20]. For each setting of our test parameters (to be described shortly), 20 independent games were played, resulting in approximately 3000 total simulations. Those involving BayesACT were carried out on the University of Waterloo’s Daytona computing cluster, which consists of four Intel[®] Xeon[®] processors, each with 12 cores, and 128 Gb RAM.

4.1.1 Modified Game Rules

As before, games consisted of several rounds, and for each round, agents chose between cooperation and defection. However, unlike the standard Iterated Prisoner’s Dilemma, one agent could simultaneously play with several partners, and was forced to send each the same action. (This adheres to the Broadcast model introduced in Section 2.1.5.) Scores were then determined by summing the rewards earned in each of the resulting one-on-one games.

Partners were selected on the basis of static network connections determined before starting the game. (We discuss the three network types used in Section 4.1.3.) It was therefore possible (depending on the type of network used) for some agents to have more partners, and therefore more earning potential, than others. Though this could certainly be viewed as unfair from a player’s perspective, it should not in principle have affected the way the game was played by BayesACT agents, as their goal was not necessarily to “beat” any

other player. However, in the case of the imitator agents (to be introduced in Section 4.1.2), this property gives more influence to highly connected agents. (i.e. Even if their average score per neighbour were low, they could still have the highest total score in their neighbourhood.) This results directly from the work of Vilone et al. [52], and is neither clearly beneficial nor detrimental to an adherence to human-like play.

4.1.2 Bots of Interest

BayesACT Bot Naturally, we were interested in testing the BayesACT bot described in Section 2.2.2 in this networked setting. However, it is designed to keep a single EPA distribution for its self-identity and another such distribution for its opponent. It is therefore not equipped to handle multiple opponents at once without alteration. Several options were considered to make BayesACT compatible with the network:

1. Allow BayesACT to keep its two EPA distributions (i.e. one for self, and one for a generic “other” encompassing all opponents), but instead of applying multiple cooperate or defect actions, average them into one aggregate action. When choosing an action to take, do so as normal, treating the aggregate opponent as any other.
2. Allow BayesACT to keep its single self-identity, but add one EPA distribution for the identity of each opponent. When choosing an action to take, use the result of the majority vote from interactions against all opponents.
3. Expand BayesACT such that it keeps an independent self-identity and opponent-identity for every neighbour in the network. When choosing an action to take, use the result of the majority vote from interactions against all opponents.

All actions within a round are supposed to occur simultaneously, but BayesACT offers no mechanism for processing simultaneous actions. Therefore, if multiple opponent actions are to be processed, they must be arranged in some order. This poses a serious problem for Option 2, as, with a single self-identity that changes after every interaction, a different ordering of these interactions can yield different results. This makes Option 2 an inappropriate choice.

Option 3 alleviates this problem, as each of its self-opponent identity pairs are independent, but strays too far from the sociological roots of BayesACT. While it is certainly possible for a person to act differently when dealing with different people, this is not the same as taking on a completely new, independent identity each time that is wholly unaffected by interactions with anyone else.

This leaves Option 1, which, while comparatively simple, is not obviously flawed and has the additional benefit of being the least computationally expensive of the three. This is therefore the system under which our BayesACT bot operates for these networked experiments.

Imitation-Based (Imitator) Bot For the purposes of comparison, we required another bot to test. However, neither Tit-for-tat (which almost immediately goes to either full cooperation or full defection) or Jerkbot (which ignores completely the actions of its opponents) were suitable choices. Instead, we turn to the imitation-based bot advocated by Vilone et al. [52] as a possible explanation for human behaviour in the Networked Iterated Prisoner's Dilemma. A full description of this bot is given in Section 2.1.5.

4.1.3 Experimental Parameters

Network Types In the literature, we have observed a few classes of networks employed in similar experiments:

- **Grid:** Agents are arranged on a square grid and interact with their nearest neighbours. These neighbours may belong to either a Moore (four neighbours, cardinal directions only) or von Neumann (eight neighbours, diagonals included) neighbourhood.
- **Erdős-Rényi (ER):** Given a desired average node degree, all networks with that property are equally likely to be chosen. i.e. Edges are chosen randomly with uniform probability until some threshold is reached.
- **Scale-free:** The number of nodes with a given degree decreases according to a power law. Unlike that of an ER network, the degree distribution of a scale-free network is characterized by a long tail, resulting in a number of "hub" nodes that have much higher degree than the average.

Given that these network types (which, of course, are not the only possible valid networks) can be varied in infinite ways (for instance, by density), we had a free choice over which would actually be incorporated into this experiment. The selections we made are as follows:

1. a grid layout with a Moore neighbourhood (Grid),
2. an ER network with average degree 5.14 (ER5),
3. an ER network with average degree 8.48 (ER8).

We included a grid network on the basis that it is the most common type found in human studies in the literature [20]. The additional inclusion of ER networks with varied densities were intended to highlight any contrast in play resulting from different, but fundamentally similar networks. The particular values of 5.14 and 8.48 were chosen to mirror those employed by Vilone et al. [52] It is additionally convenient that our first and third networks had similar density, differing primarily in the regularity of their connections.

1.		C		D		2.		C		D		3.		C		D
	C	2,2		0,3			C	1,1		0,1.4			C	10,10		0,11
	D	3,0		1,1			D	1.4,0		0,0			D	11,0		1,1

Table 4.1: Reward matrices chosen for our network experiments.

Reward Matrices Despite (or perhaps because of) the enormous number of Prisoner’s Dilemma studies, there has been little agreement on reward values outside the basic inequality given by Equation 1.1. They therefore present another free choice. In this experiment, we use the matrices given by Table 4.1. Matrix 1 is the same as was used in Chapter 3, Matrix 2 is one setting employed by Vilone et al. [52]¹, and Matrix 3 emulates that of Asghar and Hoey [4].

Other Parameters Additionally, each of the two bots tested had their own unique parameters. In the case of BayesACT, we chose to vary the initial EPA distribution between the following two options:

- the original set as presented by Hoey et al. [29]. This required that each agent be assigned a random sampling of “good” (friend:[2.75,1.88,1.38], buddy:[2.28,1.61,1.65], pal:[2.73,1.87,1.75]) and “bad” (scrooge:[-2.15,-0.21,-0.54], traitor:[-2.52,-0.29,-0.48], crook:[-2.8,-0.72,-0.31]) identities for self-sentiment, and another such sampling for the sentiment of the other player. We refer to this setting as the “default”.
- the complete set of EPA ratings that the participants of our Prisoner’s Dilemma study (described in Chapter 3) assigned to themselves and their opponents when playing against other participants.²

We also applied several different computation time limits (0, 1, and 10 seconds) to BayesACT’s POMCP search, where a zero second limit results in “myopic” agents that do no planning beyond their immediate state. This setting is the closest to the deflection minimization of classical ACT, but of course, still includes the EPA distributions and other machinery of BayesACT.

When a particular setting of these parameters must be identified, we use the shorthand BACT[X][Y], where X is one of D or S (denoting default or study EPA settings) and Y is one of 0, 1, or 10 (denoting the POMCP timeout).

For the imitation-based bots, we varied q , the probability of randomly selecting any neighbour instead of the highest scorer, from 0% to 100% in 10% intervals. We identify this via the shorthand IM[X], where $X \in [0, 100]$ is value of q .

¹Vilone et al. [52] tested a continuum of matrices by varying T . Matrix 2 uses a value of T that saw a large variation in behaviour depending on the value of their randomization parameter, q . It is possibly worth noting that this value does not adhere to the strict inequality of Equation 1.1, but nevertheless remains true to the spirit of the Prisoner’s Dilemma.

²Note that we did not use the EPA ratings of humans playing against the BayesACT bot (or either of the other bots), as it is the human-human case that we are trying to emulate.

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	32.81	33.05	33.46	0.33	0.85
R1	33.67	33.76	33.64	0.01	0.99
R2	31.12	32.51	32.87	2.64	0.27
R3	30.50	30.00	31.54	1.95	0.38
R4	30.30	30.15	30.24	0.02	0.99
...
R57	29.23	28.17	28.79	0.95	0.62
R58	27.43	27.31	28.14	0.68	0.71
R59	28.22	28.02	28.99	0.88	0.64

Table 4.2: Comparing cooperation rates by round across our three network types for a BayesACT agent using the default EPA distribution, a timeout of 1 second, and the first of our three reward matrices. Rows are shaded for p-values > 0.05 , indicating that the distributions for the three network type are not statistically discernible. A full version of this table can be found with those of all other parameter settings in the Appendix.

4.2 Results

We now examine the results of these experiments with respect to the 5 observations of Grujić et al. [20]. For nominal variables, we apply the G-test to show independence (or lack thereof) of two distributions. It produces the likelihood ratio $G = 2 \sum_i O_i \log(O_i/E_i)$, where O_i is the observed count and E_i is the expected count [36]. This can be converted to a p-value, for which we consider a value of 0.05 to constitute strong evidence that the distributions in question are different. For continuous variables, we use ANOVA, which produces a similar p-value.

4.2.1 Network Invariance

For all parameter settings of the BayesACT agents, we do not find evidence that network structure impacts agent behaviour. This is demonstrated by the consistently high p-values obtained when performing a G-test of cooperation rate per round across the 3 network types, indicating that the three distributions are not statistically discernible. In particular, for BACTD agents, 96.1% of rows have $p > 0.05$, while for BACTS agents, this is true of 90.7% of rows. As an example, Table 4.2 gives these data for one BayesACT setting. Full tables (for both BACT and IM bots) are given in the Appendix.

Imitation-based agents, on the other hand, do not seem to consistently exhibit this invariance. For IM agents, only 5.6% of rows have $p > 0.05$. We find that there is a strong tendency for these agents to gradually move towards full defection, but they frequently do so at different rates, depending on the network (with the cooperation rate of the com-

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	51.36	49.67	48.91	4.27	0.12
R1	25.15	30.83	26.09	31.18	< 0.001
R2	12.69	17.10	12.96	33.01	< 0.001
R3	6.27	8.82	5.98	24.46	< 0.001
R4	2.75	4.76	3.11	22.00	< 0.001
...
R57	0.00	0.24	0.03	13.51	0.001
R58	0.00	0.24	0.03	13.51	0.001
R59	0.00	0.24	0.03	13.51	0.001

Table 4.3: Comparing cooperation rates by round across our three network types for an imitation agent using $q = 0.5$ and the first of our three reward matrices. Rows are shaded for p-values > 0.05 , indicating that the distributions for the three network type are not statistically discernible. A full version of this table can be found with those of all other parameter settings in the Appendix.

paratively low density ER5 network frequently decaying the slowest ³). Further, when full defection has been reached for one network, any deviation in the others becomes statistically significant. This results in low G-test p-values when observing cooperation rates on a per-round basis, indicating that behaviour is indeed affected by network structure. An example of this behaviour is given by Table 4.3.

Little changes if we look at only the best parameter settings for each agent per matrix. The best BACTD agents have $p > 0.05$ for 100%, 100%, and 97% of rows for M1, M2, and M3, respectively. For BACTS agents, we have 97%, 98%, and 95%. For IM agents, we have 27%, 43%, and 12%, though the latter two values reduce to 10% and 3% if we exclude IM100 agents, which do not perform strategic imitation at all. This paints much the same picture as the aggregations of all parameter settings: that imitator bots show statistically significant differences in behaviour on different networks, while BayesACT agents do not.

4.2.2 Cooperation Rate Over Time

In human studies, the global cooperation rate has been observed to drop from 55%-70% to 20%-40% after around 20 rounds of play, after which it remains approximately constant [20]. We do not in general observe this behaviour in our BayesACT agents. While some settings of BayesACT do demonstrate a reduction in global cooperation rate over time (i.e. round number), this difference is typically less than 5%.

³In fact, if we consider only the Grid and ER8 networks, which have very similar average degree, the number of rows with $p > 0.05$ increases significantly to 27.7%, indicating that density may have a large effect on the behaviour of imitator agents

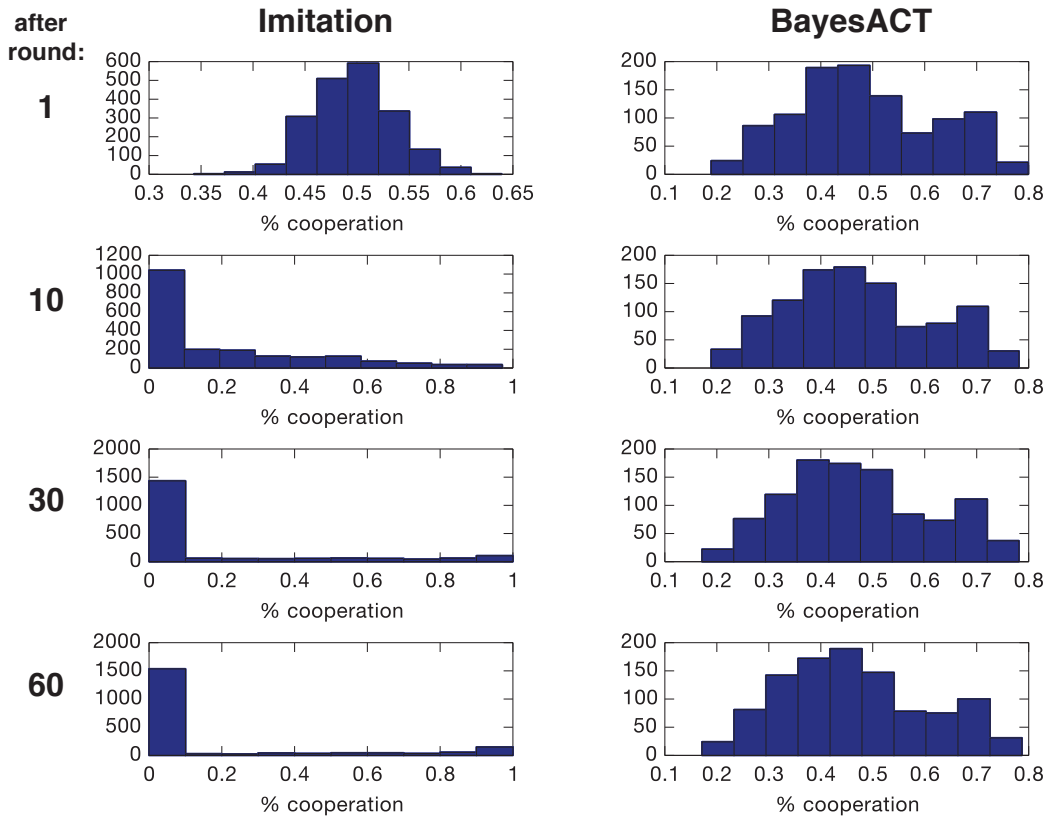


Figure 4.1: Histograms of the number of simulations at various cooperation rates for imitator agents (left) and BayesACT agents (right) at rounds 0, 10, 30, and 60 (top to bottom). BayesACT agents tend to remain fairly constant in their behaviour, while imitator agents have a strong tendency towards full defection (and to a lesser extent, full cooperation).

The imitation-based agents, on the other hand, tended to display one of two extreme behaviours: either the cooperation rate decayed to zero, or it ballooned to some constant greater than its starting value. In some cases, individual simulations of the same parameter settings were split between these final states, though a descent into full defection was generally the more common of the two. Such behaviour is also different from that of humans. These results are summarized by Figure 4.1.

4.2.3 Anti-Correlation of Earnings and Cooperation

Before calculating correlation coefficients, it is worth examining the relative scores of cooperators and defectors, which ought to be higher for the defectors. Across all parameter settings, BayesACT agents score lower when cooperating than when defecting (i.e. test passed for 100% of both BACTD and BACTS agents). While the imitator agents do display this property for Matrix 1 (for 100% of settings), they do not generally do so for

Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.
BACTD0	25.72	30.54	4.01×10^3	< 0.001
BACTD1	23.67	28.64	4.78×10^3	< 0.001
BACTD10	19.61	24.97	6.27×10^3	< 0.001
BACTS0	35.69	40.82	3.09×10^3	< 0.001
BACTS1	32.52	37.48	3.40×10^3	< 0.001
BACTS10	25.33	30.20	4.35×10^3	< 0.001
IM0	45.19	22.51	4.05×10^4	< 0.001
IM10	47.41	21.81	4.20×10^4	< 0.001
IM20	46.11	19.14	6.14×10^4	< 0.001
IM30	42.35	21.69	4.28×10^4	< 0.001
IM40	35.92	14.03	6.59×10^4	< 0.001
IM50	26.89	11.96	3.49×10^4	< 0.001
IM60	19.80	8.51	2.08×10^4	< 0.001
IM70	19.58	8.87	1.87×10^4	< 0.001
IM80	20.41	9.06	2.06×10^4	< 0.001
IM90	22.97	12.69	1.58×10^4	< 0.001
IM100	25.12	22.57	9.57×10^2	< 0.001

Table 4.4: Comparing scores earned by cooperators and defectors among different agent types. Shaded rows indicate that the average score for defection is higher than that of cooperation, as per Requirement 3, and that the difference is statistically significant ($p < 0.05$). This table presents results for network ER5 and Matrix 3. Tables for all network/matrix combinations can be found in the Appendix.

Matrices 2 and 3 (6.7% and 0% of settings, where the only successful agents were the purely random imitators, IM100). It is important to note that reward matrix values are parameters of the simulation, not of the agents. That is to say, a successful agent must have at least some parameter setting that can gracefully cope with any possible reward matrix. A failure of the imitator agents for M3 (and M2 as well, if we exclude IM100) indicates a failure overall.

Table 4.4 gives an example of these results. Full tables are given in the Appendix. In all cases, there was a statistically significant difference between the scores of cooperators and defectors, as calculated with ANOVA.

We see similar results when calculating the Pearson Correlation between the cooperation rates of individual agents and their scores (normalized by the average score of all agents in their simulation). To consider Requirement 3 satisfied, we must see a negative correlation coefficient that is statistically significant ($p < 0.05$). By this metric, we find that 100% of BACTD settings and 74.1% of BACTS settings (100% for M1, 88.9% for M2, 33.3% for M3) display the desired anti-correlation. Given that even the best BACTS settings (BACTS0 or BACTS10) only achieved 77.8% requirement satisfaction, they may be considered less successful than their BACTD counterparts. However, this difference is

Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.
BACTD0	49.79	28.13	-0.10	< 0.001
BACTD1	45.93	26.36	-0.12	< 0.001
BACTD10	38.60	22.90	-0.16	< 0.001
BACTS0	69.49	37.26	-0.02	0.212
BACTS1	63.14	34.35	0.00	0.949
BACTS10	48.99	27.81	0.00	0.857
IM0	74.06	39.30	0.16	< 0.001
IM10	80.49	42.41	0.07	< 0.001
IM20	71.99	38.56	0.09	< 0.001
IM30	64.49	35.01	0.08	< 0.001
IM40	35.96	21.90	0.10	< 0.001
IM50	21.66	15.19	0.14	< 0.001
IM60	9.89	9.63	0.04	0.021
IM70	10.74	10.02	0.05	0.007
IM80	11.49	10.37	0.05	0.004
IM90	21.11	14.86	0.05	0.008
IM100	39.95	23.59	0.10	< 0.001

Table 4.5: Comparing cooperation rates with scores earned. Shaded rows indicate that the correlation between cooperation rate and score is negative and statistically significant ($p < 0.05$). This table presents results for network ER5 and Matrix 3. Tables for all network/matrix combinations can be found in the Appendix.

small compared to the imitator agents, which displayed cooperation-score anti-correlation in only 30.3% of settings (81.8% for M1, 9.1% for M2, 0% for M3), with the best setting, IM10, succeeding in 44.4% of matrix/network combinations. By both of our metrics, then, BayesACT satisfies Requirement 3 more adequately than the imitator bots.

Table 4.5 gives an example of these results. Full tables are given in the Appendix.

4.2.4 Moody Conditional Cooperation

Moody Conditional Cooperation has two requirements: hysteresis (i.e. an agent must be more likely to cooperate if it cooperated on the last turn) and conditionality (i.e. an agent must be more likely to cooperate if its neighbours were predominantly cooperators on the last turn) [19]. Example settings for each of these are given by Table 4.6 and Table 4.7 respectively.

Though the various BayesACT agents had performed fairly similarly until this point, we see here that those using the default set of initial EPA values seem to display a strong hysteresis (in 100% of test settings), while those using the study set do not (only 4% of all test settings). Additionally, even the best of the BACTS agents, BACTS0, showed a hysteresis in only 11% of network/matrix combinations. We believe that this is most likely

Agent	C After C %	C After D %	G-test stat.	G-test p-val.
BACTD0	68.51	31.26	2.69×10^4	< 0.001
BACTD1	64.96	29.68	2.53×10^4	< 0.001
BACTD10	60.37	24.74	2.54×10^4	< 0.001
BACTS0	69.44	69.56	0.31	0.58
BACTS1	62.89	63.42	5.67	0.017
BACTS10	48.07	49.61	47.28	< 0.001
IM0	95.93	13.48	1.35×10^5	< 0.001
IM10	95.33	22.77	9.12×10^4	< 0.001
IM20	92.79	20.62	1.04×10^5	< 0.001
IM30	86.23	26.15	7.42×10^4	< 0.001
IM40	73.77	14.30	7.26×10^4	< 0.001
IM50	56.78	11.19	3.70×10^4	< 0.001
IM60	43.26	5.41	1.97×10^4	< 0.001
IM70	40.84	6.33	1.72×10^4	< 0.001
IM80	40.85	6.88	1.72×10^4	< 0.001
IM90	44.94	14.02	1.72×10^4	< 0.001
IM100	48.76	33.81	4.45×10^3	< 0.001

Table 4.6: A comparison of cooperation rates after either cooperating or defecting on the last turn. Shaded rows indicate that cooperation is higher after previously cooperating than it is after previously defecting (i.e. hysteresis is observed) and that the difference is statistically significant ($p < 0.05$). This table presents results for network ER5 and Matrix 3. Tables for all network/matrix combinations can be found in the Appendix.

a result of the larger difference between the EPAs of the cooperate and defect actions in the default set ($[2.1, 1.45, 0.82]$ and $[-2.28, -0.48, -0.84]$ vs $[1.42, 0.10, 0.18]$ and $[-0.65, 0.85, 0.70]$) resulting in higher deflections and hence more severe reactions.

Viewed in aggregate, relatively few BayesACT agents exhibit statistically significant conditionality (22% of BACTD and 44% of BACTS). Looking at the best settings reveals that BACTD0 displays conditionality in 44% of network/matrix combinations, while BACTS1 does so in 67% of them. Unfortunately, it must be noted that the actual difference in cooperation percentage tends to be very small (frequently $< 1\%$), and it is for this reason that we do not claim to observe conditionality in BayesACT agents.

All imitator agents, on the other hand, have both strong hysteresis and conditionality (i.e. 100% of settings). (Given the tendency of these systems to develop towards either high cooperation or total defection, this is not surprising.)

4.2.5 Player Type Stratification

According to Grujić et al. [19], human players can be broadly classified as belonging to one of 5 groups: those who only cooperate, those who mostly cooperate (at least two

Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.
BACTD0	50.49	49.12	28.77	< 0.001
BACTD1	46.40	45.90	3.88	0.049
BACTD10	37.36	38.96	35.79	< 0.001
BACTS0	69.49	69.33	0.25	0.62
BACTS1	63.35	62.29	14.71	< 0.001
BACTS10	49.55	48.22	28.85	< 0.001
IM0	91.01	16.70	8.15×10^4	< 0.001
IM10	94.57	18.88	8.08×10^4	< 0.001
IM20	93.07	15.73	1.06×10^5	< 0.001
IM30	88.39	17.87	9.14×10^4	< 0.001
IM40	81.65	9.99	9.83×10^4	< 0.001
IM50	72.69	8.15	5.76×10^4	< 0.001
IM60	67.73	4.21	2.88×10^4	< 0.001
IM70	68.14	4.44	3.11×10^4	< 0.001
IM80	69.59	4.47	3.71×10^4	< 0.001
IM90	75.84	8.38	5.79×10^4	< 0.001
IM100	77.40	17.68	6.22×10^4	< 0.001

Table 4.7: A comparison of cooperation rates after being surrounded by a majority of either cooperators or defectors on the last turn. Shaded rows indicate that cooperation is higher near other cooperators than near defectors (i.e. conditionality is observed) and that the difference is statistically significant ($p < 0.05$). This table presents results for network ER5 and Matrix 3. Tables for all network/matrix combinations can be found in the Appendix 5.

times in three), moody conditional cooperators, those who mostly defect (at least two times in three), and those who only defect. These groups tend to be unevenly populated, with the most in the middle group, fewer in either of the “mostly” groups, and very few in either of the “pure” groups.

For human systems that settle on a comparatively high level of cooperation, it makes sense to consider MCC as the middle group. However, given the imitator agents tendency towards full defection, MCC behaviour is not limited to the middle third of cooperation rates. Hence, we have simply called the middle group “Mixed”, and dealt with MCC on its own. For one experimental setting, this data is given by Table 4.8, where we have shaded rows that meet the stratification condition ⁴:

$$(Mixed\% > MostlyD\% > PureD\% > 0) \wedge (Mixed\% > MostlyC\% > PureC\% > 0) \quad (4.1)$$

⁴Note that this inequality is never explicitly stated by Grujić et al. [19], but is our interpretation of his result.

Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %
BACTD0	5.77	28.55	31.57	28.88	5.24
BACTD1	5.92	33.08	32.34	25.56	3.11
BACTD10	6.27	43.99	28.43	20.06	1.24
BACTS0	0.00	0.00	33.25	66.75	0.00
BACTS1	0.00	0.00	72.46	27.54	0.00
BACTS10	0.00	0.47	99.32	0.21	0.00
IM0	11.42	7.22	4.35	60.89	16.12
IM10	3.55	2.57	5.83	80.74	7.31
IM20	4.76	6.48	13.73	71.21	3.82
IM30	4.32	10.33	25.65	58.28	1.42
IM40	9.35	39.91	33.58	16.69	0.47
IM50	3.91	70.00	25.53	0.38	0.18
IM60	8.91	87.40	3.46	0.00	0.24
IM70	3.34	95.21	1.18	0.00	0.27
IM80	2.69	93.91	3.20	0.00	0.21
IM90	0.92	84.44	9.64	4.79	0.21
IM100	0.24	38.67	52.25	8.73	0.12

Table 4.8: A comparison of agent stratification according to the 5 groups of Grujić et al. [19]. Shaded rows indicate adherence to Equation 4.1. This table presents results for network ER5 and Matrix 3. Tables for all network/matrix combinations can be found in the Appendix.

Aggregating all parameter settings, none of our agent types appear to display strong stratification, with 33% of BACTD, 0% of BACTS, and 3% of IM agents adhering to Equation 4.1. However, when viewing only the best parameter setting from each category, a different picture emerges. While BACTS remains unstratified, we see 100% satisfaction of Equation 4.1 from BACTD0. There is therefore at least one setting of BayesACT that behaves in a human-like fashion according to Requirement 5 of Grujić et al. [19].

On the other hand, the best IM bot, IM100, only satisfies Equation 4.1 in 33% of network/matrix combinations. If IM100 is discounted (because $p = 100$ corresponds to never actually using strategic imitation, but rather always imitating a neighbour at random), then there are no imitator bots that meet the stratification requirement in any test setting.

4.3 Discussion and Future Work

BayesACT agents meet the criteria of network invariance and cooperation-score anti-correlation where imitation does not, and in all areas where BayesACT is deficient, excepting the conditionality requirement of MCC, imitation is as well. (Arguably, BayesACT displays stratification as well, but as this is for only one setting, we are cautious of making

this claim.) Additionally, exposing more of BayesACT’s parameters may alleviate some of its deficiencies.

A BayesACT agent keeps an EPA distribution for the perception of its opponent. (As one action must be chosen to be applied to all partners, we modeled the complete set of them as one general “opponent”.) Both this distribution and the one for self are allowed to change as observations are received. For instance, after its partner defects, a BayesACT agent will view that partner through a more negative EPA. However, this process of change is slow by default. By increasing the value of the corresponding tuning parameter (which was held at its default value for these experiments), larger changes in identity may be allowed after every round, allowing for sooner retributive action. Such an outcome could help these agents to better conform to both the conditionality aspect of MCC and the overall drop in cooperation rate over time observed in human players.

While the imitation-based agents appear to come up short in all requirements but one, it must be noted here that due to the computational cost of BayesACT, we were not able to test the full space of reward as completely as Vilone et al. [52]. It is therefore possible that an ideal setting for the imitator agents was missed amidst that continuous space.

Looking to future work, we would be interested in applying BayesACT to other types of networks. In particular, scale-free networks, which were examined by Vilone et al. [52], are highly non-uniform, unlike their grid and ER counterparts, and more closely resemble human social networks [30]. However, given that Grujić et al. [20] did not have data from human studies on scale-free networks when making their observations, it is not clear that invariance ought to continue in that domain.

It would also be interesting to adjust the clustering of agents within a network. Currently, BayesACT agents are given random initial EPA distributions, creating a continuum of “good” to “bad” identities. However, these agents are mixed homogeneously throughout the network. If clusters of nodes were assigned similar identities, it could produce persistent microcosms within a wider network, much as envisioned by Hamilton and Axelrod [23].

Removing the Broadcast restriction opens up further opportunities for future work. If agents do not act simultaneously, then there is freedom in selecting the ordering of these actions. A simple solution would be to rotate the agents such that each gets a turn, but this is not the only option. Recalling Heise’s jury model [28], we could allow the agent with the highest personal tension (i.e. the squared difference between that agent’s fundamental self-sentiment, and the transient self-sentiment resulting from the last interaction in which it participated) to act next, although the computational costs of checking this quantity for every agent after every action may be prohibitive.

Finally, we introduce the possibility of applying BayesACT to networks in the wild. Though such networks do not generally explicitly involve the Prisoner’s Dilemma, they may contain features that can be cast as normal-form games. When a FaceBook user ignores a friend request, or a GitHub user denies a pull request, there is an implicit defection-like interaction with another agent somewhere in the world. If one supposes

that such scenarios come with even a portion of the emotional baggage of a Prisoner's Dilemma, then BayesACT may be able to help explain them.

Chapter 5

Conclusions

In both of our experiments, BayesACT appeared definitively more human (or at least, human in more areas) than the bots against which it was compared. As a result, we believe that this work brings us a step closer to reproducing human behaviour in the Iterated Prisoner’s Dilemma, with ample opportunity for expansion into other normal-form games. For detailed discussions of these results and possibilities for future work, we refer the reader to Sections 3.3 and 4.3.

Final Remarks In the field of Artificial Intelligence, it has often been the case that a game is studied with the explicit goal of creating a program that can play it better than the best humans, and many researchers have had great success in the pursuit of that goal. We now have bots that can defeat human world champions in very computationally difficult games, like chess (IBM’s Deep Blue [10]) and Go (Google DeepMind’s AlphaGo [46]), and provably unbeatable bots for simpler games like checkers and heads-up limit hold’em poker (the University of Alberta’s Chinook [44] and Cepheus [50], respectively).

However, as impressive as such advances are, they exploit the computer’s ability to perform a humanly impossible number of calculations at a humanly impossible speed, and so offer little insight into a person’s approach to the game. Of course, doing so was never their goal, but it is nevertheless a goal worthy of pursuit. For, what larger purpose can a game with no implicit value serve once it is over, if not to give insight into the mind of the player?

We have experimented with BayesACT, a model of human behaviour that not only strives to behave like a person, but attempts to do so in a way consistent with the human mind. For certain, it is not the highest scoring bot to have ever played the Iterated Prisoner’s Dilemma, but generating such a bot was never our goal. We wanted to show that our BayesACT bot played the game more like a human than other bots, and have done so. There is a place in AI for both the study of bots that play to win, and those that strive to emulate human behaviour. We have here helped to bolster that oft-overlooked second category.

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Appendix

Study Materials

Here, we reproduce the Prisoner’s Dilemma application as it was seen by participants of the study. Upon entering the Prisoner’s Dilemma URL, participants arrived at the welcome screen shown in section 5. They were instructed to review the game information given in section 5 before signing up. Signing up consisted of three phases: answering a short demographic questionnaire, reviewing and accepting/declining an informed consent form, and assigning E, P, and A values to each of the key concepts of “Self”, “Other Player”, “Give”, and “Take”. These materials can be found in sections 5 and 5 respectively.

Once signed up, participants were able to begin play. Upon being assigned a match, a participant would arrive at the Start of Game screen given in section 5 with the option to either Give 2 or Take 1. After making a selection, the participant had to wait for the server to respond with her opponent’s move. Note that, even in the case where the opponent was a bot, some time was always allowed before a reply was sent to preserve the illusion that all players were human. On completion of the final round (decided randomly to be a value in the range 12-18), the participant was asked to again evaluate E, P, and A values for each of the four key concepts. An example End of Game screen can be found in section 5 and sliders, as before, in section 5.

When the allotted play time of a group of participants ran out, they were instructed to stop playing and open the (previously hidden) debriefing page. This page, which can be found in section 5, revealed to the participants that they played against bots as well as each other, and gave them the option to withdraw their data from the study. This was the final interaction participants had with the Prisoner’s Dilemma application.

Welcome Screen

Welcome to the Prisoner's Dilemma Experiment

Some important stuff:

- Use Chrome, Firefox, or Internet Explorer. Other browsers (including Safari) may not work
- Don't use the back or refresh buttons
- Don't exit the window until you are finished
- Don't manually edit the URL

Username

<--Go here before signing up!

Game Information

The Iterated Prisoner's Dilemma

The game you will be playing is a variant of the much studied class of matrix games referred to as iterated prisoner's dilemmas. In this game, you are partnered with another player and given the choices "Give 2" or "Take 1". If you choose "Give 2", the other player will be given 2 points. If you choose "Take 1", you will be given 1 point. After both players have made a choice, each will be able to see what the other chose, and points will be distributed. Then a new round will begin in which both players are again given the options of "Give 2" or "Take 1".

For any given round of play, the point structure can be summarized as follows.

Reward Matrix		
(your payoff/opponent's payoff)		
	Opponent Gives 2 (G)	Opponent Takes 1 (T)
You Give 2 (G)	2/2	0/3
You Take 1 (T)	3/0	1/1

At some point, the game will end abruptly and you will be asked to perform EPA ratings based on the game you just played. It is important to note here that a single game does not have a winner and loser. You will add your points to your total and the other player will add theirs. At the end of the assignment, every point you earn will be counted as one entry into a draw for ten \$20 Amazon gift cards.

A Review of EPA Ratings

Psychologists agree that emotions have three dimensions:

- Evaluation** - is it something good/nice or rather bad/awful;
- Potency** - is it strong/powerful or rather weak/powerless; and
- Activity** - is it slow/inactive or rather fast/lively.

For example, if someone said to you: "I like you", you might perceive this as very good/nice (Evaluation), quite powerful/big (Potency), and possibly neutral on the third dimension, i.e. neither very slow/quiet nor very lively/noisy (Activity). On the other hand, if someone said "let's go dancing!" you might perceive this as a bit good/nice (Evaluation), neutral potency, but very active.

Note that there are no right or wrong answers; we are interested in your quick and spontaneous emotional reactions. If in doubt about a rating, consider how the average member of society might rate, having been subject to the same experiences as you.

[Return to Login](#)

Sign-Up Questionnaire

UWaterloo student ID (eg. t25smith)

gender

major

year in program

Consent Information

Study Title: Applying BayesACT to the Iterated Prisoner's Dilemma

Faculty Supervisor: Dr. Jesse Hoey, Department of Computer Science, (***) ***_**** ext. *****, *****@****

Student Investigator: Josh Jung, Department of Computer Science, (***) ***_**** ext. *****, *****@****

Course Assignment

During class on October 20 and 22, instead of the lectures, you will be asked to play a series of iterated prisoner's dilemma games in *****/****. You may bring your own laptop or use one of the Macs in the lab. The game is very simple; you select one of two options and receive a score based on the combined choices made by you and your opponent. After each set of approximately 20 such games, you will be asked to rate both yourself and your opponent on the evaluation, potency, and activity scales prescribed by Affect Control Theory. You will then be matched with another player to play another set.

For this course assignment you will be asked to sign up online at *****. You will

be asked for your UWaterloo ID, as well as your major and gender, which you can choose not to share if you wish. You will also be assigned an ID, which you must bring to class on the days of the assignment. Completion of the assignment is worth 5% of your mark and is expected to take approximately 3 hours of your time. At the end of the assignment each point you earn while playing the game will be counted as one entry into a draw for one of ten (10) \$20 Amazon gift cards.

If you are unable to attend these two classes you can choose to complete a paper review instead and will still be entered into the draw with odds equivalent to the median player participating in the study. This requires that you choose a research paper in artificial intelligence, read it, and write a 2-page review of the paper. Reviews will be assigned a pass/fail (5%/0%) grade based on the suitability of the review, where a suitable review is one that is coherent and makes it clear that its author has read the paper. Your odds of winning one of the prizes is based on the number of individuals who complete the in-class assignment or paper review. We expect that approximately 120 individuals will complete the in-class assignment.

You are invited to participate in a study

You are invited to participate in a study assessing the validity of Bayesian Affect Control Theory (BayesACT) as a predictor of human behaviour. The study is being conducted by Josh as a Master's student in the Department of Computer Science under the supervision of Dr. Jesse Hoey.

Affect Control Theory posits that people strive to behave in the manner most in line with the expectations of their society. BayesACT extends this theory to allow it to deal with uncertainty. This study will provide data from humans playing a game, the iterated prisoner's dilemma, for the purposes of comparing human behaviour to the predictions of BayesACT.

We would like to use the results from the course assignment described above (the Prisoner's dilemma assignment) for our research.

You are under no obligation to provide your consent for the use of your assignment for our research. Further, a decision to participate or not will have no impact on your grade in ****. Professor Hoey will not know who consented to the use of their assignment in this research. Note that completion of the assignment does not imply consent to use your assignment, which you may choose not to give after reading this form. You will receive 5% credit for the assignment regardless of whether or not you give consent to be part of the research.

Information collected to draw for the prizes will not be linked to the data in any way, and this identifying information will be stored separately, then destroyed after the prizes have been provided. The amount received is taxable. It is your responsibility to report this amount for income tax purposes.

You may opt out of the study at any time by contacting Josh. Also note that the student IDs of consenting students will not be viewable by Jesse Hoey or any of the TAs associated

with this course.

Personal Benefits of the Study

This study will help to determine the efficacy and generalizability of BayesACT. It will also produce initial conditions based on real data that can be used in future BayesACT projects. BayesACT has, for example, been used to create assisted living devices for patients with Alzheimer's disease, including hand-washing stations developed at the University of Waterloo.

Risks to Participation in the Study

There is some risk that you may feel coerced into consenting to the use of your assignment due to Jesse Hoey's dual roles as professor and researcher. However, we would like to assure you that he will never see a list of students who give/don't give their consent, and that he will not be involved in the drawing or distribution of Amazon gift cards.

Confidentiality

All information you provide is considered completely confidential; indeed, your name will not be included or in any other way associated, with the data collected in the study. Furthermore, because the interest of this study is in the average responses of the entire group of participants, you will not be identified individually in any way in any written reports of this research. The data, with identifying information removed, will be kept for a period of 10 years following publication of the research, after which it will be deleted. The data will be securely stored in the research laboratory of Dr. Jesse Hoey in the DC building to which only researchers associated with this study have access.

Questions and Research Ethics Clearance

If after receiving this letter, you have any questions about this study, or would like additional information to assist you in reaching a decision about participation, please feel free to ask the student investigator or faculty supervisor listed at the top of this sheet. Alternatively, you may contact *****, a senior PhD student in the Computational Health Informatics Lab, at ****@****, who is not directly affiliated with the study, but can provide additional information to assist you in reaching a decision about consent.

We would like to assure you that this study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee. However, the final decision about consent is yours. Should you have any comments or concerns resulting from your participation in this study, please contact *****, the Director, Office of Research Ethics, at *_**_**_**, Ext. ***** or ****@****.

Thank you for your interest in our research and for your assistance with this project.

Consent of Participant

By consenting to the use of your assignment below, you are not waiving your legal rights or releasing the investigator(s) or involved institution(s) from their legal and professional responsibilities.

I have read the information presented in the information letter about a study being conducted by Josh Jung under the supervision of Dr. Jesse Hoey of the Department of Computer Science at the University of Waterloo. I have had the opportunity to ask any questions related to this study, to receive satisfactory answers to my questions, and any additional details I wanted. I am aware that I may withdraw consent for the use of my assignment from the study without loss of credit at any time by advising Josh of this decision.

This project has been reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee. I was informed that if I have any comments or concerns resulting from my participation in this study, I may contact the Director, Office of Research Ethics, at *_**_*_*_*_*_****, Ext. ***** or *****@****.

Please select an option ▼

submit

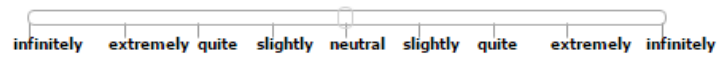
ACT Sliders

Please assign the following EPA values. (There are 4 groups of 4 ratings each.)

Assign EPA values to **YOURSELF** as a player of the game.

Yourself - Evaluation

Bad
Awful



Good
Nice

Yourself - Potency

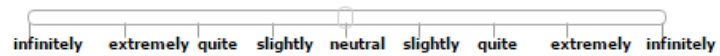
Powerless
Little



Powerful
Big

Yourself - Activity

Quiet
Slow



Noisy
Fast

Continue

Note that each of “Yourself”, “Other Player”, “Give”, and “Take” had its own page of three sliders.

Game Interface

Start of Game

Reward Matrix (your payoff/opponent's payoff)		
	Opponent Gives 2 (G)	Opponent Takes 1 (T)
You Give 2 (G)	2/2	0/3
You Take 1 (T)	3/0	1/1

Your Choices:
Opponent's Choices:

Your Score: 0
Opponent's Score: 0

Example End of Game

Reward Matrix (your payoff/opponent's payoff)		
	Opponent Gives 2 (G)	Opponent Takes 1 (T)
You Give 2 (G)	2/2	0/3
You Take 1 (T)	3/0	1/1

Your Choices: G G T G G G T T T T T T T T T
Opponent's Choices: G G G T G G G T T T T T T T T

Your Score: 22
Opponent's Score: 19

Your game is over. Please assign the following EPA values. (There are 4 groups of 4 ratings each.)

Debriefing

Debriefing Letter

Study Title: Applying BayesACT to the Iterated Prisoner's Dilemma

Faculty Supervisor: Dr. Jesse Hoey, Department of Computer Science, (***) ***-**** ext. *****, ****@****

Student Investigator: Josh Jung, Department of Computer Science, (***) ***-**** ext. *****, ****@****

Thank-you for completing this assignment. When you began the assignment, you were told that the purpose of this assignment was to observe human behavior in the iterated prisoner's dilemma game. However, the game was slightly more complicated than we explained at the beginning. Only 25% of the games you played were against your fellow classmates. The remainder were played in equal parts against three different artificially intelligent (AI) opponents (bots). One of the three bots was built using BayesACT and initialized with the ratings given by you over the course of the study. The other two played static strategies: one played Tit-for-tat (i.e. always did exactly the same as what you did the last time you played), and the other cooperated three times and defected thereafter.

It was necessary to conceal this information to avoid spoiling the ratings you gave to yourselves and your opponents. We thought it likely that if you knew there was a high probability that your opponent was a bot, you would be unlikely to have a significant emotional response to the plays of your opponent. We apologize for omitting details about the tasks in this assignment. We hope that you understand the need for not informing you of this aspect of the assignment now this it has been more fully explained to you.

If you consented to the use of your assignment in our research please note that once all the data are collected and analyzed for this project, we plan on sharing this information with the research community through seminars, conferences, presentations, and journal articles. If you are interested in receiving more information regarding the results of this study, or would like a summary of the results, please email Josh Jung, and when the study is completed, anticipated by December, 2015, to send you the information.

The information you provided will be kept confidential by not associating your name with the responses. The data will be stored with all identifying or potentially identifying information removed. Electronic data will be stored 10 years on a password protected computer in DC 2584 then erased. No one other than the researchers will have access to the data.

This project was reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee. Should you have any comments or concerns resulting from your participation in this study, please contact *****, the Director, Office of Research Ethics, at *_**_**_**, Ext. **** or ****@****.

We really appreciate your participation, and hope that this has been an interesting experience for you.

Please enter your username and choose a consent option below.

Username

Consent Options

Network Experiment Full Results

Network Invariance - Full Tables

Full tables for the network invariance analysis of Section 4.2.1 are given here. For each table, cooperation rates by round are compared across our three network types. The caption of each table contains the agent type and reward matrix used. Rows are shaded for p-values > 0.05 , indicating that the distributions for the three network type are not statistically discernible.

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	50.59	48.76	48.79	2.98	0.225	R0	32.81	33.05	33.46	0.33	0.847
R1	51.45	49.53	49.67	3.10	0.213	R1	33.67	33.76	33.64	1.15×10^{-2}	0.994
R2	49.70	50.24	48.49	2.16	0.339	R2	31.12	32.51	32.87	2.64	0.267
R3	50.24	49.11	49.76	0.86	0.650	R3	30.50	30.00	31.54	1.95	0.377
R4	51.12	49.44	48.61	4.44	0.109	R4	30.30	30.15	30.24	1.78×10^{-2}	0.991
R5	50.03	50.36	48.08	4.11	0.128	R5	30.12	29.20	29.53	0.70	0.704
R6	49.47	48.91	50.36	1.44	0.486	R6	30.24	29.44	29.50	0.64	0.726
R7	49.76	49.35	49.35	0.15	0.926	R7	29.41	29.73	29.11	0.31	0.855
R8	49.32	49.14	48.55	0.44	0.803	R8	29.64	29.53	30.53	0.97	0.615
R9	49.88	49.73	48.76	1.01	0.604	R9	30.18	30.12	30.62	0.24	0.886
R10	50.65	49.26	48.91	2.30	0.316	R10	30.15	29.67	30.30	0.34	0.844
R11	49.50	48.82	47.90	1.74	0.419	R11	30.71	30.65	31.30	0.41	0.815
R12	49.14	48.85	47.22	2.90	0.234	R12	30.65	29.11	29.73	1.93	0.380
R13	50.95	50.53	48.85	3.35	0.188	R13	29.20	29.38	30.33	1.18	0.554
R14	48.61	48.64	49.23	0.33	0.847	R14	29.53	28.99	29.97	0.78	0.678
R15	50.21	49.91	49.76	0.14	0.933	R15	29.47	28.99	29.64	0.37	0.831
R16	50.30	49.11	50.41	1.40	0.496	R16	30.09	30.98	29.56	1.65	0.439
R17	49.26	49.53	49.56	7.18×10^{-2}	0.965	R17	29.82	29.64	30.83	1.31	0.520
R18	50.15	49.56	48.55	1.76	0.414	R18	30.12	30.12	30.50	0.16	0.924
R19	50.71	49.23	49.94	1.48	0.477	R19	29.88	29.88	29.91	9.41×10^{-4}	1.000
R20	51.78	49.17	47.60	12.01	0.002	R20	28.25	28.20	29.79	2.70	0.259
R21	50.44	49.82	48.67	2.19	0.334	R21	28.64	29.82	29.76	1.45	0.484
R22	49.47	49.02	48.46	0.69	0.709	R22	29.82	30.21	30.18	0.15	0.929
R23	50.18	48.88	48.73	1.72	0.423	R23	29.59	28.73	31.09	4.63	0.099
R24	49.64	48.76	48.17	1.50	0.472	R24	29.56	29.67	29.50	2.65×10^{-2}	0.987
R25	49.67	50.00	49.35	0.29	0.867	R25	29.41	29.59	30.36	0.82	0.665
R26	50.83	49.38	47.75	6.41	0.041	R26	29.53	28.88	29.88	0.85	0.654
R27	50.56	49.56	48.76	2.21	0.331	R27	29.91	29.50	29.73	0.14	0.932
R28	49.91	49.05	48.61	1.18	0.553	R28	30.47	30.24	29.70	0.50	0.779
R29	50.36	48.91	47.25	6.54	0.038	R29	29.64	29.38	29.47	5.97×10^{-2}	0.971
R30	49.67	49.79	48.64	1.09	0.580	R30	28.82	30.21	29.67	1.60	0.449
R31	50.86	50.18	49.26	1.74	0.419	R31	28.91	29.47	30.71	2.76	0.252
R32	50.74	50.33	50.18	0.23	0.892	R32	28.85	29.29	29.73	0.64	0.725
R33	49.20	49.26	49.32	9.47×10^{-3}	0.995	R33	30.18	29.62	30.44	0.58	0.750
R34	49.76	48.52	49.50	1.16	0.561	R34	29.02	29.91	30.50	1.79	0.408
R35	49.08	48.67	48.31	0.40	0.818	R35	29.94	30.38	30.62	0.38	0.826
R36	48.93	49.17	48.46	0.35	0.838	R36	28.99	29.88	31.18	3.90	0.142
R37	49.73	49.56	50.09	0.20	0.905	R37	29.05	29.41	29.91	0.60	0.739
R38	50.00	48.76	49.94	1.33	0.515	R38	29.35	29.53	31.42	4.22	0.121
R39	49.85	49.62	49.20	0.29	0.864	R39	28.25	30.03	29.53	2.74	0.254
R40	49.73	50.27	47.04	8.09	0.018	R40	30.36	28.31	29.32	3.40	0.183
R41	51.27	49.64	49.73	2.26	0.322	R41	30.06	30.86	30.27	0.55	0.760
R42	49.32	48.40	49.14	0.64	0.726	R42	30.09	28.79	29.56	1.39	0.498
R43	50.74	49.85	48.64	3.01	0.222	R43	29.82	30.12	28.40	2.75	0.253
R44	50.15	49.32	48.20	2.60	0.273	R44	30.33	28.40	29.50	3.03	0.219
R45	50.12	49.88	49.23	0.57	0.752	R45	30.41	29.20	30.62	1.90	0.387
R46	48.02	50.12	49.38	3.07	0.215	R46	30.21	29.85	29.23	0.79	0.674
R47	50.06	48.31	49.67	2.28	0.321	R47	29.05	29.26	28.64	0.33	0.848
R48	49.88	49.62	49.82	5.29×10^{-2}	0.974	R48	29.20	28.73	30.21	1.86	0.395
R49	48.43	49.32	49.76	1.24	0.537	R49	30.30	29.14	29.62	1.09	0.580
R50	49.73	48.64	48.73	1.00	0.607	R50	28.88	28.96	30.12	1.56	0.458
R51	49.94	48.37	49.38	1.71	0.426	R51	28.70	27.63	29.38	2.57	0.277
R52	50.00	49.14	47.69	3.68	0.159	R52	29.47	27.31	28.85	4.11	0.128
R53	49.64	49.56	49.44	2.92×10^{-2}	0.986	R53	30.24	27.87	29.02	4.60	0.101
R54	51.69	48.88	49.97	5.43	0.066	R54	28.05	28.93	29.32	1.41	0.495
R55	50.95	49.11	48.37	4.75	0.093	R55	29.41	28.25	28.85	1.10	0.578
R56	49.08	49.29	48.02	1.26	0.532	R56	28.43	28.14	28.79	0.35	0.838
R57	50.65	50.03	48.76	2.52	0.284	R57	29.23	28.17	28.79	0.95	0.623
R58	51.04	48.96	48.96	3.87	0.145	R58	27.43	27.31	28.14	0.68	0.713
R59	50.80	49.11	48.93	2.86	0.239	R59	28.22	28.02	28.99	0.88	0.645

Table 5.1: Left: BACTD0, Matrix 1; Right: BACTD1, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	25.68	26.01	26.18	0.23	0.892	R0	69.41	68.61	70.15	1.88	0.390
R1	27.10	26.83	26.24	0.67	0.717	R1	68.79	69.38	69.64	0.61	0.736
R2	26.57	26.80	26.04	0.54	0.763	R2	69.62	69.67	69.94	9.63×10^{-2}	0.953
R3	26.09	26.75	25.74	0.91	0.635	R3	69.20	68.76	69.76	0.81	0.668
R4	25.44	25.77	25.53	0.10	0.951	R4	69.14	68.99	68.82	8.39×10^{-2}	0.959
R5	25.44	24.76	25.62	0.74	0.692	R5	69.73	69.23	69.32	0.23	0.891
R6	25.83	24.50	24.50	2.13	0.346	R6	68.91	69.79	69.79	0.84	0.658
R7	23.64	25.15	24.17	2.15	0.342	R7	68.31	68.40	68.52	3.38×10^{-2}	0.983
R8	24.26	25.18	25.36	1.25	0.535	R8	69.79	68.93	69.79	0.78	0.677
R9	24.35	25.36	24.82	0.92	0.632	R9	69.70	68.40	69.56	1.61	0.448
R10	23.93	25.30	24.08	2.03	0.362	R10	69.11	68.28	69.82	1.88	0.391
R11	25.18	24.91	25.24	0.11	0.947	R11	69.44	68.20	68.05	1.83	0.400
R12	25.36	23.91	24.73	1.93	0.382	R12	69.38	69.47	69.23	4.55×10^{-2}	0.978
R13	24.91	25.83	24.23	2.32	0.314	R13	68.08	70.80	70.33	6.74	0.034
R14	23.88	24.91	24.47	0.99	0.610	R14	68.14	69.97	69.67	3.07	0.215
R15	25.12	24.20	24.23	0.99	0.610	R15	68.76	70.36	69.32	2.10	0.351
R16	24.38	24.82	23.37	2.04	0.361	R16	70.12	68.88	69.26	1.29	0.525
R17	25.33	24.91	23.96	1.77	0.412	R17	69.53	68.40	69.85	1.83	0.400
R18	24.67	24.64	24.47	4.58×10^{-2}	0.977	R18	68.79	68.91	68.61	6.98×10^{-2}	0.966
R19	24.38	25.53	24.50	1.46	0.483	R19	70.33	68.99	69.14	1.70	0.427
R20	25.12	24.76	24.56	0.29	0.864	R20	68.88	68.96	71.15	5.35	0.069
R21	24.05	24.82	23.28	2.19	0.335	R21	71.21	69.44	68.82	4.98	0.083
R22	24.44	24.88	24.14	0.51	0.776	R22	70.18	69.79	69.14	0.88	0.645
R23	23.99	24.47	25.30	1.58	0.454	R23	69.08	67.72	71.09	9.17	0.010
R24	25.27	24.62	22.96	5.23	0.073	R24	68.88	69.97	69.35	0.96	0.619
R25	24.38	23.40	23.58	1.01	0.605	R25	69.85	70.12	70.00	5.73×10^{-2}	0.972
R26	24.76	24.38	24.29	0.23	0.891	R26	70.03	69.73	69.26	0.48	0.786
R27	24.26	24.91	24.38	0.44	0.803	R27	69.53	69.82	69.94	0.15	0.930
R28	24.64	24.20	22.69	3.92	0.141	R28	70.50	70.71	69.97	0.47	0.790
R29	24.32	24.91	24.32	0.43	0.808	R29	69.02	70.06	69.64	0.87	0.648
R30	25.36	25.68	23.85	3.47	0.176	R30	68.93	68.40	68.40	0.30	0.862
R31	23.93	24.32	25.03	1.13	0.569	R31	69.94	70.21	69.44	0.49	0.783
R32	23.96	25.15	23.58	2.45	0.294	R32	70.74	69.17	70.00	1.98	0.372
R33	24.50	24.73	23.61	1.30	0.523	R33	68.93	70.03	70.68	2.50	0.287
R34	24.62	25.27	24.14	1.16	0.560	R34	69.29	69.73	70.41	1.03	0.598
R35	24.38	23.93	24.26	0.19	0.907	R35	68.67	68.55	70.56	4.06	0.131
R36	24.50	25.06	24.20	0.69	0.708	R36	68.67	69.26	68.55	0.46	0.796
R37	24.29	25.18	23.96	1.44	0.487	R37	69.97	69.08	69.70	0.66	0.718
R38	24.08	25.00	23.64	1.77	0.413	R38	68.67	69.05	70.27	2.22	0.330
R39	24.88	24.76	23.37	2.60	0.273	R39	69.47	70.41	68.96	1.73	0.420
R40	24.26	24.35	24.62	0.12	0.939	R40	70.83	68.70	69.88	3.65	0.161
R41	23.64	24.17	24.02	0.28	0.869	R41	69.23	68.17	68.91	0.94	0.626
R42	25.74	24.47	23.67	3.97	0.138	R42	70.03	69.23	69.97	0.63	0.728
R43	24.59	24.97	24.41	0.30	0.861	R43	69.94	68.88	69.17	0.96	0.618
R44	24.41	25.59	23.91	2.72	0.256	R44	70.24	68.82	68.82	2.14	0.343
R45	25.80	25.36	24.38	1.90	0.387	R45	69.97	69.59	69.32	0.34	0.843
R46	23.73	24.64	25.18	1.97	0.374	R46	68.55	69.82	69.91	1.84	0.398
R47	23.61	24.67	24.47	1.18	0.555	R47	69.56	68.46	69.26	1.01	0.602
R48	25.18	24.73	25.30	0.32	0.854	R48	69.08	69.64	69.76	0.42	0.810
R49	23.76	25.59	24.32	3.21	0.201	R49	70.00	69.97	70.92	0.94	0.625
R50	25.21	24.82	23.93	1.55	0.460	R50	69.64	67.51	68.88	3.65	0.161
R51	24.47	25.41	24.47	1.08	0.583	R51	68.96	69.73	70.53	1.97	0.373
R52	24.53	26.07	23.55	5.83	0.054	R52	68.99	70.24	68.52	2.50	0.287
R53	25.80	25.09	23.70	4.14	0.126	R53	69.70	70.06	70.06	0.13	0.935
R54	23.05	23.05	24.26	1.84	0.399	R54	71.39	68.96	70.41	4.81	0.090
R55	24.94	24.79	23.67	1.78	0.411	R55	69.20	70.09	69.67	0.63	0.730
R56	24.35	25.09	23.55	2.17	0.337	R56	68.43	69.82	68.76	1.68	0.433
R57	24.14	24.53	25.95	3.26	0.196	R57	69.11	69.56	69.35	0.16	0.925
R58	23.61	24.67	24.29	1.07	0.585	R58	70.41	68.61	69.76	2.66	0.264
R59	24.91	24.53	25.30	0.53	0.765	R59	69.26	70.53	68.99	2.17	0.339

Table 5.2: Left: BACTD10, Matrix 1; Right: BACTS0, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	41.86	40.92	40.24	1.87	0.393	R0	33.20	34.91	34.97	3.06	0.217
R1	43.20	41.54	42.75	2.04	0.361	R1	34.17	34.02	34.64	0.32	0.854
R2	40.92	40.38	42.81	4.53	0.104	R2	32.93	33.17	33.82	0.64	0.725
R3	40.59	39.29	39.23	1.67	0.434	R3	33.40	32.87	32.90	0.27	0.872
R4	39.53	38.05	40.65	4.83	0.089	R4	33.93	32.34	32.87	2.02	0.364
R5	39.79	36.92	39.67	7.53	0.023	R5	32.84	32.37	32.57	0.17	0.917
R6	39.14	37.93	41.48	9.20	0.010	R6	31.57	31.80	31.15	0.34	0.844
R7	40.06	38.20	39.82	2.92	0.232	R7	33.08	31.42	31.04	3.65	0.161
R8	40.09	37.01	39.26	7.23	0.027	R8	32.25	32.10	31.09	1.23	0.540
R9	39.53	38.25	38.08	1.78	0.411	R9	29.38	31.45	32.54	8.18	0.017
R10	39.97	38.61	40.24	2.16	0.340	R10	29.53	32.13	30.24	5.75	0.057
R11	39.73	37.19	38.52	4.63	0.099	R11	31.42	32.04	30.65	1.52	0.467
R12	39.05	37.93	40.24	3.78	0.151	R12	30.89	31.89	30.62	1.42	0.492
R13	38.25	38.05	40.15	3.81	0.149	R13	30.92	31.09	31.89	0.85	0.654
R14	39.38	38.70	38.96	0.33	0.846	R14	31.83	31.45	30.53	1.41	0.494
R15	38.40	39.50	38.82	0.87	0.648	R15	32.87	32.13	32.04	0.64	0.727
R16	40.38	38.91	41.12	3.60	0.166	R16	31.86	31.21	31.21	0.44	0.802
R17	39.14	38.58	40.09	1.65	0.439	R17	29.56	30.77	32.16	5.38	0.068
R18	40.15	36.98	38.85	7.23	0.027	R18	31.78	29.79	30.71	3.12	0.210
R19	40.09	37.22	42.13	17.20	<0.001	R19	30.33	33.25	30.30	9.03	0.011
R20	39.88	38.20	39.82	2.60	0.273	R20	30.98	31.15	31.01	2.86×10^{-2}	0.986
R21	39.05	39.20	39.79	0.43	0.805	R21	30.53	31.66	32.57	3.27	0.195
R22	40.06	37.13	39.20	6.47	0.039	R22	31.48	30.80	30.65	0.62	0.735
R23	40.95	39.85	39.97	1.01	0.602	R23	29.91	31.01	31.48	2.06	0.358
R24	40.38	38.31	39.20	3.06	0.217	R24	33.55	32.19	30.77	5.99	0.050
R25	38.49	39.50	38.82	0.75	0.688	R25	32.54	32.25	31.01	2.08	0.354
R26	38.64	40.24	38.40	2.82	0.244	R26	30.92	32.40	31.42	1.77	0.413
R27	39.32	38.20	39.11	1.02	0.601	R27	29.94	33.20	31.95	8.44	0.015
R28	40.68	37.78	38.91	6.06	0.048	R28	30.21	31.21	31.72	1.87	0.393
R29	38.61	38.22	39.64	1.53	0.464	R29	31.36	30.74	32.28	1.88	0.391
R30	38.55	39.44	38.17	1.21	0.546	R30	31.75	30.44	32.04	2.27	0.321
R31	39.56	37.81	40.68	5.93	0.052	R31	31.18	32.16	32.31	1.16	0.559
R32	40.71	37.10	40.83	12.75	0.002	R32	32.78	30.98	31.07	3.23	0.199
R33	39.64	37.99	37.60	3.36	0.187	R33	31.48	30.44	31.01	0.85	0.654
R34	40.30	38.46	39.02	2.50	0.286	R34	31.69	31.36	32.34	0.77	0.681
R35	41.69	37.90	38.96	10.77	0.005	R35	31.89	32.96	30.74	3.84	0.147
R36	39.62	38.73	39.35	0.59	0.745	R36	30.53	30.38	31.39	0.93	0.627
R37	38.31	38.20	40.74	5.84	0.054	R37	31.42	32.57	31.39	1.42	0.492
R38	39.11	37.84	39.67	2.52	0.284	R38	30.83	32.54	29.97	5.41	0.067
R39	40.21	38.05	39.14	3.31	0.191	R39	31.24	31.01	30.71	0.23	0.894
R40	39.56	37.40	39.94	5.36	0.069	R40	31.92	32.78	31.69	1.03	0.598
R41	38.25	38.64	38.76	0.20	0.906	R41	31.89	32.54	30.83	2.34	0.310
R42	35.36	38.49	37.16	7.19	0.027	R42	31.69	31.78	33.08	1.87	0.392
R43	36.92	37.31	36.24	0.85	0.655	R43	30.71	32.40	31.48	2.23	0.328
R44	35.98	37.84	38.88	6.23	0.044	R44	31.75	31.24	30.30	1.71	0.425
R45	37.93	37.57	36.60	1.37	0.503	R45	32.16	29.97	31.51	3.99	0.136
R46	37.63	37.40	36.04	2.16	0.340	R46	30.74	30.86	31.12	0.12	0.940
R47	36.78	38.31	38.49	2.56	0.278	R47	32.10	31.45	32.81	1.44	0.488
R48	36.80	37.96	39.02	3.54	0.171	R48	31.75	32.78	29.62	8.21	0.017
R49	35.56	38.34	37.19	5.67	0.059	R49	29.73	31.07	31.86	3.67	0.159
R50	37.49	38.37	37.22	1.05	0.592	R50	31.12	30.77	31.72	0.72	0.698
R51	37.57	39.70	36.33	8.35	0.015	R51	31.21	32.75	32.75	2.45	0.294
R52	37.28	37.49	36.75	0.42	0.810	R52	31.12	31.69	31.86	0.47	0.792
R53	36.57	36.83	38.37	2.74	0.254	R53	32.01	31.18	31.78	0.57	0.752
R54	38.08	36.98	37.25	0.94	0.625	R54	30.74	32.40	31.04	2.44	0.295
R55	37.13	38.49	38.02	1.37	0.504	R55	31.80	31.54	31.80	7.38×10^{-2}	0.964
R56	38.64	36.78	38.73	3.49	0.174	R56	31.12	31.39	31.92	0.52	0.772
R57	37.37	37.04	39.26	4.12	0.128	R57	33.61	33.28	30.38	9.78	0.008
R58	35.62	36.63	38.46	6.01	0.049	R58	31.24	32.43	31.18	1.53	0.465
R59	36.89	36.21	37.51	1.23	0.540	R59	31.33	32.96	32.01	2.07	0.355

Table 5.3: Left: BACTS1, Matrix 1; Right: BACTS10, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	49.47	49.97	49.41	0.26	0.879	R0	43.25	42.75	45.38	5.36	0.069
R1	49.67	48.96	50.09	0.87	0.646	R1	45.00	43.88	46.04	3.19	0.203
R2	48.91	49.35	50.33	1.43	0.490	R2	45.09	43.67	46.15	4.25	0.120
R3	49.20	50.56	48.96	2.01	0.366	R3	43.85	43.73	45.09	1.56	0.459
R4	48.28	49.94	50.00	2.57	0.277	R4	43.31	44.14	44.41	0.89	0.639
R5	50.24	50.12	49.94	6.00×10^{-2}	0.970	R5	44.20	42.04	43.43	3.30	0.192
R6	49.11	49.53	48.70	0.46	0.793	R6	42.90	42.13	45.15	6.76	0.034
R7	49.50	49.62	50.56	0.92	0.631	R7	42.75	43.17	44.70	2.91	0.234
R8	49.50	50.50	50.09	0.69	0.708	R8	44.20	43.58	44.47	0.57	0.752
R9	49.35	49.59	50.12	0.42	0.811	R9	43.67	43.82	44.76	0.97	0.617
R10	49.88	50.41	49.38	0.73	0.696	R10	43.79	42.96	44.79	2.32	0.314
R11	49.05	49.62	50.86	2.31	0.316	R11	43.28	42.81	43.61	0.44	0.801
R12	48.58	48.58	49.14	0.28	0.867	R12	42.10	43.11	43.99	2.47	0.290
R13	50.15	48.99	49.79	0.94	0.624	R13	43.52	42.96	44.08	0.87	0.648
R14	49.82	48.61	50.68	2.93	0.231	R14	43.25	44.08	42.99	0.90	0.639
R15	48.67	49.44	50.44	2.14	0.342	R15	43.93	41.45	43.96	5.75	0.056
R16	49.88	48.99	49.41	0.53	0.766	R16	43.67	42.63	42.69	0.93	0.627
R17	49.08	51.12	51.18	3.87	0.145	R17	43.79	45.33	43.76	2.20	0.332
R18	50.15	48.93	49.64	1.00	0.605	R18	43.17	43.64	45.89	5.79	0.055
R19	50.71	49.08	49.59	1.88	0.391	R19	44.17	43.52	43.70	0.31	0.856
R20	50.15	50.09	50.68	0.29	0.866	R20	44.91	42.57	44.62	4.45	0.108
R21	49.26	49.11	50.74	2.19	0.335	R21	44.67	44.26	44.05	0.27	0.872
R22	50.24	49.05	50.77	2.09	0.352	R22	43.49	43.20	44.26	0.83	0.660
R23	49.64	49.23	48.88	0.40	0.818	R23	44.35	42.22	43.85	3.41	0.181
R24	49.05	50.15	50.06	1.00	0.607	R24	43.55	43.08	44.11	0.74	0.691
R25	49.79	49.11	50.77	1.88	0.392	R25	43.43	43.22	44.91	2.32	0.313
R26	50.03	48.55	49.94	1.86	0.394	R26	45.18	42.69	43.55	4.37	0.112
R27	48.08	49.08	48.91	0.78	0.677	R27	43.55	43.76	44.14	0.25	0.884
R28	49.14	48.91	50.59	2.25	0.324	R28	44.17	43.96	43.61	0.22	0.895
R29	50.53	49.79	50.77	0.70	0.704	R29	44.59	42.75	44.50	2.94	0.230
R30	48.37	49.67	50.62	3.45	0.178	R30	44.59	43.11	44.26	1.66	0.436
R31	48.70	49.79	51.15	4.09	0.129	R31	43.08	43.58	44.05	0.66	0.721
R32	48.96	50.12	49.05	1.11	0.573	R32	42.99	43.46	44.41	1.44	0.488
R33	49.79	49.23	49.88	0.34	0.845	R33	44.08	42.72	45.15	4.06	0.131
R34	49.88	49.05	50.30	1.08	0.582	R34	44.05	42.96	44.70	2.14	0.344
R35	48.08	48.05	50.33	4.62	0.099	R35	44.02	42.43	43.08	1.78	0.411
R36	50.18	49.26	51.09	2.27	0.321	R36	42.87	42.69	45.09	4.90	0.086
R37	48.31	50.12	50.71	4.21	0.122	R37	43.40	43.76	44.53	0.91	0.636
R38	50.09	50.03	48.76	1.53	0.465	R38	44.05	43.76	43.91	6.01×10^{-2}	0.970
R39	49.53	48.61	49.20	0.58	0.746	R39	44.11	43.22	44.11	0.72	0.697
R40	49.26	50.06	49.76	0.44	0.802	R40	43.58	44.35	44.50	0.67	0.717
R41	49.70	48.34	49.91	1.96	0.375	R41	42.90	42.96	43.88	0.82	0.662
R42	49.82	48.76	50.98	3.33	0.189	R42	43.14	44.29	43.91	0.95	0.622
R43	50.41	49.73	49.91	0.34	0.845	R43	43.73	43.79	45.44	2.60	0.273
R44	48.96	49.76	49.44	0.44	0.804	R44	43.34	42.93	43.99	0.79	0.673
R45	49.05	48.49	49.82	1.21	0.547	R45	44.38	41.72	43.58	5.15	0.076
R46	49.38	49.35	51.69	4.86	0.088	R46	42.75	43.31	43.52	0.44	0.804
R47	49.26	50.00	49.97	0.47	0.789	R47	44.11	42.31	43.88	2.65	0.266
R48	50.89	49.56	50.95	1.67	0.433	R48	42.90	44.26	42.93	1.66	0.436
R49	49.35	48.79	51.09	3.92	0.141	R49	43.40	41.60	43.99	4.30	0.116
R50	48.46	48.91	49.62	0.92	0.632	R50	42.99	43.58	43.96	0.67	0.717
R51	49.88	49.53	49.73	8.60×10^{-2}	0.958	R51	43.14	44.02	45.03	2.46	0.292
R52	49.59	49.76	51.66	3.56	0.168	R52	43.61	43.43	42.49	1.01	0.604
R53	49.91	50.50	49.64	0.52	0.770	R53	42.60	43.28	43.49	0.59	0.743
R54	49.97	50.09	49.62	0.16	0.921	R54	43.79	43.22	43.49	0.22	0.897
R55	48.34	50.59	50.62	4.62	0.099	R55	43.70	42.72	44.02	1.26	0.532
R56	48.82	49.02	51.18	4.65	0.098	R56	43.49	42.19	43.49	1.56	0.459
R57	49.14	48.82	51.39	5.31	0.070	R57	43.17	42.96	43.17	3.94×10^{-2}	0.980
R58	48.22	50.38	49.76	3.34	0.188	R58	42.90	41.75	43.76	2.82	0.245
R59	49.50	49.64	49.73	3.87×10^{-2}	0.981	R59	42.46	42.99	43.99	1.68	0.431

Table 5.4: Left: BACTD0, Matrix 2; Right: BACTD1, Matrix 2

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	34.35	34.88	33.20	2.24	0.327	R0	69.50	68.61	71.21	5.63	0.060
R1	35.83	39.08	36.18	9.21	0.010	R1	69.73	70.44	69.64	0.62	0.734
R2	32.96	35.95	33.46	7.67	0.022	R2	68.96	71.01	70.00	3.35	0.187
R3	32.75	34.08	34.50	2.52	0.284	R3	70.36	69.41	70.00	0.73	0.693
R4	34.70	34.08	33.08	2.03	0.362	R4	69.14	68.76	68.91	0.12	0.942
R5	35.24	35.65	35.21	0.18	0.913	R5	69.79	68.96	68.58	1.22	0.544
R6	34.70	37.07	35.59	4.20	0.122	R6	69.62	70.36	69.79	0.48	0.787
R7	35.95	37.04	35.98	1.14	0.567	R7	69.88	69.32	68.61	1.29	0.525
R8	35.09	36.33	36.15	1.33	0.514	R8	70.33	68.82	68.25	3.64	0.162
R9	36.54	36.86	36.42	0.15	0.926	R9	69.14	69.85	70.68	1.91	0.386
R10	35.50	37.16	36.48	2.03	0.363	R10	70.09	69.76	70.33	0.26	0.880
R11	36.86	36.15	36.30	0.41	0.815	R11	69.23	69.53	68.82	0.40	0.817
R12	35.56	38.17	36.80	4.93	0.085	R12	69.53	69.88	68.73	1.11	0.574
R13	35.59	36.89	34.44	4.45	0.108	R13	69.38	69.97	69.62	0.28	0.868
R14	36.09	36.45	35.86	0.26	0.878	R14	70.18	68.17	70.95	6.59	0.037
R15	35.77	36.51	37.22	1.53	0.465	R15	71.30	69.79	69.59	2.85	0.241
R16	36.63	36.21	36.45	0.13	0.939	R16	68.64	68.85	69.32	0.38	0.825
R17	34.94	36.07	34.91	1.28	0.528	R17	69.56	70.65	69.82	1.05	0.591
R18	35.50	37.63	36.01	3.61	0.164	R18	69.67	69.26	68.88	0.51	0.776
R19	36.95	37.07	35.68	1.74	0.420	R19	69.50	69.47	68.43	1.16	0.559
R20	35.41	37.04	36.51	2.01	0.365	R20	69.85	68.61	69.38	1.25	0.536
R21	36.69	36.63	35.77	0.77	0.680	R21	69.02	69.32	69.73	0.40	0.817
R22	34.76	36.54	37.04	4.21	0.122	R22	69.91	69.02	71.57	5.40	0.067
R23	35.56	36.66	36.01	0.89	0.641	R23	68.99	68.79	69.29	0.20	0.904
R24	35.65	35.33	36.04	0.37	0.830	R24	70.74	69.82	69.35	1.61	0.447
R25	36.27	36.27	36.48	4.18×10^{-2}	0.979	R25	70.33	69.02	69.41	1.43	0.489
R26	35.53	36.95	36.39	1.50	0.473	R26	70.30	69.44	69.41	0.82	0.665
R27	36.51	37.04	36.01	0.78	0.676	R27	69.38	69.38	69.64	7.54×10^{-2}	0.963
R28	35.44	37.22	36.30	2.30	0.316	R28	69.73	68.67	69.44	0.96	0.619
R29	35.03	38.17	36.57	7.17	0.028	R29	67.96	68.73	70.56	5.68	0.058
R30	35.50	38.34	37.66	6.38	0.041	R30	69.97	70.74	69.59	1.11	0.573
R31	36.24	37.54	36.04	1.95	0.378	R31	70.18	69.05	69.85	1.07	0.586
R32	36.33	37.49	35.77	2.23	0.328	R32	68.55	67.93	67.96	0.38	0.826
R33	35.92	37.72	37.28	2.57	0.277	R33	68.46	69.64	68.58	1.34	0.511
R34	35.50	37.37	36.04	2.69	0.260	R34	69.79	69.29	68.79	0.80	0.669
R35	35.50	37.43	36.83	2.83	0.243	R35	69.76	69.79	69.67	1.21×10^{-2}	0.994
R36	37.10	36.92	36.18	0.69	0.709	R36	68.88	68.05	70.00	3.04	0.219
R37	36.09	35.41	36.69	1.19	0.552	R37	69.59	68.88	71.01	3.78	0.151
R38	35.36	38.73	36.21	8.91	0.012	R38	68.91	68.79	70.21	1.98	0.372
R39	35.92	37.49	35.56	3.05	0.217	R39	69.53	68.20	70.65	4.81	0.090
R40	36.75	38.52	36.51	3.49	0.175	R40	67.93	68.20	69.67	2.78	0.249
R41	34.91	36.75	35.68	2.49	0.287	R41	69.70	69.02	68.67	0.88	0.645
R42	36.57	36.78	35.68	0.99	0.610	R42	69.59	69.85	69.14	0.41	0.815
R43	35.00	37.46	36.98	4.96	0.084	R43	67.93	69.62	70.03	3.91	0.141
R44	34.88	36.69	35.71	2.40	0.301	R44	69.59	71.39	69.35	4.04	0.133
R45	36.12	36.51	36.07	0.17	0.919	R45	69.32	68.70	70.56	2.88	0.237
R46	36.51	37.60	36.04	1.88	0.391	R46	69.82	69.67	68.70	1.19	0.553
R47	36.21	36.72	35.74	0.70	0.706	R47	69.53	69.88	69.53	0.13	0.935
R48	35.53	36.66	35.80	1.01	0.603	R48	69.56	69.62	69.23	0.14	0.934
R49	34.94	35.86	35.56	0.65	0.723	R49	68.43	69.82	69.62	1.78	0.410
R50	35.03	37.90	36.57	6.02	0.049	R50	69.85	70.38	70.03	0.24	0.888
R51	36.18	36.63	35.44	1.05	0.592	R51	69.94	68.73	69.70	1.31	0.518
R52	36.36	36.83	35.30	1.82	0.402	R52	69.44	69.47	70.15	0.52	0.772
R53	35.77	37.54	36.09	2.60	0.272	R53	70.03	67.93	68.52	3.71	0.157
R54	36.30	35.47	35.95	0.51	0.776	R54	69.56	69.47	69.08	0.20	0.904
R55	35.36	37.66	36.89	4.03	0.134	R55	70.21	70.00	68.61	2.41	0.300
R56	35.98	36.18	37.75	2.74	0.254	R56	69.82	69.35	71.01	2.35	0.308
R57	36.09	36.04	35.41	0.42	0.811	R57	69.11	68.34	69.73	1.53	0.464
R58	34.44	37.01	37.07	6.64	0.036	R58	69.17	68.99	70.09	1.10	0.577
R59	36.12	37.22	35.59	2.01	0.366	R59	69.64	69.29	69.41	0.10	0.949

Table 5.5: Left: BACTD10, Matrix 2; Right: BACTS0, Matrix 2

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	58.46	57.54	55.47	6.46	0.039	R0	39.85	39.91	40.80	0.79	0.674
R1	58.76	58.96	59.38	0.28	0.869	R1	42.57	44.11	43.76	1.79	0.409
R2	57.34	58.02	58.20	0.57	0.753	R2	39.94	41.12	41.21	1.41	0.493
R3	56.83	57.34	58.52	2.08	0.354	R3	39.73	41.18	40.27	1.51	0.470
R4	56.33	57.28	57.16	0.73	0.693	R4	40.62	40.71	40.89	5.15×10^{-2}	0.975
R5	56.33	55.98	57.10	0.91	0.635	R5	41.57	40.62	42.25	1.86	0.394
R6	56.95	58.55	55.71	5.60	0.061	R6	40.98	42.13	43.88	5.90	0.052
R7	56.07	56.57	57.46	1.37	0.505	R7	42.28	40.15	41.18	3.17	0.205
R8	57.04	56.60	57.34	0.38	0.826	R8	41.04	43.55	41.18	5.52	0.063
R9	56.30	56.69	57.81	1.70	0.428	R9	41.86	41.48	42.34	0.51	0.774
R10	58.22	57.10	58.17	1.11	0.574	R10	40.83	42.43	43.37	4.59	0.101
R11	57.22	58.76	58.37	1.78	0.411	R11	42.10	41.98	41.57	0.22	0.897
R12	57.37	56.30	58.05	2.14	0.343	R12	40.80	40.80	42.78	3.64	0.162
R13	56.04	57.81	57.37	2.35	0.308	R13	40.71	41.39	41.54	0.54	0.761
R14	56.98	57.10	58.88	3.12	0.210	R14	41.95	41.80	41.54	0.12	0.941
R15	56.69	57.78	57.13	0.84	0.658	R15	41.54	41.63	42.22	0.38	0.827
R16	58.99	56.12	58.88	7.30	0.026	R16	41.98	41.69	42.46	0.42	0.812
R17	57.37	56.63	58.20	1.70	0.427	R17	41.12	43.08	41.24	3.33	0.190
R18	56.21	57.78	57.84	2.35	0.309	R18	40.56	42.31	42.43	3.03	0.220
R19	56.45	56.15	58.70	5.35	0.069	R19	41.30	42.43	42.49	1.23	0.539
R20	57.46	56.83	59.23	4.29	0.117	R20	41.66	41.69	42.66	0.91	0.635
R21	59.26	59.11	58.08	1.16	0.560	R21	41.07	41.89	42.51	1.47	0.479
R22	56.12	56.78	59.35	8.06	0.018	R22	39.73	43.20	41.42	8.35	0.015
R23	58.52	57.60	56.27	3.53	0.171	R23	40.27	42.43	41.57	3.30	0.192
R24	56.86	58.67	56.66	3.39	0.184	R24	40.12	41.75	41.80	2.56	0.278
R25	57.49	56.45	56.18	1.30	0.521	R25	40.95	41.51	41.69	0.42	0.812
R26	56.95	57.07	59.08	3.98	0.137	R26	41.12	41.21	42.60	1.91	0.384
R27	56.92	57.34	57.31	0.15	0.929	R27	40.38	41.63	41.92	1.86	0.395
R28	58.70	57.78	57.96	0.66	0.720	R28	41.45	41.09	43.64	5.26	0.072
R29	57.04	55.86	58.40	4.47	0.107	R29	41.57	42.31	41.18	0.91	0.635
R30	56.78	57.75	57.04	0.70	0.703	R30	41.51	42.43	43.22	2.04	0.360
R31	57.69	57.25	56.48	1.04	0.595	R31	40.59	42.40	41.33	2.29	0.318
R32	58.67	56.21	55.06	9.37	0.009	R32	40.47	41.75	42.19	2.21	0.331
R33	57.49	55.83	56.66	1.89	0.389	R33	40.06	42.75	42.16	5.58	0.062
R34	57.49	57.99	57.43	0.26	0.876	R34	41.09	41.72	43.08	2.85	0.240
R35	57.66	57.46	58.31	0.56	0.757	R35	40.41	40.30	42.22	3.24	0.198
R36	56.57	54.97	57.90	5.91	0.052	R36	42.49	41.75	42.25	0.40	0.821
R37	56.51	55.83	56.86	0.76	0.684	R37	41.24	43.31	42.87	3.29	0.193
R38	57.81	55.53	56.95	3.64	0.162	R38	40.33	41.69	40.44	1.59	0.452
R39	57.13	55.74	57.28	1.98	0.371	R39	42.25	40.53	41.30	2.06	0.357
R40	57.60	55.21	58.93	9.85	0.007	R40	41.51	42.16	41.30	0.56	0.757
R41	57.84	55.50	57.04	3.89	0.143	R41	41.60	40.95	40.80	0.50	0.777
R42	56.66	57.10	57.87	1.04	0.594	R42	42.81	42.49	41.21	1.98	0.372
R43	56.69	57.81	57.72	1.08	0.583	R43	41.15	42.51	43.22	3.07	0.215
R44	56.75	55.47	59.05	9.10	0.011	R44	40.95	40.95	42.28	1.64	0.439
R45	56.27	56.66	58.34	3.35	0.187	R45	41.63	41.66	40.92	0.49	0.783
R46	57.28	56.30	58.14	2.33	0.312	R46	42.07	41.66	42.22	0.24	0.889
R47	56.09	56.95	58.96	6.00	0.050	R47	42.34	42.31	42.16	2.51×10^{-2}	0.988
R48	57.10	56.27	57.72	1.46	0.482	R48	41.60	42.01	44.08	4.90	0.086
R49	57.31	55.18	58.34	7.18	0.028	R49	41.89	41.36	40.77	0.88	0.643
R50	57.13	56.07	58.37	3.68	0.158	R50	40.92	42.87	41.63	2.71	0.258
R51	57.43	55.89	58.34	4.25	0.119	R51	38.79	41.80	43.82	17.88	<0.001
R52	57.81	54.85	56.51	6.04	0.049	R52	39.97	42.60	41.27	4.83	0.089
R53	57.63	55.74	57.16	2.67	0.263	R53	39.35	41.33	42.75	8.16	0.017
R54	57.51	57.13	57.51	0.14	0.934	R54	41.92	40.80	41.98	1.24	0.538
R55	56.12	55.98	56.09	1.68×10^{-2}	0.992	R55	39.88	41.18	41.04	1.42	0.491
R56	55.24	53.82	56.36	4.44	0.108	R56	40.56	42.25	42.19	2.55	0.279
R57	55.95	54.70	56.42	2.15	0.341	R57	38.55	42.81	38.61	16.75	<0.001
R58	56.69	55.74	56.42	0.65	0.721	R58	40.44	41.98	40.33	2.39	0.303
R59	57.16	54.23	55.53	5.90	0.052	R59	40.24	40.50	40.24	6.64×10^{-2}	0.967

Table 5.6: Left: BACTS1, Matrix 2; Right: BACTS10, Matrix 2

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	49.73	49.14	50.36	0.99	0.608	R0	47.04	48.08	48.52	1.56	0.458
R1	50.80	50.18	48.11	5.37	0.068	R1	50.30	49.94	49.05	1.11	0.575
R2	50.30	49.02	49.20	1.28	0.526	R2	49.11	47.46	48.14	1.88	0.391
R3	50.95	48.96	49.50	2.85	0.241	R3	47.54	47.78	47.28	0.17	0.918
R4	50.44	49.23	49.08	1.51	0.471	R4	46.39	45.71	47.40	1.96	0.376
R5	50.15	49.56	48.37	2.21	0.331	R5	46.30	46.30	46.45	1.98×10^{-2}	0.990
R6	50.77	49.88	49.38	1.34	0.512	R6	46.95	47.10	46.15	0.70	0.703
R7	49.62	50.68	48.43	3.42	0.181	R7	45.50	45.95	45.95	0.18	0.914
R8	50.71	50.44	48.46	4.08	0.130	R8	46.18	45.83	46.57	0.37	0.830
R9	49.47	48.55	48.79	0.61	0.736	R9	45.53	44.59	46.21	1.82	0.402
R10	48.08	49.64	48.40	1.85	0.396	R10	46.27	44.62	46.07	2.22	0.329
R11	49.88	49.64	48.05	2.69	0.260	R11	44.73	45.83	44.88	0.96	0.618
R12	51.57	49.59	47.93	8.98	0.011	R12	45.12	47.16	45.21	3.62	0.163
R13	50.21	49.79	50.06	0.12	0.942	R13	45.18	46.45	46.36	1.37	0.503
R14	50.06	50.06	49.59	0.20	0.904	R14	45.59	45.59	45.62	7.95×10^{-4}	1.000
R15	51.48	48.93	49.94	4.44	0.109	R15	45.92	46.27	45.30	0.67	0.717
R16	50.36	49.82	50.36	0.26	0.880	R16	45.86	46.07	45.80	5.32×10^{-2}	0.974
R17	49.82	50.92	50.00	0.93	0.627	R17	47.07	47.75	46.24	1.55	0.461
R18	50.15	49.20	48.43	2.00	0.368	R18	45.77	45.98	46.24	0.15	0.926
R19	49.17	51.04	49.11	3.23	0.198	R19	43.73	46.75	46.15	6.98	0.031
R20	49.35	49.73	48.73	0.70	0.706	R20	44.82	45.71	45.56	0.62	0.735
R21	50.68	49.38	50.21	1.17	0.556	R21	46.66	46.27	45.00	2.05	0.359
R22	49.67	49.50	49.08	0.25	0.883	R22	44.85	45.71	46.18	1.24	0.538
R23	50.86	49.79	48.76	2.98	0.225	R23	44.76	46.30	45.06	1.82	0.403
R24	49.08	50.03	49.02	0.86	0.650	R24	45.21	45.74	45.71	0.24	0.885
R25	48.31	48.79	49.70	1.35	0.509	R25	45.03	47.28	44.50	5.93	0.051
R26	50.15	49.23	48.82	1.26	0.534	R26	44.17	45.36	44.44	1.05	0.590
R27	50.56	50.47	47.63	7.51	0.023	R27	46.51	44.79	46.33	2.43	0.297
R28	49.62	49.62	50.36	0.49	0.781	R28	45.86	47.34	43.88	8.22	0.016
R29	51.72	50.44	48.64	6.46	0.039	R29	44.20	46.66	45.77	4.22	0.121
R30	49.32	48.28	49.70	1.46	0.482	R30	44.79	45.74	44.70	0.90	0.638
R31	50.24	50.06	48.73	1.84	0.399	R31	45.56	45.77	46.18	0.27	0.873
R32	50.98	50.50	48.67	4.02	0.134	R32	46.63	46.24	45.36	1.16	0.560
R33	48.85	50.80	49.41	2.73	0.255	R33	45.36	47.01	46.60	2.02	0.364
R34	49.73	49.02	48.22	1.54	0.463	R34	45.21	46.45	44.94	1.77	0.413
R35	50.09	50.18	48.40	2.71	0.258	R35	45.95	45.33	45.41	0.31	0.857
R36	49.70	49.26	48.28	1.43	0.490	R36	44.94	45.44	45.71	0.42	0.812
R37	49.44	50.95	49.53	1.94	0.379	R37	45.18	45.03	45.41	0.10	0.950
R38	49.73	49.14	50.27	0.86	0.652	R38	47.10	45.38	46.01	2.05	0.358
R39	48.28	50.71	49.32	4.01	0.135	R39	45.38	45.89	45.65	0.17	0.917
R40	49.97	51.30	49.76	1.89	0.390	R40	45.77	45.56	44.47	1.34	0.513
R41	49.67	50.71	48.73	2.66	0.265	R41	45.80	45.27	45.38	0.21	0.899
R42	51.75	49.20	49.47	5.29	0.071	R42	45.59	44.53	45.89	1.40	0.497
R43	49.64	49.73	48.17	2.10	0.350	R43	45.65	45.06	45.53	0.27	0.875
R44	50.56	50.24	49.79	0.40	0.817	R44	44.97	44.67	45.24	0.22	0.898
R45	49.70	49.17	48.11	1.79	0.409	R45	45.77	45.53	45.09	0.33	0.850
R46	50.50	49.85	49.29	1.00	0.608	R46	44.67	44.11	45.50	1.34	0.512
R47	49.44	48.55	48.85	0.55	0.759	R47	44.91	44.64	45.30	0.29	0.864
R48	49.79	50.03	49.32	0.35	0.838	R48	44.56	45.98	45.06	1.41	0.493
R49	49.11	49.79	48.73	0.79	0.675	R49	46.45	45.50	46.15	0.64	0.727
R50	49.88	49.70	50.00	6.00×10^{-2}	0.970	R50	45.12	46.45	45.77	1.21	0.547
R51	49.62	50.50	50.15	0.54	0.764	R51	46.86	44.64	44.88	4.05	0.132
R52	51.04	50.38	48.31	5.46	0.065	R52	45.44	46.48	45.38	1.03	0.597
R53	49.70	49.85	49.26	0.26	0.880	R53	46.54	45.62	46.01	0.58	0.749
R54	50.30	50.21	49.82	0.17	0.918	R54	46.30	45.68	45.33	0.67	0.717
R55	48.43	49.70	49.53	1.28	0.526	R55	46.21	46.36	45.80	0.23	0.891
R56	49.26	49.53	49.26	6.39×10^{-2}	0.969	R56	45.86	44.67	45.38	0.97	0.616
R57	49.64	48.64	47.19	4.13	0.127	R57	44.70	45.53	46.63	2.54	0.282
R58	50.03	50.21	48.14	3.56	0.168	R58	44.56	44.14	45.41	1.15	0.562
R59	49.41	49.82	48.91	0.57	0.752	R59	44.79	44.44	46.48	3.24	0.198

Table 5.7: Left: BACTD0, Matrix 3; Right: BACTD1, Matrix 3

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	44.88	44.44	43.88	0.70	0.706	R0	69.32	70.33	70.62	1.50	0.473
R1	48.43	47.66	49.17	1.54	0.463	R1	70.65	68.88	70.33	2.86	0.239
R2	45.89	45.56	45.53	0.11	0.949	R2	70.89	69.08	68.64	4.54	0.103
R3	42.84	42.04	42.87	0.61	0.737	R3	69.91	68.73	69.62	1.21	0.547
R4	40.95	41.42	41.36	0.19	0.911	R4	68.79	69.64	69.08	0.60	0.740
R5	40.06	39.14	40.98	2.37	0.306	R5	68.58	69.70	69.14	1.00	0.606
R6	40.47	38.93	39.88	1.70	0.427	R6	69.73	69.53	69.67	3.64×10^{-2}	0.982
R7	39.64	40.59	39.70	0.79	0.673	R7	70.30	67.46	69.11	6.42	0.040
R8	38.52	37.46	38.70	1.29	0.523	R8	67.96	68.79	68.22	0.56	0.756
R9	39.67	38.55	38.40	1.38	0.503	R9	69.32	68.61	69.14	0.43	0.806
R10	39.14	37.13	38.11	2.90	0.235	R10	69.41	69.26	69.26	2.32×10^{-2}	0.988
R11	38.25	37.63	39.53	2.66	0.265	R11	70.98	69.38	68.99	3.55	0.169
R12	39.26	38.55	38.02	1.11	0.575	R12	68.64	69.94	68.34	2.29	0.319
R13	37.99	39.05	38.64	0.82	0.663	R13	69.26	69.23	71.42	5.10	0.078
R14	37.87	39.38	39.20	1.94	0.379	R14	69.56	70.47	69.88	0.70	0.706
R15	38.61	39.97	38.55	1.83	0.400	R15	70.33	70.89	69.94	0.74	0.692
R16	39.59	38.76	38.22	1.34	0.512	R16	68.91	70.09	68.96	1.42	0.492
R17	38.31	38.43	39.20	0.66	0.718	R17	69.82	70.24	68.22	3.58	0.167
R18	38.43	38.64	39.08	0.31	0.854	R18	70.12	70.21	68.64	2.47	0.290
R19	38.14	38.37	38.05	8.10×10^{-2}	0.960	R19	68.85	69.62	67.81	2.58	0.275
R20	38.34	38.88	39.32	0.68	0.712	R20	70.15	70.12	69.73	0.17	0.918
R21	38.93	39.23	38.58	0.30	0.860	R21	70.56	70.38	70.56	3.41×10^{-2}	0.983
R22	39.53	39.67	38.99	0.36	0.834	R22	69.91	68.99	69.41	0.67	0.715
R23	37.81	37.01	38.70	2.05	0.360	R23	70.09	68.93	70.47	2.05	0.358
R24	38.79	39.53	38.46	0.85	0.655	R24	69.26	70.03	69.44	0.52	0.772
R25	37.69	39.50	37.63	3.21	0.201	R25	69.08	71.15	68.76	5.43	0.066
R26	37.93	38.52	39.20	1.16	0.561	R26	70.98	70.06	70.77	0.75	0.686
R27	38.17	38.67	39.14	0.68	0.712	R27	69.73	66.60	68.82	8.10	0.017
R28	38.17	37.51	37.34	0.55	0.761	R28	70.50	68.88	70.47	2.78	0.249
R29	38.93	38.88	38.40	0.24	0.886	R29	70.62	70.59	68.93	2.99	0.224
R30	37.69	38.37	39.08	1.38	0.501	R30	69.88	69.50	70.80	1.44	0.486
R31	37.96	37.01	39.17	3.36	0.186	R31	70.36	68.28	69.11	3.45	0.178
R32	38.20	39.23	39.85	1.99	0.370	R32	69.94	69.08	69.17	0.71	0.701
R33	38.28	38.43	38.61	7.58×10^{-2}	0.963	R33	69.79	69.67	69.76	1.21×10^{-2}	0.994
R34	38.11	37.84	38.61	0.44	0.804	R34	69.67	69.05	70.41	1.49	0.475
R35	39.11	37.54	39.05	2.26	0.323	R35	69.97	69.97	69.44	0.30	0.860
R36	38.64	39.26	38.49	0.47	0.789	R36	68.76	70.92	69.26	4.10	0.129
R37	39.67	37.72	38.79	2.72	0.256	R37	69.02	69.94	69.94	0.89	0.639
R38	38.64	37.60	38.08	0.77	0.680	R38	69.82	70.15	68.64	2.01	0.366
R39	39.62	38.28	38.99	1.26	0.532	R39	69.38	69.73	70.36	0.78	0.676
R40	38.22	37.10	39.82	5.34	0.069	R40	69.91	68.99	67.84	3.40	0.183
R41	36.83	37.49	39.11	3.95	0.139	R41	69.94	68.88	69.20	0.95	0.622
R42	38.76	38.28	39.14	0.53	0.769	R42	70.41	69.76	69.59	0.61	0.736
R43	39.62	36.48	38.67	7.42	0.024	R43	70.38	69.50	68.88	1.84	0.399
R44	38.08	37.25	38.28	0.86	0.649	R44	69.41	69.35	70.47	1.29	0.526
R45	39.02	37.96	39.14	1.21	0.546	R45	71.30	69.76	69.88	2.38	0.304
R46	38.85	37.93	38.14	0.66	0.718	R46	68.58	70.65	68.55	4.63	0.099
R47	38.43	36.78	37.75	2.00	0.368	R47	69.88	69.97	70.33	0.18	0.915
R48	37.07	36.92	39.08	4.18	0.124	R48	69.88	68.76	69.38	1.01	0.604
R49	38.14	37.37	38.02	0.49	0.781	R49	70.68	69.88	69.73	0.84	0.658
R50	39.20	37.81	38.76	1.44	0.487	R50	69.08	69.17	69.88	0.61	0.737
R51	39.23	36.04	37.43	7.39	0.025	R51	68.76	70.00	69.32	1.23	0.540
R52	38.02	37.84	37.90	2.35×10^{-2}	0.988	R52	68.55	69.85	69.76	1.68	0.432
R53	37.93	38.08	38.88	0.74	0.690	R53	68.40	69.70	69.44	1.50	0.473
R54	37.93	36.75	39.70	6.35	0.042	R54	68.99	68.02	69.88	2.74	0.253
R55	37.54	37.66	39.32	2.82	0.245	R55	70.12	68.11	67.25	6.82	0.033
R56	37.28	36.83	39.38	5.30	0.071	R56	69.76	69.59	70.44	0.66	0.719
R57	39.32	36.45	37.51	6.05	0.049	R57	70.77	68.96	68.73	3.99	0.136
R58	36.95	37.87	38.64	2.05	0.359	R58	68.76	69.88	69.14	1.04	0.595
R59	37.99	36.98	38.11	1.10	0.577	R59	69.82	68.43	69.64	1.82	0.403

Table 5.8: Left: BACTD10, Matrix 3; Right: BACTS0, Matrix 3

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	66.54	66.45	65.30	1.45	0.485	R0	55.41	56.83	56.78	1.77	0.412
R1	67.13	67.93	65.77	3.64	0.162	R1	57.51	57.84	58.20	0.32	0.852
R2	64.23	66.24	64.70	3.30	0.192	R2	55.41	55.12	54.59	0.48	0.786
R3	63.96	64.76	64.29	0.48	0.788	R3	51.69	50.62	49.94	2.09	0.351
R4	63.46	65.62	64.41	3.46	0.177	R4	50.53	51.04	50.65	0.19	0.911
R5	63.79	62.96	63.93	0.81	0.668	R5	50.06	50.56	49.64	0.57	0.752
R6	63.67	62.99	62.31	1.34	0.511	R6	49.47	49.56	49.97	0.19	0.907
R7	62.31	62.57	63.14	0.52	0.772	R7	49.79	52.84	50.03	7.78	0.020
R8	63.17	63.28	62.78	0.20	0.905	R8	50.12	51.69	49.26	4.09	0.129
R9	61.89	62.40	62.75	0.54	0.765	R9	51.54	50.44	50.38	1.14	0.565
R10	62.84	63.76	63.20	0.62	0.733	R10	47.75	48.88	49.62	2.38	0.304
R11	63.11	62.31	62.10	0.81	0.665	R11	49.73	49.73	48.52	1.33	0.515
R12	62.69	62.01	62.28	0.34	0.844	R12	48.64	49.73	49.67	1.03	0.599
R13	62.19	64.14	62.28	3.53	0.171	R13	50.24	49.29	49.29	0.81	0.668
R14	62.34	62.31	63.22	0.79	0.675	R14	50.30	47.49	47.31	7.60	0.022
R15	63.20	62.25	62.04	1.09	0.579	R15	48.73	50.33	48.82	2.18	0.336
R16	62.51	63.88	63.58	1.49	0.475	R16	51.36	50.62	48.17	7.57	0.023
R17	62.66	63.40	61.63	2.29	0.318	R17	50.03	48.46	49.20	1.66	0.435
R18	61.98	62.13	62.28	6.29×10^{-2}	0.969	R18	51.57	50.27	48.58	6.07	0.048
R19	63.58	62.72	62.57	0.86	0.652	R19	50.44	48.76	50.00	2.07	0.356
R20	63.52	61.89	62.63	1.92	0.383	R20	50.92	48.88	47.51	7.93	0.019
R21	62.28	62.04	62.46	0.12	0.940	R21	50.53	47.57	48.05	6.83	0.033
R22	62.99	63.96	62.46	1.70	0.427	R22	51.48	48.79	48.99	6.07	0.048
R23	62.78	63.11	61.09	3.35	0.187	R23	50.65	46.04	49.35	15.33	<0.001
R24	62.22	62.93	61.80	0.93	0.628	R24	49.76	46.78	49.97	8.65	0.013
R25	62.54	63.46	61.39	3.10	0.212	R25	50.53	47.99	49.08	4.41	0.110
R26	62.90	62.34	62.10	0.49	0.784	R26	50.50	47.93	50.09	5.17	0.076
R27	64.56	61.63	63.52	6.41	0.041	R27	50.38	46.45	48.88	10.67	0.005
R28	63.14	62.16	61.57	1.81	0.405	R28	51.83	47.13	48.14	16.60	<0.001
R29	64.38	63.28	61.72	5.20	0.074	R29	50.30	47.19	48.73	6.53	0.038
R30	62.28	63.46	60.68	5.59	0.061	R30	49.64	47.99	50.15	3.45	0.178
R31	63.28	63.58	62.69	0.59	0.743	R31	50.00	46.66	49.67	9.20	0.010
R32	63.05	61.98	62.46	0.82	0.663	R32	49.73	47.37	48.91	3.90	0.142
R33	62.90	64.88	64.11	2.93	0.231	R33	49.05	46.66	49.02	5.12	0.077
R34	61.27	62.57	63.46	3.49	0.174	R34	50.44	48.28	49.17	3.19	0.203
R35	61.60	65.03	62.72	8.91	0.012	R35	49.20	46.63	48.96	5.48	0.064
R36	62.13	62.87	63.31	1.03	0.596	R36	49.85	47.66	49.50	3.74	0.154
R37	62.28	64.11	63.34	2.47	0.291	R37	50.18	47.96	49.59	3.57	0.168
R38	62.28	62.69	62.93	0.31	0.855	R38	47.87	48.08	49.62	2.46	0.292
R39	63.22	62.22	62.81	0.74	0.691	R39	48.52	48.05	48.11	0.18	0.914
R40	62.72	63.08	63.25	0.21	0.899	R40	50.27	48.49	49.29	2.14	0.343
R41	62.54	62.90	62.04	0.54	0.765	R41	48.34	47.51	49.44	2.52	0.284
R42	61.63	63.99	61.86	4.91	0.086	R42	50.62	48.49	48.91	3.45	0.178
R43	62.31	62.04	63.22	1.11	0.573	R43	49.38	49.29	48.40	0.79	0.674
R44	62.04	62.63	61.12	1.66	0.437	R44	50.15	48.46	49.20	1.93	0.380
R45	62.22	64.41	62.49	4.15	0.126	R45	50.68	50.77	48.70	3.71	0.157
R46	63.08	61.30	62.81	2.64	0.268	R46	48.28	49.35	47.75	1.79	0.408
R47	63.05	63.96	62.40	1.80	0.406	R47	47.34	48.25	48.67	1.26	0.533
R48	61.92	62.10	62.07	2.60×10^{-2}	0.987	R48	49.50	48.88	47.43	3.06	0.217
R49	60.50	62.31	62.81	4.21	0.122	R49	48.67	47.90	48.46	0.43	0.807
R50	62.60	63.52	61.57	2.75	0.252	R50	48.25	49.32	49.50	1.22	0.543
R51	62.51	62.04	62.19	0.17	0.919	R51	47.37	49.14	48.93	2.55	0.279
R52	63.17	62.01	61.36	2.40	0.301	R52	48.73	48.70	48.37	0.11	0.949
R53	63.49	63.11	60.92	5.55	0.062	R53	49.26	49.11	49.41	5.92×10^{-2}	0.971
R54	62.01	63.67	61.98	2.69	0.260	R54	49.62	48.52	49.97	1.54	0.462
R55	61.54	62.37	61.09	1.19	0.551	R55	46.07	46.27	50.18	14.54	<0.001
R56	60.53	61.27	62.07	1.69	0.430	R56	47.25	46.80	50.68	12.18	0.002
R57	63.58	61.63	59.82	10.11	0.006	R57	48.58	47.90	49.56	1.88	0.391
R58	62.87	63.08	58.91	15.74	<0.001	R58	49.59	49.02	49.35	0.22	0.898
R59	60.21	62.72	60.12	6.23	0.044	R59	48.91	46.92	48.55	3.03	0.220

Table 5.9: Left: BACTS1, Matrix 3; Right: BACTS10, Matrix 3

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	49.67	48.28	49.76	1.86	0.394	R0	50.59	49.82	49.97	0.45	0.798
R1	0.21	8.96	3.43	3.84×10^2	<0.001	R1	5.38	14.94	8.85	1.80×10^2	<0.001
R2	0.00	1.04	0.00	77.15	<0.001	R2	0.50	2.63	0.71	68.88	<0.001
R3	0.00	0.62	0.00	46.23	<0.001	R3	0.03	0.92	0.06	50.77	<0.001
R4	0.00	0.56	0.00	41.82	<0.001	R4	0.00	0.83	0.00	61.68	<0.001
R5	0.00	0.56	0.00	41.82	<0.001	R5	0.00	0.86	0.00	63.89	<0.001
R6	0.00	0.56	0.00	41.82	<0.001	R6	0.00	0.98	0.00	72.72	<0.001
R7	0.00	0.56	0.00	41.82	<0.001	R7	0.00	0.89	0.00	66.09	<0.001
R8	0.00	0.56	0.00	41.82	<0.001	R8	0.00	0.95	0.00	70.51	<0.001
R9	0.00	0.56	0.00	41.82	<0.001	R9	0.00	0.98	0.00	72.72	<0.001
R10	0.00	0.56	0.00	41.82	<0.001	R10	0.00	1.18	0.00	88.21	<0.001
R11	0.00	0.56	0.00	41.82	<0.001	R11	0.00	1.18	0.00	88.21	<0.001
R12	0.00	0.56	0.00	41.82	<0.001	R12	0.00	1.12	0.00	83.78	<0.001
R13	0.00	0.56	0.00	41.82	<0.001	R13	0.00	0.98	0.00	72.72	<0.001
R14	0.00	0.56	0.00	41.82	<0.001	R14	0.00	1.04	0.00	77.15	<0.001
R15	0.00	0.56	0.00	41.82	<0.001	R15	0.00	1.15	0.00	85.99	<0.001
R16	0.00	0.56	0.00	41.82	<0.001	R16	0.00	1.12	0.00	83.78	<0.001
R17	0.00	0.56	0.00	41.82	<0.001	R17	0.00	1.12	0.00	83.78	<0.001
R18	0.00	0.56	0.00	41.82	<0.001	R18	0.00	1.15	0.00	85.99	<0.001
R19	0.00	0.56	0.00	41.82	<0.001	R19	0.00	1.04	0.00	77.15	<0.001
R20	0.00	0.56	0.00	41.82	<0.001	R20	0.00	1.18	0.00	88.21	<0.001
R21	0.00	0.56	0.00	41.82	<0.001	R21	0.00	1.07	0.00	79.36	<0.001
R22	0.00	0.56	0.00	41.82	<0.001	R22	0.00	1.09	0.00	81.57	<0.001
R23	0.00	0.56	0.00	41.82	<0.001	R23	0.00	1.15	0.00	85.99	<0.001
R24	0.00	0.56	0.00	41.82	<0.001	R24	0.00	1.15	0.00	85.99	<0.001
R25	0.00	0.56	0.00	41.82	<0.001	R25	0.00	1.15	0.00	85.99	<0.001
R26	0.00	0.56	0.00	41.82	<0.001	R26	0.00	1.15	0.00	85.99	<0.001
R27	0.00	0.56	0.00	41.82	<0.001	R27	0.00	1.12	0.00	83.78	<0.001
R28	0.00	0.56	0.00	41.82	<0.001	R28	0.00	1.12	0.00	83.78	<0.001
R29	0.00	0.56	0.00	41.82	<0.001	R29	0.00	1.18	0.00	88.21	<0.001
R30	0.00	0.56	0.00	41.82	<0.001	R30	0.00	1.15	0.00	85.99	<0.001
R31	0.00	0.56	0.00	41.82	<0.001	R31	0.00	1.15	0.00	85.99	<0.001
R32	0.00	0.56	0.00	41.82	<0.001	R32	0.00	1.15	0.00	85.99	<0.001
R33	0.00	0.56	0.00	41.82	<0.001	R33	0.00	1.07	0.00	79.36	<0.001
R34	0.00	0.56	0.00	41.82	<0.001	R34	0.00	1.09	0.00	81.57	<0.001
R35	0.00	0.56	0.00	41.82	<0.001	R35	0.00	1.15	0.00	85.99	<0.001
R36	0.00	0.56	0.00	41.82	<0.001	R36	0.00	1.12	0.00	83.78	<0.001
R37	0.00	0.56	0.00	41.82	<0.001	R37	0.00	1.15	0.00	85.99	<0.001
R38	0.00	0.56	0.00	41.82	<0.001	R38	0.00	1.09	0.00	81.57	<0.001
R39	0.00	0.56	0.00	41.82	<0.001	R39	0.00	1.18	0.00	88.21	<0.001
R40	0.00	0.56	0.00	41.82	<0.001	R40	0.00	1.15	0.00	85.99	<0.001
R41	0.00	0.56	0.00	41.82	<0.001	R41	0.00	0.98	0.00	72.72	<0.001
R42	0.00	0.56	0.00	41.82	<0.001	R42	0.00	1.09	0.00	81.57	<0.001
R43	0.00	0.56	0.00	41.82	<0.001	R43	0.00	1.18	0.00	88.21	<0.001
R44	0.00	0.56	0.00	41.82	<0.001	R44	0.00	1.21	0.00	90.42	<0.001
R45	0.00	0.56	0.00	41.82	<0.001	R45	0.00	1.15	0.00	85.99	<0.001
R46	0.00	0.56	0.00	41.82	<0.001	R46	0.00	1.12	0.00	83.78	<0.001
R47	0.00	0.56	0.00	41.82	<0.001	R47	0.00	1.09	0.00	81.57	<0.001
R48	0.00	0.56	0.00	41.82	<0.001	R48	0.00	1.09	0.00	81.57	<0.001
R49	0.00	0.56	0.00	41.82	<0.001	R49	0.00	1.12	0.00	83.78	<0.001
R50	0.00	0.56	0.00	41.82	<0.001	R50	0.00	1.15	0.00	85.99	<0.001
R51	0.00	0.56	0.00	41.82	<0.001	R51	0.00	1.18	0.00	88.21	<0.001
R52	0.00	0.56	0.00	41.82	<0.001	R52	0.00	1.04	0.00	77.15	<0.001
R53	0.00	0.56	0.00	41.82	<0.001	R53	0.00	1.15	0.00	85.99	<0.001
R54	0.00	0.56	0.00	41.82	<0.001	R54	0.00	1.12	0.00	83.78	<0.001
R55	0.00	0.56	0.00	41.82	<0.001	R55	0.00	1.15	0.00	85.99	<0.001
R56	0.00	0.56	0.00	41.82	<0.001	R56	0.00	1.09	0.00	81.57	<0.001
R57	0.00	0.56	0.00	41.82	<0.001	R57	0.00	1.09	0.00	81.57	<0.001
R58	0.00	0.56	0.00	41.82	<0.001	R58	0.00	1.18	0.00	88.21	<0.001
R59	0.00	0.56	0.00	41.82	<0.001	R59	0.00	1.07	0.00	79.36	<0.001

Table 5.10: Left: IM0, Matrix 1; Right: IM10, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	49.29	48.55	49.76	1.01	0.603	R0	50.36	48.96	48.64	2.25	0.325
R1	10.21	17.87	11.66	94.47	<0.001	R1	15.30	23.64	17.07	84.14	<0.001
R2	1.92	5.12	2.37	62.98	<0.001	R2	4.14	9.88	4.97	1.04×10^2	<0.001
R3	0.38	1.86	0.44	49.42	<0.001	R3	1.30	4.76	1.78	88.00	<0.001
R4	0.12	0.68	0.03	30.33	<0.001	R4	0.36	2.51	0.86	69.17	<0.001
R5	0.03	0.62	0.03	34.25	<0.001	R5	0.21	1.15	0.83	25.35	<0.001
R6	0.03	0.59	0.00	38.18	<0.001	R6	0.00	0.71	0.71	39.04	<0.001
R7	0.00	0.62	0.00	46.23	<0.001	R7	0.00	0.59	0.62	33.36	<0.001
R8	0.00	0.68	0.00	50.64	<0.001	R8	0.00	0.56	0.59	31.73	<0.001
R9	0.00	0.59	0.00	44.02	<0.001	R9	0.00	0.62	0.12	33.02	<0.001
R10	0.00	0.36	0.00	26.40	<0.001	R10	0.00	0.62	0.03	40.29	<0.001
R11	0.00	0.27	0.00	19.79	<0.001	R11	0.00	0.59	0.03	38.18	<0.001
R12	0.00	0.27	0.00	19.79	<0.001	R12	0.00	0.56	0.00	41.82	<0.001
R13	0.00	0.27	0.00	19.79	<0.001	R13	0.00	0.47	0.00	35.21	<0.001
R14	0.00	0.27	0.00	19.79	<0.001	R14	0.00	0.33	0.00	24.19	<0.001
R15	0.00	0.27	0.00	19.79	<0.001	R15	0.00	0.24	0.00	17.59	<0.001
R16	0.00	0.27	0.00	19.79	<0.001	R16	0.00	0.24	0.00	17.59	<0.001
R17	0.00	0.27	0.00	19.79	<0.001	R17	0.00	0.24	0.00	17.59	<0.001
R18	0.00	0.27	0.00	19.79	<0.001	R18	0.00	0.24	0.00	17.59	<0.001
R19	0.00	0.27	0.00	19.79	<0.001	R19	0.00	0.24	0.00	17.59	<0.001
R20	0.00	0.27	0.00	19.79	<0.001	R20	0.00	0.24	0.00	17.59	<0.001
R21	0.00	0.27	0.00	19.79	<0.001	R21	0.00	0.24	0.00	17.59	<0.001
R22	0.00	0.27	0.00	19.79	<0.001	R22	0.00	0.24	0.00	17.59	<0.001
R23	0.00	0.27	0.00	19.79	<0.001	R23	0.00	0.24	0.00	17.59	<0.001
R24	0.00	0.27	0.00	19.79	<0.001	R24	0.00	0.24	0.00	17.59	<0.001
R25	0.00	0.27	0.00	19.79	<0.001	R25	0.00	0.24	0.00	17.59	<0.001
R26	0.00	0.27	0.00	19.79	<0.001	R26	0.00	0.24	0.00	17.59	<0.001
R27	0.00	0.27	0.00	19.79	<0.001	R27	0.00	0.24	0.00	17.59	<0.001
R28	0.00	0.27	0.00	19.79	<0.001	R28	0.00	0.24	0.00	17.59	<0.001
R29	0.00	0.27	0.00	19.79	<0.001	R29	0.00	0.24	0.00	17.59	<0.001
R30	0.00	0.27	0.00	19.79	<0.001	R30	0.00	0.24	0.00	17.59	<0.001
R31	0.00	0.27	0.00	19.79	<0.001	R31	0.00	0.24	0.00	17.59	<0.001
R32	0.00	0.27	0.00	19.79	<0.001	R32	0.00	0.24	0.00	17.59	<0.001
R33	0.00	0.27	0.00	19.79	<0.001	R33	0.00	0.24	0.00	17.59	<0.001
R34	0.00	0.27	0.00	19.79	<0.001	R34	0.00	0.24	0.00	17.59	<0.001
R35	0.00	0.27	0.00	19.79	<0.001	R35	0.00	0.24	0.00	17.59	<0.001
R36	0.00	0.27	0.00	19.79	<0.001	R36	0.00	0.24	0.00	17.59	<0.001
R37	0.00	0.27	0.00	19.79	<0.001	R37	0.00	0.24	0.00	17.59	<0.001
R38	0.00	0.27	0.00	19.79	<0.001	R38	0.00	0.24	0.00	17.59	<0.001
R39	0.00	0.27	0.00	19.79	<0.001	R39	0.00	0.24	0.00	17.59	<0.001
R40	0.00	0.27	0.00	19.79	<0.001	R40	0.00	0.24	0.00	17.59	<0.001
R41	0.00	0.27	0.00	19.79	<0.001	R41	0.00	0.24	0.00	17.59	<0.001
R42	0.00	0.27	0.00	19.79	<0.001	R42	0.00	0.24	0.00	17.59	<0.001
R43	0.00	0.27	0.00	19.79	<0.001	R43	0.00	0.24	0.00	17.59	<0.001
R44	0.00	0.27	0.00	19.79	<0.001	R44	0.00	0.24	0.00	17.59	<0.001
R45	0.00	0.27	0.00	19.79	<0.001	R45	0.00	0.24	0.00	17.59	<0.001
R46	0.00	0.27	0.00	19.79	<0.001	R46	0.00	0.24	0.00	17.59	<0.001
R47	0.00	0.27	0.00	19.79	<0.001	R47	0.00	0.24	0.00	17.59	<0.001
R48	0.00	0.27	0.00	19.79	<0.001	R48	0.00	0.24	0.00	17.59	<0.001
R49	0.00	0.27	0.00	19.79	<0.001	R49	0.00	0.24	0.00	17.59	<0.001
R50	0.00	0.27	0.00	19.79	<0.001	R50	0.00	0.24	0.00	17.59	<0.001
R51	0.00	0.27	0.00	19.79	<0.001	R51	0.00	0.24	0.00	17.59	<0.001
R52	0.00	0.27	0.00	19.79	<0.001	R52	0.00	0.24	0.00	17.59	<0.001
R53	0.00	0.27	0.00	19.79	<0.001	R53	0.00	0.24	0.00	17.59	<0.001
R54	0.00	0.27	0.00	19.79	<0.001	R54	0.00	0.24	0.00	17.59	<0.001
R55	0.00	0.27	0.00	19.79	<0.001	R55	0.00	0.24	0.00	17.59	<0.001
R56	0.00	0.27	0.00	19.79	<0.001	R56	0.00	0.24	0.00	17.59	<0.001
R57	0.00	0.27	0.00	19.79	<0.001	R57	0.00	0.24	0.00	17.59	<0.001
R58	0.00	0.27	0.00	19.79	<0.001	R58	0.00	0.24	0.00	17.59	<0.001
R59	0.00	0.27	0.00	19.79	<0.001	R59	0.00	0.24	0.00	17.59	<0.001

Table 5.11: Left: IM20, Matrix 1; Right: IM30, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	51.04	50.44	49.79	1.04	0.593	R0	51.36	49.67	48.91	4.27	0.118
R1	21.33	27.93	24.41	39.78	<0.001	R1	25.15	30.83	26.09	31.18	<0.001
R2	9.62	12.81	9.59	23.74	<0.001	R2	12.69	17.10	12.96	33.01	<0.001
R3	3.99	6.12	3.52	28.89	<0.001	R3	6.27	8.82	5.98	24.46	<0.001
R4	1.45	2.31	1.18	13.92	<0.001	R4	2.75	4.76	3.11	22.00	<0.001
R5	0.53	1.30	0.62	13.89	<0.001	R5	1.39	2.84	1.48	22.59	<0.001
R6	0.18	0.98	0.27	25.78	<0.001	R6	0.77	1.66	0.80	15.19	<0.001
R7	0.06	0.62	0.06	27.47	<0.001	R7	0.36	0.83	0.44	7.57	0.023
R8	0.03	0.50	0.03	26.24	<0.001	R8	0.24	0.62	0.15	12.19	0.002
R9	0.03	0.27	0.03	10.98	0.004	R9	0.18	0.36	0.03	11.02	0.004
R10	0.06	0.27	0.00	13.75	0.001	R10	0.15	0.27	0.03	7.37	0.025
R11	0.06	0.24	0.00	11.97	0.003	R11	0.12	0.24	0.03	6.24	0.044
R12	0.03	0.24	0.00	13.51	0.001	R12	0.09	0.24	0.03	6.60	0.037
R13	0.03	0.24	0.00	13.51	0.001	R13	0.03	0.24	0.03	9.20	0.010
R14	0.03	0.24	0.00	13.51	0.001	R14	0.03	0.24	0.03	9.20	0.010
R15	0.03	0.24	0.00	13.51	0.001	R15	0.03	0.24	0.03	9.20	0.010
R16	0.06	0.24	0.00	11.97	0.003	R16	0.00	0.24	0.03	13.51	0.001
R17	0.06	0.24	0.00	11.97	0.003	R17	0.00	0.24	0.03	13.51	0.001
R18	0.00	0.24	0.00	17.59	<0.001	R18	0.00	0.24	0.03	13.51	0.001
R19	0.00	0.24	0.00	17.59	<0.001	R19	0.00	0.24	0.03	13.51	0.001
R20	0.00	0.24	0.00	17.59	<0.001	R20	0.00	0.24	0.03	13.51	0.001
R21	0.00	0.24	0.00	17.59	<0.001	R21	0.00	0.24	0.03	13.51	0.001
R22	0.00	0.24	0.00	17.59	<0.001	R22	0.00	0.24	0.03	13.51	0.001
R23	0.00	0.24	0.00	17.59	<0.001	R23	0.00	0.24	0.03	13.51	0.001
R24	0.00	0.24	0.00	17.59	<0.001	R24	0.00	0.24	0.03	13.51	0.001
R25	0.00	0.24	0.00	17.59	<0.001	R25	0.00	0.24	0.03	13.51	0.001
R26	0.00	0.24	0.00	17.59	<0.001	R26	0.00	0.24	0.03	13.51	0.001
R27	0.00	0.24	0.00	17.59	<0.001	R27	0.00	0.24	0.03	13.51	0.001
R28	0.00	0.24	0.00	17.59	<0.001	R28	0.00	0.24	0.03	13.51	0.001
R29	0.00	0.24	0.00	17.59	<0.001	R29	0.00	0.24	0.03	13.51	0.001
R30	0.00	0.24	0.00	17.59	<0.001	R30	0.00	0.24	0.03	13.51	0.001
R31	0.00	0.24	0.00	17.59	<0.001	R31	0.00	0.24	0.03	13.51	0.001
R32	0.00	0.24	0.00	17.59	<0.001	R32	0.00	0.24	0.03	13.51	0.001
R33	0.00	0.24	0.00	17.59	<0.001	R33	0.00	0.24	0.03	13.51	0.001
R34	0.00	0.24	0.00	17.59	<0.001	R34	0.00	0.24	0.03	13.51	0.001
R35	0.00	0.24	0.00	17.59	<0.001	R35	0.00	0.24	0.03	13.51	0.001
R36	0.00	0.24	0.00	17.59	<0.001	R36	0.00	0.24	0.03	13.51	0.001
R37	0.00	0.24	0.00	17.59	<0.001	R37	0.00	0.24	0.03	13.51	0.001
R38	0.00	0.24	0.00	17.59	<0.001	R38	0.00	0.24	0.03	13.51	0.001
R39	0.00	0.24	0.00	17.59	<0.001	R39	0.00	0.24	0.03	13.51	0.001
R40	0.00	0.24	0.00	17.59	<0.001	R40	0.00	0.24	0.03	13.51	0.001
R41	0.00	0.24	0.00	17.59	<0.001	R41	0.00	0.24	0.03	13.51	0.001
R42	0.00	0.24	0.00	17.59	<0.001	R42	0.00	0.24	0.03	13.51	0.001
R43	0.00	0.24	0.00	17.59	<0.001	R43	0.00	0.24	0.03	13.51	0.001
R44	0.00	0.24	0.00	17.59	<0.001	R44	0.00	0.24	0.03	13.51	0.001
R45	0.00	0.24	0.00	17.59	<0.001	R45	0.00	0.24	0.03	13.51	0.001
R46	0.00	0.24	0.00	17.59	<0.001	R46	0.00	0.24	0.03	13.51	0.001
R47	0.00	0.24	0.00	17.59	<0.001	R47	0.00	0.24	0.03	13.51	0.001
R48	0.00	0.24	0.00	17.59	<0.001	R48	0.00	0.24	0.03	13.51	0.001
R49	0.00	0.24	0.00	17.59	<0.001	R49	0.00	0.24	0.03	13.51	0.001
R50	0.00	0.24	0.00	17.59	<0.001	R50	0.00	0.24	0.03	13.51	0.001
R51	0.00	0.24	0.00	17.59	<0.001	R51	0.00	0.24	0.03	13.51	0.001
R52	0.00	0.24	0.00	17.59	<0.001	R52	0.00	0.24	0.03	13.51	0.001
R53	0.00	0.24	0.00	17.59	<0.001	R53	0.00	0.24	0.03	13.51	0.001
R54	0.00	0.24	0.00	17.59	<0.001	R54	0.00	0.24	0.03	13.51	0.001
R55	0.00	0.24	0.00	17.59	<0.001	R55	0.00	0.24	0.03	13.51	0.001
R56	0.00	0.24	0.00	17.59	<0.001	R56	0.00	0.24	0.03	13.51	0.001
R57	0.00	0.24	0.00	17.59	<0.001	R57	0.00	0.24	0.03	13.51	0.001
R58	0.00	0.24	0.00	17.59	<0.001	R58	0.00	0.24	0.03	13.51	0.001
R59	0.00	0.24	0.00	17.59	<0.001	R59	0.00	0.24	0.03	13.51	0.001

Table 5.12: Left: IM40, Matrix 1; Right: IM50, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	51.54	48.85	49.97	4.95	0.084	R0	50.12	48.43	49.50	1.97	0.374
R1	32.46	35.36	32.43	8.56	0.014	R1	35.06	36.80	35.86	2.24	0.326
R2	19.56	23.70	18.34	32.23	<0.001	R2	25.50	27.60	25.06	6.45	0.040
R3	11.39	14.14	11.09	17.47	<0.001	R3	18.25	20.00	18.17	4.70	0.095
R4	6.51	8.82	5.68	26.82	<0.001	R4	12.93	13.49	11.72	5.05	0.080
R5	3.96	5.53	3.46	18.59	<0.001	R5	9.08	9.47	8.64	1.41	0.494
R6	1.92	3.22	1.86	16.71	<0.001	R6	6.07	6.39	6.54	0.67	0.715
R7	1.12	2.22	1.18	16.31	<0.001	R7	4.17	4.29	4.02	0.30	0.860
R8	0.71	0.98	0.74	1.74	0.418	R8	3.14	2.75	3.11	1.08	0.583
R9	0.36	0.65	0.44	3.17	0.205	R9	2.13	1.78	1.80	1.38	0.501
R10	0.24	0.47	0.24	3.78	0.151	R10	1.33	1.30	1.80	3.58	0.167
R11	0.12	0.27	0.06	5.14	0.077	R11	1.01	0.95	1.21	1.24	0.537
R12	0.03	0.27	0.00	15.49	<0.001	R12	0.56	0.62	0.92	3.39	0.183
R13	0.03	0.15	0.00	7.78	0.020	R13	0.36	0.62	0.53	2.59	0.274
R14	0.00	0.18	0.00	13.19	0.001	R14	0.18	0.44	0.44	5.09	0.079
R15	0.00	0.18	0.00	13.19	0.001	R15	0.06	0.56	0.33	15.96	<0.001
R16	0.00	0.21	0.00	15.39	<0.001	R16	0.09	0.38	0.18	7.13	0.028
R17	0.00	0.12	0.00	8.79	0.012	R17	0.03	0.41	0.21	13.49	0.001
R18	0.00	0.12	0.00	8.79	0.012	R18	0.03	0.36	0.15	11.25	0.004
R19	0.00	0.12	0.00	8.79	0.012	R19	0.00	0.33	0.09	16.23	<0.001
R20	0.00	0.12	0.00	8.79	0.012	R20	0.00	0.33	0.12	15.58	<0.001
R21	0.00	0.12	0.00	8.79	0.012	R21	0.00	0.33	0.12	15.58	<0.001
R22	0.00	0.12	0.00	8.79	0.012	R22	0.00	0.33	0.09	16.23	<0.001
R23	0.00	0.12	0.00	8.79	0.012	R23	0.00	0.33	0.06	17.42	<0.001
R24	0.00	0.12	0.00	8.79	0.012	R24	0.00	0.33	0.06	17.42	<0.001
R25	0.00	0.12	0.00	8.79	0.012	R25	0.00	0.33	0.03	19.50	<0.001
R26	0.00	0.12	0.00	8.79	0.012	R26	0.00	0.33	0.03	19.50	<0.001
R27	0.00	0.12	0.00	8.79	0.012	R27	0.00	0.33	0.03	19.50	<0.001
R28	0.00	0.12	0.00	8.79	0.012	R28	0.00	0.33	0.03	19.50	<0.001
R29	0.00	0.12	0.00	8.79	0.012	R29	0.00	0.33	0.03	19.50	<0.001
R30	0.00	0.12	0.00	8.79	0.012	R30	0.00	0.33	0.03	19.50	<0.001
R31	0.00	0.12	0.00	8.79	0.012	R31	0.00	0.33	0.03	19.50	<0.001
R32	0.00	0.12	0.00	8.79	0.012	R32	0.00	0.33	0.03	19.50	<0.001
R33	0.00	0.12	0.00	8.79	0.012	R33	0.00	0.33	0.03	19.50	<0.001
R34	0.00	0.12	0.00	8.79	0.012	R34	0.00	0.33	0.03	19.50	<0.001
R35	0.00	0.12	0.00	8.79	0.012	R35	0.00	0.33	0.03	19.50	<0.001
R36	0.00	0.12	0.00	8.79	0.012	R36	0.00	0.33	0.03	19.50	<0.001
R37	0.00	0.12	0.00	8.79	0.012	R37	0.00	0.33	0.03	19.50	<0.001
R38	0.00	0.12	0.00	8.79	0.012	R38	0.00	0.33	0.03	19.50	<0.001
R39	0.00	0.12	0.00	8.79	0.012	R39	0.00	0.33	0.03	19.50	<0.001
R40	0.00	0.12	0.00	8.79	0.012	R40	0.00	0.33	0.03	19.50	<0.001
R41	0.00	0.12	0.00	8.79	0.012	R41	0.00	0.33	0.03	19.50	<0.001
R42	0.00	0.12	0.00	8.79	0.012	R42	0.00	0.33	0.03	19.50	<0.001
R43	0.00	0.12	0.00	8.79	0.012	R43	0.00	0.33	0.03	19.50	<0.001
R44	0.00	0.12	0.00	8.79	0.012	R44	0.00	0.33	0.03	19.50	<0.001
R45	0.00	0.12	0.00	8.79	0.012	R45	0.00	0.33	0.03	19.50	<0.001
R46	0.00	0.12	0.00	8.79	0.012	R46	0.00	0.33	0.03	19.50	<0.001
R47	0.00	0.12	0.00	8.79	0.012	R47	0.00	0.33	0.03	19.50	<0.001
R48	0.00	0.12	0.00	8.79	0.012	R48	0.00	0.33	0.03	19.50	<0.001
R49	0.00	0.12	0.00	8.79	0.012	R49	0.00	0.33	0.03	19.50	<0.001
R50	0.00	0.12	0.00	8.79	0.012	R50	0.00	0.33	0.03	19.50	<0.001
R51	0.00	0.12	0.00	8.79	0.012	R51	0.00	0.33	0.03	19.50	<0.001
R52	0.00	0.12	0.00	8.79	0.012	R52	0.00	0.33	0.03	19.50	<0.001
R53	0.00	0.12	0.00	8.79	0.012	R53	0.00	0.33	0.03	19.50	<0.001
R54	0.00	0.12	0.00	8.79	0.012	R54	0.00	0.33	0.03	19.50	<0.001
R55	0.00	0.12	0.00	8.79	0.012	R55	0.00	0.33	0.03	19.50	<0.001
R56	0.00	0.12	0.00	8.79	0.012	R56	0.00	0.33	0.03	19.50	<0.001
R57	0.00	0.12	0.00	8.79	0.012	R57	0.00	0.33	0.03	19.50	<0.001
R58	0.00	0.12	0.00	8.79	0.012	R58	0.00	0.33	0.03	19.50	<0.001
R59	0.00	0.12	0.00	8.79	0.012	R59	0.00	0.33	0.03	19.50	<0.001

Table 5.13: Left: IM60, Matrix 1; Right: IM70, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	47.57	49.53	51.09	8.42	0.015	R0	50.50	49.50	51.60	2.99	0.225
R1	37.90	40.86	42.22	13.73	0.001	R1	45.24	46.01	45.89	0.47	0.792
R2	30.65	32.31	34.88	13.95	<0.001	R2	41.18	43.02	42.25	2.35	0.308
R3	23.28	25.71	28.34	22.63	<0.001	R3	35.80	39.32	38.34	9.52	0.009
R4	19.94	20.89	23.17	11.00	0.004	R4	31.45	36.54	34.44	19.71	<0.001
R5	16.42	15.77	18.85	12.45	0.002	R5	26.80	34.73	32.04	51.68	<0.001
R6	12.96	11.98	15.33	17.00	<0.001	R6	23.76	30.92	29.26	47.83	<0.001
R7	10.41	10.50	12.46	8.96	0.011	R7	21.42	26.72	24.70	26.47	<0.001
R8	8.02	8.46	9.85	7.63	0.022	R8	19.23	23.02	21.36	14.64	<0.001
R9	6.86	6.60	7.54	2.46	0.293	R9	17.60	21.45	18.73	16.86	<0.001
R10	5.09	5.00	6.01	4.06	0.131	R10	16.15	19.08	16.04	14.02	<0.001
R11	4.38	3.96	5.03	4.55	0.103	R11	14.08	17.69	15.09	17.60	<0.001
R12	3.61	3.11	3.31	1.33	0.514	R12	12.72	15.83	13.17	15.68	<0.001
R13	2.63	2.19	2.46	1.44	0.488	R13	11.83	13.31	12.25	3.59	0.167
R14	1.95	2.01	2.46	2.39	0.303	R14	10.62	11.42	11.24	1.21	0.545
R15	1.63	1.42	1.78	1.37	0.504	R15	9.38	10.27	9.82	1.50	0.472
R16	1.01	1.27	1.27	1.40	0.496	R16	8.58	9.17	9.14	0.93	0.629
R17	0.56	1.09	1.12	8.02	0.018	R17	7.63	8.28	8.61	2.24	0.326
R18	0.50	0.89	1.24	11.03	0.004	R18	6.45	8.02	8.73	13.13	0.001
R19	0.47	0.83	0.77	3.79	0.150	R19	5.92	7.07	7.54	7.55	0.023
R20	0.27	0.62	0.65	6.78	0.034	R20	5.80	6.45	7.07	4.55	0.103
R21	0.15	0.53	0.47	8.83	0.012	R21	5.74	5.59	6.63	3.71	0.156
R22	0.12	0.44	0.27	6.82	0.033	R22	4.79	5.47	6.27	7.11	0.029
R23	0.09	0.36	0.15	6.45	0.040	R23	3.93	4.59	5.80	13.15	0.001
R24	0.03	0.36	0.09	12.68	0.002	R24	3.34	4.41	4.88	10.69	0.005
R25	0.03	0.36	0.12	11.77	0.003	R25	2.87	4.53	4.62	17.96	<0.001
R26	0.00	0.30	0.12	14.02	<0.001	R26	2.78	3.49	4.14	9.43	0.009
R27	0.00	0.30	0.09	14.53	<0.001	R27	2.37	3.20	3.61	9.39	0.009
R28	0.00	0.30	0.12	14.02	<0.001	R28	2.81	2.96	3.11	0.52	0.773
R29	0.00	0.30	0.18	14.00	<0.001	R29	2.99	2.60	3.20	2.17	0.338
R30	0.00	0.30	0.09	14.53	<0.001	R30	2.78	2.69	2.87	0.20	0.906
R31	0.00	0.30	0.06	15.57	<0.001	R31	2.49	2.13	2.40	1.02	0.600
R32	0.00	0.30	0.09	14.53	<0.001	R32	2.07	1.98	1.75	1.02	0.600
R33	0.00	0.30	0.06	15.57	<0.001	R33	1.98	1.80	1.51	2.26	0.323
R34	0.00	0.30	0.03	17.49	<0.001	R34	2.13	1.54	1.39	6.07	0.048
R35	0.00	0.30	0.03	17.49	<0.001	R35	1.89	1.30	1.21	6.16	0.046
R36	0.00	0.30	0.03	17.49	<0.001	R36	1.72	1.09	0.98	8.22	0.016
R37	0.00	0.30	0.03	17.49	<0.001	R37	1.57	1.09	0.74	10.47	0.005
R38	0.00	0.30	0.03	17.49	<0.001	R38	1.33	0.95	0.53	12.07	0.002
R39	0.00	0.30	0.03	17.49	<0.001	R39	1.39	0.86	0.44	17.58	<0.001
R40	0.00	0.30	0.03	17.49	<0.001	R40	1.18	0.98	0.41	13.97	<0.001
R41	0.00	0.30	0.03	17.49	<0.001	R41	1.07	1.09	0.36	16.49	<0.001
R42	0.00	0.30	0.03	17.49	<0.001	R42	0.95	0.80	0.27	14.98	<0.001
R43	0.00	0.30	0.03	17.49	<0.001	R43	0.65	0.83	0.24	12.37	0.002
R44	0.00	0.30	0.03	17.49	<0.001	R44	0.41	0.71	0.18	11.66	0.003
R45	0.00	0.30	0.03	17.49	<0.001	R45	0.24	0.68	0.03	26.08	<0.001
R46	0.00	0.30	0.03	17.49	<0.001	R46	0.27	0.56	0.03	19.90	<0.001
R47	0.00	0.30	0.03	17.49	<0.001	R47	0.18	0.47	0.03	16.56	<0.001
R48	0.00	0.30	0.03	17.49	<0.001	R48	0.24	0.47	0.03	16.01	<0.001
R49	0.00	0.30	0.03	17.49	<0.001	R49	0.12	0.47	0.00	23.97	<0.001
R50	0.00	0.30	0.03	17.49	<0.001	R50	0.03	0.38	0.00	23.59	<0.001
R51	0.00	0.30	0.03	17.49	<0.001	R51	0.00	0.36	0.00	26.40	<0.001
R52	0.00	0.30	0.03	17.49	<0.001	R52	0.00	0.36	0.00	26.40	<0.001
R53	0.00	0.30	0.03	17.49	<0.001	R53	0.00	0.36	0.00	26.40	<0.001
R54	0.00	0.30	0.03	17.49	<0.001	R54	0.00	0.27	0.00	19.79	<0.001
R55	0.00	0.30	0.03	17.49	<0.001	R55	0.00	0.27	0.00	19.79	<0.001
R56	0.00	0.30	0.03	17.49	<0.001	R56	0.00	0.24	0.00	17.59	<0.001
R57	0.00	0.30	0.03	17.49	<0.001	R57	0.00	0.24	0.00	17.59	<0.001
R58	0.00	0.30	0.03	17.49	<0.001	R58	0.00	0.24	0.00	17.59	<0.001
R59	0.00	0.30	0.03	17.49	<0.001	R59	0.00	0.24	0.00	17.59	<0.001

Table 5.14: Left: IM80, Matrix 1; Right: IM90, Matrix 1

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.	Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	50.83	49.29	50.71	1.98	0.371	R0	50.62	49.62	48.58	2.82	0.244
R1	25.95	35.27	33.46	77.77	<0.001	R1	31.45	40.15	34.82	56.68	<0.001
R2	14.53	27.16	23.02	1.72×10^2	<0.001	R2	20.21	30.41	25.53	93.69	<0.001
R3	7.54	22.63	16.57	3.16×10^2	<0.001	R3	11.33	23.96	19.85	1.96×10^2	<0.001
R4	4.56	18.52	14.17	3.58×10^2	<0.001	R4	6.69	19.62	15.36	2.66×10^2	<0.001
R5	2.34	13.88	11.39	3.60×10^2	<0.001	R5	4.56	15.09	12.63	2.40×10^2	<0.001
R6	1.27	11.69	8.93	3.65×10^2	<0.001	R6	2.69	12.90	9.64	2.75×10^2	<0.001
R7	0.71	9.50	7.81	3.46×10^2	<0.001	R7	1.80	9.79	8.37	2.39×10^2	<0.001
R8	0.33	8.20	5.33	3.22×10^2	<0.001	R8	1.45	7.25	6.21	1.65×10^2	<0.001
R9	0.09	7.25	5.06	3.31×10^2	<0.001	R9	0.86	5.09	4.44	1.30×10^2	<0.001
R10	0.00	7.07	4.08	3.42×10^2	<0.001	R10	0.41	3.43	4.11	1.32×10^2	<0.001
R11	0.00	5.36	3.22	2.58×10^2	<0.001	R11	0.24	2.49	3.67	1.28×10^2	<0.001
R12	0.00	4.94	2.54	2.36×10^2	<0.001	R12	0.15	1.95	2.37	87.77	<0.001
R13	0.00	4.85	2.40	2.31×10^2	<0.001	R13	0.15	1.78	1.75	66.18	<0.001
R14	0.00	3.31	1.69	1.57×10^2	<0.001	R14	0.21	1.75	1.07	47.43	<0.001
R15	0.00	2.22	1.86	1.14×10^2	<0.001	R15	0.24	1.42	0.71	32.35	<0.001
R16	0.00	1.54	1.66	88.31	<0.001	R16	0.24	1.51	0.62	37.13	<0.001
R17	0.00	1.07	1.51	73.56	<0.001	R17	0.09	1.39	0.83	47.14	<0.001
R18	0.00	1.04	0.95	54.69	<0.001	R18	0.12	1.69	0.68	56.85	<0.001
R19	0.00	0.86	0.77	44.92	<0.001	R19	0.03	1.63	0.47	72.35	<0.001
R20	0.00	0.74	1.01	49.41	<0.001	R20	0.00	1.18	0.41	57.09	<0.001
R21	0.00	0.83	0.83	45.57	<0.001	R21	0.00	0.92	0.44	43.13	<0.001
R22	0.00	1.01	0.86	51.69	<0.001	R22	0.00	0.80	0.36	37.66	<0.001
R23	0.00	0.95	0.89	50.53	<0.001	R23	0.00	0.56	0.21	26.89	<0.001
R24	0.00	0.86	0.71	43.59	<0.001	R24	0.00	0.53	0.06	31.00	<0.001
R25	0.00	0.77	0.95	47.83	<0.001	R25	0.00	0.50	0.00	37.41	<0.001
R26	0.00	0.68	0.95	46.24	<0.001	R26	0.00	0.53	0.00	39.61	<0.001
R27	0.00	0.68	1.54	72.74	<0.001	R27	0.00	0.53	0.00	39.61	<0.001
R28	0.00	0.44	1.36	66.31	<0.001	R28	0.00	0.41	0.00	30.80	<0.001
R29	0.00	0.33	1.04	50.66	<0.001	R29	0.00	0.38	0.00	28.60	<0.001
R30	0.00	0.30	0.62	29.19	<0.001	R30	0.00	0.36	0.00	26.40	<0.001
R31	0.00	0.27	0.18	12.78	0.002	R31	0.00	0.36	0.00	26.40	<0.001
R32	0.00	0.27	0.09	12.88	0.002	R32	0.00	0.36	0.00	26.40	<0.001
R33	0.00	0.27	0.03	15.49	<0.001	R33	0.00	0.36	0.00	26.40	<0.001
R34	0.00	0.27	0.03	15.49	<0.001	R34	0.00	0.36	0.00	26.40	<0.001
R35	0.00	0.27	0.03	15.49	<0.001	R35	0.00	0.36	0.00	26.40	<0.001
R36	0.00	0.27	0.03	15.49	<0.001	R36	0.00	0.36	0.00	26.40	<0.001
R37	0.00	0.27	0.03	15.49	<0.001	R37	0.00	0.36	0.00	26.40	<0.001
R38	0.00	0.27	0.03	15.49	<0.001	R38	0.00	0.36	0.00	26.40	<0.001
R39	0.00	0.27	0.03	15.49	<0.001	R39	0.00	0.36	0.00	26.40	<0.001
R40	0.00	0.27	0.03	15.49	<0.001	R40	0.00	0.36	0.00	26.40	<0.001
R41	0.00	0.27	0.03	15.49	<0.001	R41	0.00	0.36	0.00	26.40	<0.001
R42	0.00	0.27	0.03	15.49	<0.001	R42	0.00	0.36	0.00	26.40	<0.001
R43	0.00	0.27	0.03	15.49	<0.001	R43	0.00	0.36	0.00	26.40	<0.001
R44	0.00	0.27	0.03	15.49	<0.001	R44	0.00	0.36	0.00	26.40	<0.001
R45	0.00	0.27	0.03	15.49	<0.001	R45	0.00	0.36	0.00	26.40	<0.001
R46	0.00	0.27	0.03	15.49	<0.001	R46	0.00	0.36	0.00	26.40	<0.001
R47	0.00	0.27	0.03	15.49	<0.001	R47	0.00	0.36	0.00	26.40	<0.001
R48	0.00	0.27	0.03	15.49	<0.001	R48	0.00	0.36	0.00	26.40	<0.001
R49	0.00	0.27	0.03	15.49	<0.001	R49	0.00	0.36	0.00	26.40	<0.001
R50	0.00	0.27	0.03	15.49	<0.001	R50	0.00	0.36	0.00	26.40	<0.001
R51	0.00	0.27	0.03	15.49	<0.001	R51	0.00	0.36	0.00	26.40	<0.001
R52	0.00	0.27	0.03	15.49	<0.001	R52	0.00	0.36	0.00	26.40	<0.001
R53	0.00	0.27	0.03	15.49	<0.001	R53	0.00	0.36	0.00	26.40	<0.001
R54	0.00	0.27	0.03	15.49	<0.001	R54	0.00	0.36	0.00	26.40	<0.001
R55	0.00	0.27	0.03	15.49	<0.001	R55	0.00	0.36	0.00	26.40	<0.001
R56	0.00	0.27	0.03	15.49	<0.001	R56	0.00	0.36	0.00	26.40	<0.001
R57	0.00	0.27	0.03	15.49	<0.001	R57	0.00	0.36	0.00	26.40	<0.001
R58	0.00	0.27	0.03	15.49	<0.001	R58	0.00	0.36	0.00	26.40	<0.001
R59	0.00	0.27	0.03	15.49	<0.001	R59	0.00	0.36	0.00	26.40	<0.001

Table 5.18: Left: IM50, Matrix 2; Right: IM60, Matrix 2

Round	Grid C %	ER5 C %	ER8 C %	G-test stat.	G-test p-val.
R0	49.85	49.38	48.58	1.12	0.572
R1	50.03	48.40	48.46	2.30	0.316
R2	50.65	47.40	46.98	10.93	0.004
R3	50.30	47.04	47.37	8.70	0.013
R4	49.73	47.04	47.51	5.59	0.061
R5	48.49	47.69	47.57	0.67	0.714
R6	49.38	46.72	48.46	4.96	0.084
R7	49.62	47.13	47.75	4.53	0.104
R8	49.64	46.27	47.25	8.16	0.017
R9	50.30	45.21	48.64	18.26	<0.001
R10	50.27	44.73	50.00	26.39	<0.001
R11	49.82	44.41	50.18	28.35	<0.001
R12	50.86	44.56	50.27	32.83	<0.001
R13	50.92	43.73	49.23	38.36	<0.001
R14	50.80	42.13	48.58	55.16	<0.001
R15	51.18	41.54	47.99	65.72	<0.001
R16	51.27	41.80	47.78	62.37	<0.001
R17	50.65	41.39	47.37	60.07	<0.001
R18	50.44	42.63	48.49	44.93	<0.001
R19	49.23	42.60	48.25	34.85	<0.001
R20	48.61	41.78	47.96	38.83	<0.001
R21	49.79	42.43	48.76	43.28	<0.001
R22	48.46	40.92	49.56	60.40	<0.001
R23	47.60	39.35	48.43	69.23	<0.001
R24	48.17	38.05	48.61	98.21	<0.001
R25	48.58	38.58	47.78	84.90	<0.001
R26	47.96	39.05	47.87	71.92	<0.001
R27	47.69	38.88	46.45	62.73	<0.001
R28	46.54	38.02	45.95	62.66	<0.001
R29	46.39	37.75	44.79	58.63	<0.001
R30	45.47	36.18	42.96	64.68	<0.001
R31	45.74	36.95	42.13	54.46	<0.001
R32	44.82	36.12	41.63	54.39	<0.001
R33	44.50	36.01	41.04	51.31	<0.001
R34	43.79	35.71	38.43	47.74	<0.001
R35	44.85	36.54	37.57	57.67	<0.001
R36	42.78	35.33	36.98	43.61	<0.001
R37	42.87	36.66	38.40	29.01	<0.001
R38	42.49	37.96	37.19	23.13	<0.001
R39	43.08	38.11	37.07	29.06	<0.001
R40	41.24	37.99	36.36	17.60	<0.001
R41	40.59	37.07	36.30	14.96	<0.001
R42	39.62	38.17	37.04	4.76	0.092
R43	39.82	37.46	36.54	8.23	0.016
R44	39.70	36.30	37.07	9.14	0.010
R45	40.36	35.21	37.25	19.34	<0.001
R46	39.41	36.21	36.92	8.10	0.017
R47	40.00	36.57	37.57	8.91	0.012
R48	40.27	36.45	38.64	10.49	0.005
R49	41.09	35.95	40.30	21.90	<0.001
R50	41.48	36.21	38.40	19.93	<0.001
R51	40.65	36.83	37.99	10.92	0.004
R52	41.39	36.72	38.73	15.62	<0.001
R53	40.71	36.33	39.32	14.29	<0.001
R54	40.21	37.25	41.33	12.61	0.002
R55	41.66	36.42	41.69	26.06	<0.001
R56	42.60	36.18	41.92	35.18	<0.001
R57	42.66	37.07	41.80	25.56	<0.001
R58	42.40	36.95	41.98	25.91	<0.001
R59	43.08	37.43	41.36	23.60	<0.001

Table 5.26: IM100, Matrix 3

Anti-Correlation of Earnings and Cooperation - Full Tables

Full tables for the anti-correlation analysis of Section 4.2.3 are given here. For tables comparing scores of cooperators to scores of defectors among different agent types, shaded rows indicate that the average score for defection is higher than that of cooperation, and that the difference is statistically significant ($p < 0.05$). For tables calculating the Pearson Correlation, shaded rows indicate that the correlation between cooperation rate and score is negative and statistically significant ($p < 0.05$). Captions give the network type and reward matrix associated with each table.

Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.	Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.
BACTD0	5.14	10.16	7.04×10^4	<0.001	BACTD0	8.28	16.80	1.34×10^5	<0.001
BACTD1	3.00	8.17	8.68×10^4	<0.001	BACTD1	5.16	13.57	1.34×10^5	<0.001
BACTD10	2.58	7.71	7.90×10^4	<0.001	BACTD10	4.11	12.64	1.32×10^5	<0.001
BACTS0	7.13	12.23	5.85×10^4	<0.001	BACTS0	11.81	20.30	9.81×10^4	<0.001
BACTS1	3.93	9.05	8.33×10^4	<0.001	BACTS1	6.63	15.12	1.39×10^5	<0.001
BACTS10	3.28	8.40	8.22×10^4	<0.001	BACTS10	5.37	13.85	1.41×10^5	<0.001
IM0	3.61	5.23	1.42×10^3	<0.001	IM0	7.77	8.57	1.25×10^2	<0.001
IM10	3.93	5.26	1.26×10^3	<0.001	IM10	7.18	8.58	4.21×10^2	<0.001
IM20	3.23	5.23	2.21×10^3	<0.001	IM20	6.78	8.59	7.82×10^2	<0.001
IM30	3.33	5.25	2.37×10^3	<0.001	IM30	6.38	8.62	1.36×10^3	<0.001
IM40	3.22	5.26	2.86×10^3	<0.001	IM40	6.18	8.65	1.85×10^3	<0.001
IM50	3.08	5.28	3.32×10^3	<0.001	IM50	5.53	8.68	3.52×10^3	<0.001
IM60	3.18	5.31	3.74×10^3	<0.001	IM60	5.54	8.73	4.05×10^3	<0.001
IM70	2.73	5.36	6.69×10^3	<0.001	IM70	5.04	8.83	7.32×10^3	<0.001
IM80	2.80	5.45	8.43×10^3	<0.001	IM80	5.08	9.05	1.10×10^4	<0.001
IM90	3.03	5.84	1.45×10^4	<0.001	IM90	4.92	9.61	2.17×10^4	<0.001
IM100	5.76	8.82	2.29×10^4	<0.001	IM100	9.82	15.95	5.16×10^4	<0.001

Table 5.27: Left: ER5, Matrix 1; Right: ER8, Matrix 1

Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.	Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.
BACTD0	8.01	16.01	4.07×10^5	<0.001	BACTD0	2.51	3.58	1.56×10^4	<0.001
BACTD1	4.74	12.76	4.07×10^5	<0.001	BACTD1	2.24	3.10	1.10×10^4	<0.001
BACTD10	4.00	11.93	3.98×10^5	<0.001	BACTD10	1.82	2.67	1.15×10^4	<0.001
BACTS0	11.11	19.11	4.10×10^5	<0.001	BACTS0	3.56	4.99	1.99×10^4	<0.001
BACTS1	6.26	14.21	3.96×10^5	<0.001	BACTS1	2.91	4.07	1.64×10^4	<0.001
BACTS10	5.05	13.05	4.07×10^5	<0.001	BACTS10	2.16	3.00	1.09×10^4	<0.001
IM0	7.82	8.07	1.49×10^2	<0.001	IM0	3.75	1.35	5.63×10^4	<0.001
IM10	7.44	8.08	1.04×10^3	<0.001	IM10	3.04	0.89	5.14×10^4	<0.001
IM20	6.61	8.10	5.57×10^3	<0.001	IM20	2.68	0.83	3.94×10^4	<0.001
IM30	6.25	8.12	8.84×10^3	<0.001	IM30	2.16	0.53	3.06×10^4	<0.001
IM40	5.78	8.15	1.45×10^4	<0.001	IM40	1.80	0.23	2.89×10^4	<0.001
IM50	5.64	8.18	1.66×10^4	<0.001	IM50	1.59	0.20	2.26×10^4	<0.001
IM60	5.40	8.23	2.09×10^4	<0.001	IM60	1.59	0.19	2.22×10^4	<0.001
IM70	5.17	8.32	2.65×10^4	<0.001	IM70	1.43	0.22	1.67×10^4	<0.001
IM80	4.94	8.45	3.38×10^4	<0.001	IM80	1.60	0.38	1.61×10^4	<0.001
IM90	5.22	8.93	3.92×10^4	<0.001	IM90	1.71	0.67	1.13×10^4	<0.001
IM100	9.22	13.53	5.65×10^4	<0.001	IM100	2.90	3.02	1.37×10^2	<0.001

Table 5.28: Left: Grid, Matrix 1; Right: ER5, Matrix 2

Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.	Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.
BACTD0	4.25	5.97	2.44×10^4	<0.001	BACTD0	3.96	5.53	4.24×10^4	<0.001
BACTD1	3.72	5.27	2.21×10^4	<0.001	BACTD1	3.44	4.94	3.80×10^4	<0.001
BACTD10	3.00	4.30	1.65×10^4	<0.001	BACTD10	2.79	4.04	2.56×10^4	<0.001
BACTS0	5.90	8.27	3.30×10^4	<0.001	BACTS0	5.57	7.77	9.55×10^4	<0.001
BACTS1	4.89	6.84	2.80×10^4	<0.001	BACTS1	4.57	6.40	5.98×10^4	<0.001
BACTS10	3.56	4.98	1.86×10^4	<0.001	BACTS10	3.28	4.59	2.74×10^4	<0.001
IM0	5.69	1.52	8.20×10^4	<0.001	IM0	6.88	0.52	5.58×10^5	<0.001
IM10	4.62	0.70	7.32×10^4	<0.001	IM10	5.13	0.21	2.00×10^5	<0.001
IM20	3.56	0.44	4.84×10^4	<0.001	IM20	4.32	0.14	1.24×10^5	<0.001
IM30	3.22	0.62	3.50×10^4	<0.001	IM30	3.06	8.79×10^{-2}	4.97×10^4	<0.001
IM40	2.71	0.19	3.11×10^4	<0.001	IM40	2.83	0.10	4.33×10^4	<0.001
IM50	2.51	0.30	2.55×10^4	<0.001	IM50	2.79	0.13	4.14×10^4	<0.001
IM60	2.55	0.29	2.55×10^4	<0.001	IM60	2.71	0.17	3.82×10^4	<0.001
IM70	2.49	0.35	2.26×10^4	<0.001	IM70	2.55	0.23	3.21×10^4	<0.001
IM80	2.37	0.54	1.72×10^4	<0.001	IM80	2.57	0.38	2.96×10^4	<0.001
IM90	2.32	1.14	7.76×10^3	<0.001	IM90	2.81	0.90	2.35×10^4	<0.001
IM100	4.91	5.33	9.38×10^2	<0.001	IM100	4.87	4.15	4.29×10^3	<0.001

Table 5.29: Left: ER8, Matrix 2; Right: Grid, Matrix 2

Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.	Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.
BACTD0	25.71	30.54	4.25×10^3	<0.001	BACTD0	41.27	50.24	9.23×10^3	<0.001
BACTD1	23.67	28.64	4.78×10^3	<0.001	BACTD1	38.46	47.37	9.36×10^3	<0.001
BACTD10	19.61	24.97	6.27×10^3	<0.001	BACTD10	33.37	41.89	9.51×10^3	<0.001
BACTS0	35.69	40.82	3.09×10^3	<0.001	BACTS0	58.96	67.36	4.98×10^3	<0.001
BACTS1	32.52	37.48	3.40×10^3	<0.001	BACTS1	53.01	61.48	6.23×10^3	<0.001
BACTS10	25.33	30.20	4.35×10^3	<0.001	BACTS10	42.06	50.48	8.02×10^3	<0.001
IM0	45.19	22.51	4.05×10^4	<0.001	IM0	76.79	34.74	6.88×10^4	<0.001
IM10	47.41	21.81	4.20×10^4	<0.001	IM10	72.61	23.53	1.44×10^5	<0.001
IM20	46.11	19.14	6.14×10^4	<0.001	IM20	69.73	20.59	1.61×10^5	<0.001
IM30	42.35	21.69	4.28×10^4	<0.001	IM30	53.63	17.47	9.24×10^4	<0.001
IM40	35.92	14.03	6.59×10^4	<0.001	IM40	42.44	11.79	6.69×10^4	<0.001
IM50	26.89	11.96	3.49×10^4	<0.001	IM50	30.20	10.90	2.79×10^4	<0.001
IM60	19.80	8.51	2.08×10^4	<0.001	IM60	31.20	11.25	2.95×10^4	<0.001
IM70	19.58	8.87	1.87×10^4	<0.001	IM70	28.93	11.93	2.23×10^4	<0.001
IM80	20.41	9.06	2.06×10^4	<0.001	IM80	26.02	12.66	1.42×10^4	<0.001
IM90	22.97	12.69	1.58×10^4	<0.001	IM90	26.57	17.84	6.47×10^3	<0.001
IM100	25.12	22.57	9.57×10^2	<0.001	IM100	45.19	39.03	2.82×10^3	<0.001

Table 5.30: Left: ER5, Matrix 3; Right: ER8, Matrix 3

Agent	Avg. C Score	Avg. D Score	ANOVA stat.	ANOVA p-val.
BACTD0	39.89	48.04	1.69×10^4	<0.001
BACTD1	36.53	44.65	1.69×10^4	<0.001
BACTD10	31.26	39.20	1.58×10^4	<0.001
BACTS0	55.77	63.75	1.62×10^4	<0.001
BACTS1	50.30	58.12	1.54×10^4	<0.001
BACTS10	40.07	47.89	1.52×10^4	<0.001
IM0	73.11	38.85	1.29×10^5	<0.001
IM10	75.50	25.27	4.00×10^5	<0.001
IM20	71.06	26.42	2.77×10^5	<0.001
IM30	64.23	29.73	1.47×10^5	<0.001
IM40	57.99	21.70	1.61×10^5	<0.001
IM50	44.07	13.39	1.09×10^5	<0.001
IM60	35.53	10.52	6.76×10^4	<0.001
IM70	29.35	10.56	3.86×10^4	<0.001
IM80	29.52	11.65	3.48×10^4	<0.001
IM90	30.57	16.72	2.19×10^4	<0.001
IM100	46.32	36.36	1.23×10^4	<0.001

Table 5.31: Grid, Matrix 3

Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.	Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.
BACTD0	49.34	7.68	-0.38	<0.001	BACTD0	48.93	12.63	-0.51	<0.001
BACTD1	29.50	6.65	-0.43	<0.001	BACTD1	30.03	11.04	-0.51	<0.001
BACTD10	24.95	6.43	-0.42	<0.001	BACTD10	24.39	10.56	-0.53	<0.001
BACTS0	69.32	8.70	-0.07	<0.001	BACTS0	69.58	14.39	-0.10	<0.001
BACTS1	38.20	7.10	-0.11	<0.001	BACTS1	39.11	11.80	-0.13	<0.001
BACTS10	31.85	6.77	-0.10	<0.001	BACTS10	31.61	11.17	-0.14	<0.001
IM0	1.51	5.21	-0.11	<0.001	IM0	0.89	8.56	-0.09	<0.001
IM10	2.17	5.23	-0.08	<0.001	IM10	0.99	8.57	-0.09	<0.001
IM20	1.51	5.20	-0.14	<0.001	IM20	1.07	8.57	-0.07	<0.001
IM30	1.78	5.21	-0.12	<0.001	IM30	1.27	8.59	-0.03	0.076
IM40	1.92	5.22	-0.13	<0.001	IM40	1.49	8.61	-0.03	0.051
IM50	2.16	5.23	-0.12	<0.001	IM50	1.69	8.63	-0.07	<0.001
IM60	2.50	5.26	-0.09	<0.001	IM60	2.09	8.66	-0.06	<0.001
IM70	3.17	5.28	-0.14	<0.001	IM70	2.86	8.73	-0.06	<0.001
IM80	4.29	5.34	-0.14	<0.001	IM80	4.54	8.87	-0.08	<0.001
IM90	9.00	5.59	-0.09	<0.001	IM90	8.58	9.21	-0.07	<0.001
IM100	44.93	7.44	-0.02	0.376	IM100	51.01	12.82	-0.03	0.136

Table 5.32: Left: ER5, Matrix 1; Right: ER8, Matrix 1

Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.	Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.
BACTD0	50.05	12.00	-0.82	<0.001	BACTD0	49.48	3.05	-0.22	<0.001
BACTD1	29.69	10.38	-0.83	<0.001	BACTD1	43.17	2.73	-0.18	<0.001
BACTD10	24.68	9.97	-0.82	<0.001	BACTD10	36.83	2.36	-0.24	<0.001
BACTS0	69.45	13.56	-0.82	<0.001	BACTS0	69.33	4.00	-0.04	0.018
BACTS1	38.94	11.12	-0.80	<0.001	BACTS1	56.66	3.41	-0.06	<0.001
BACTS10	31.56	10.52	-0.82	<0.001	BACTS10	41.80	2.65	-0.03	0.099
IM0	0.83	8.07	-0.82	<0.001	IM0	40.70	2.32	0.06	0.001
IM10	0.94	8.08	-0.78	<0.001	IM10	23.12	1.39	0.01	0.651
IM20	1.03	8.08	-0.75	<0.001	IM20	19.61	1.20	0.03	0.058
IM30	1.19	8.10	-0.73	<0.001	IM30	11.41	0.72	0.10	<0.001
IM40	1.48	8.12	-0.70	<0.001	IM40	5.07	0.31	0.14	<0.001
IM50	1.69	8.14	-0.60	<0.001	IM50	4.18	0.26	0.03	0.112
IM60	2.17	8.17	-0.57	<0.001	IM60	4.17	0.25	0.03	0.096
IM70	2.83	8.23	-0.36	<0.001	IM70	4.63	0.28	-0.01	0.704
IM80	3.94	8.32	-0.22	<0.001	IM80	7.35	0.47	0.16	<0.001
IM90	7.97	8.64	-0.01	0.571	IM90	12.63	0.80	0.11	<0.001
IM100	44.92	11.59	0.35	<0.001	IM100	49.16	2.96	0.03	0.043

Table 5.33: Left: Grid, Matrix 1; Right: ER5, Matrix 2

Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.	Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.
BACTD0	50.13	5.11	-0.26	<0.001	BACTD0	49.42	4.75	-0.43	<0.001
BACTD1	44.17	4.59	-0.27	<0.001	BACTD1	43.64	4.29	-0.47	<0.001
BACTD10	35.99	3.83	-0.26	<0.001	BACTD10	35.65	3.60	-0.43	<0.001
BACTS0	69.58	6.62	-0.06	<0.001	BACTS0	69.53	6.24	-0.57	<0.001
BACTS1	57.58	5.72	-0.05	0.002	BACTS1	57.16	5.36	-0.47	<0.001
BACTS10	41.90	4.38	-0.07	<0.001	BACTS10	41.00	4.05	-0.35	<0.001
IM0	26.97	2.64	0.04	0.015	IM0	24.80	2.10	-0.11	<0.001
IM10	11.17	1.14	0.07	<0.001	IM10	4.95	0.45	-0.22	<0.001
IM20	6.00	0.63	0.03	0.145	IM20	2.68	0.25	0.00	0.932
IM30	7.69	0.82	0.15	<0.001	IM30	1.25	0.13	-0.04	0.021
IM40	2.40	0.25	0.07	<0.001	IM40	1.43	0.14	0.09	<0.001
IM50	3.48	0.37	0.11	<0.001	IM50	1.80	0.18	0.30	<0.001
IM60	3.39	0.37	0.10	<0.001	IM60	2.23	0.23	0.41	<0.001
IM70	4.02	0.43	0.14	<0.001	IM70	2.88	0.29	0.45	<0.001
IM80	5.98	0.65	0.14	<0.001	IM80	4.72	0.48	0.58	<0.001
IM90	11.66	1.27	0.14	<0.001	IM90	10.99	1.11	0.72	<0.001
IM100	51.65	5.12	0.02	0.194	IM100	48.65	4.50	0.83	<0.001

Table 5.34: Left: ER8, Matrix 2; Right: Grid, Matrix 2

Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.	Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.
BACTD0	49.79	28.13	-0.10	<0.001	BACTD0	49.06	45.84	-0.18	<0.001
BACTD1	45.93	26.36	-0.12	<0.001	BACTD1	45.81	43.29	-0.18	<0.001
BACTD10	38.60	22.90	-0.16	<0.001	BACTD10	39.24	38.55	-0.18	<0.001
BACTS0	69.49	37.26	-0.02	0.212	BACTS0	69.44	61.53	-0.02	0.213
BACTS1	63.14	34.35	0.00	0.949	BACTS1	62.47	56.19	-0.03	0.076
BACTS10	48.99	27.81	0.00	0.857	BACTS10	49.51	46.31	-0.02	0.155
IM0	74.06	39.30	0.16	<0.001	IM0	76.67	66.98	0.05	0.002
IM10	80.49	42.41	0.07	<0.001	IM10	55.20	50.62	0.02	0.217
IM20	71.99	38.56	0.09	<0.001	IM20	44.48	42.45	0.02	0.351
IM30	64.49	35.01	0.08	<0.001	IM30	22.39	25.56	0.05	0.002
IM40	35.96	21.90	0.10	<0.001	IM40	7.29	14.02	0.02	0.254
IM50	21.66	15.19	0.14	<0.001	IM50	4.27	11.72	0.03	0.142
IM60	9.89	9.63	0.04	0.021	IM60	4.93	12.23	0.02	0.172
IM70	10.74	10.02	0.05	0.007	IM70	5.87	12.92	0.00	0.930
IM80	11.49	10.37	0.05	0.004	IM80	6.66	13.55	0.04	0.026
IM90	21.11	14.86	0.05	0.008	IM90	13.90	19.06	0.03	0.141
IM100	39.95	23.59	0.10	<0.001	IM100	43.58	41.72	0.02	0.184

Table 5.35: Left: ER5, Matrix 3; Right: ER8, Matrix 3

Agent	Avg. C %	Avg. Score	Pearson coef.	Pearson p-val.
BACTD0	49.96	43.97	-0.30	<0.001
BACTD1	45.75	40.94	-0.31	<0.001
BACTD10	39.03	36.10	-0.30	<0.001
BACTS0	69.70	58.19	-0.28	<0.001
BACTS1	62.79	53.21	-0.22	<0.001
BACTS10	49.98	43.98	-0.25	<0.001
IM0	81.75	66.86	0.18	<0.001
IM10	79.33	65.12	0.29	<0.001
IM20	67.33	56.47	0.34	<0.001
IM30	57.95	49.72	0.53	<0.001
IM40	38.36	35.62	0.53	<0.001
IM50	13.04	17.39	0.68	<0.001
IM60	5.36	11.86	0.70	<0.001
IM70	4.80	11.46	0.65	<0.001
IM80	6.75	12.86	0.74	<0.001
IM90	14.99	18.79	0.72	<0.001
IM100	45.71	40.91	0.81	<0.001

Table 5.36: Grid, Matrix 3

Cooperation Hysteresis - Full Tables

Full tables for the hysteresis portion of the MCC analysis of Section 4.2.4 are given here. For each table, we compare cooperation rates after either cooperating or defecting on the last turn. Shaded rows indicate that cooperation is higher after previously cooperating than it is after previously defecting (i.e. hysteresis is observed) and that the difference is statistically significant ($p < 0.05$). Captions give the network type and reward matrix associated with each table.

Agent	C After C %	C After D %	G-test stat.	G-test p-val.	Agent	C After C %	C After D %	G-test stat.	G-test p-val.
BACTD0	68.42	30.77	2.90×10^4	<0.001	BACTD0	68.25	30.43	2.92×10^4	<0.001
BACTD1	56.94	17.92	2.91×10^4	<0.001	BACTD1	57.63	18.09	3.00×10^4	<0.001
BACTD10	58.47	13.78	3.64×10^4	<0.001	BACTD10	57.69	13.62	3.52×10^4	<0.001
BACTS0	69.26	69.49	1.12	0.290	BACTS0	69.50	69.73	1.10	0.293
BACTS1	37.34	38.66	34.86	<0.001	BACTS1	38.15	39.69	47.23	<0.001
BACTS10	31.74	31.82	0.14	0.707	BACTS10	31.59	31.53	5.56×10^{-2}	0.814
IM0	44.27	0.04	1.13×10^4	<0.001	IM0	3.84	0.02	4.92×10^2	<0.001
IM10	52.87	0.21	1.68×10^4	<0.001	IM10	8.99	0.07	1.23×10^3	<0.001
IM20	33.77	0.20	7.34×10^3	<0.001	IM20	9.76	0.14	1.27×10^3	<0.001
IM30	34.40	0.36	7.87×10^3	<0.001	IM30	16.26	0.26	2.44×10^3	<0.001
IM40	32.13	0.48	7.31×10^3	<0.001	IM40	18.08	0.40	2.89×10^3	<0.001
IM50	30.61	0.70	6.97×10^3	<0.001	IM50	19.61	0.56	3.27×10^3	<0.001
IM60	27.25	1.05	6.01×10^3	<0.001	IM60	21.22	0.85	3.87×10^3	<0.001
IM70	30.98	1.45	7.95×10^3	<0.001	IM70	22.47	1.46	4.51×10^3	<0.001
IM80	30.06	2.31	8.21×10^3	<0.001	IM80	25.13	2.72	5.96×10^3	<0.001
IM90	29.73	6.16	8.21×10^3	<0.001	IM90	26.46	6.07	6.27×10^3	<0.001
IM100	56.11	35.66	8.38×10^3	<0.001	IM100	57.72	44.04	3.74×10^3	<0.001

Table 5.37: Left: ER5, Matrix 1; Right: ER8, Matrix 1

Agent	C After C %	C After D %	G-test stat.	G-test p-val.	Agent	C After C %	C After D %	G-test stat.	G-test p-val.
BACTD0	68.17	31.88	2.69×10^4	<0.001	BACTD0	68.30	31.04	2.84×10^4	<0.001
BACTD1	57.22	17.98	2.94×10^4	<0.001	BACTD1	62.40	28.57	2.31×10^4	<0.001
BACTD10	57.50	13.91	3.45×10^4	<0.001	BACTD10	56.84	25.22	1.98×10^4	<0.001
BACTS0	69.37	69.64	1.37	0.242	BACTS0	69.33	69.37	3.76×10^{-2}	0.846
BACTS1	38.44	39.18	10.87	<0.001	BACTS1	55.36	58.33	1.76×10^2	<0.001
BACTS10	31.62	31.49	0.31	0.579	BACTS10	39.43	43.56	3.41×10^2	<0.001
IM0	0.42	0.00	58.48	<0.001	IM0	91.00	6.01	1.66×10^5	<0.001
IM10	5.86	0.04	7.70×10^2	<0.001	IM10	74.44	7.12	8.24×10^4	<0.001
IM20	8.07	0.13	9.79×10^2	<0.001	IM20	64.79	7.89	5.51×10^4	<0.001
IM30	12.35	0.21	1.70×10^3	<0.001	IM30	51.57	5.42	2.98×10^4	<0.001
IM40	15.73	0.41	2.37×10^3	<0.001	IM40	42.19	2.23	1.62×10^4	<0.001
IM50	17.21	0.56	2.74×10^3	<0.001	IM50	35.88	1.98	1.13×10^4	<0.001
IM60	20.36	0.90	3.69×10^3	<0.001	IM60	36.64	1.93	1.17×10^4	<0.001
IM70	22.80	1.42	4.63×10^3	<0.001	IM70	32.65	2.45	9.75×10^3	<0.001
IM80	25.28	2.28	5.84×10^3	<0.001	IM80	31.78	4.59	9.84×10^3	<0.001
IM90	29.43	5.30	8.23×10^3	<0.001	IM90	33.71	8.77	1.01×10^4	<0.001
IM100	57.40	34.55	1.05×10^4	<0.001	IM100	56.52	41.98	4.23×10^3	<0.001

Table 5.38: Left: Grid, Matrix 1; Right: ER5, Matrix 2

Agent	C After C %	C After D %	G-test stat.	G-test p-val.	Agent	C After C %	C After D %	G-test stat.	G-test p-val.
BACTD0	68.40	31.79	2.74×10^4	<0.001	BACTD0	67.73	31.53	2.67×10^4	<0.001
BACTD1	63.09	29.17	2.33×10^4	<0.001	BACTD1	62.60	28.95	2.29×10^4	<0.001
BACTD10	56.75	24.38	2.07×10^4	<0.001	BACTD10	56.70	24.03	2.11×10^4	<0.001
BACTS0	69.69	69.24	3.99	0.046	BACTS0	69.47	69.65	0.64	0.422
BACTS1	56.64	58.96	1.07×10^2	<0.001	BACTS1	55.99	58.66	1.42×10^2	<0.001
BACTS10	39.69	43.54	2.96×10^2	<0.001	BACTS10	38.86	42.53	2.69×10^2	<0.001
IM0	91.54	2.62	1.64×10^5	<0.001	IM0	82.13	5.28	1.13×10^5	<0.001
IM10	67.47	3.30	5.45×10^4	<0.001	IM10	59.15	1.31	2.94×10^4	<0.001
IM20	49.90	2.34	2.35×10^4	<0.001	IM20	42.32	0.75	1.26×10^4	<0.001
IM30	46.97	3.60	2.24×10^4	<0.001	IM30	13.53	0.26	1.91×10^3	<0.001
IM40	25.06	1.01	5.22×10^3	<0.001	IM40	17.04	0.39	2.59×10^3	<0.001
IM50	27.06	1.79	6.53×10^3	<0.001	IM50	19.75	0.62	3.40×10^3	<0.001
IM60	24.59	1.84	5.43×10^3	<0.001	IM60	21.52	0.94	4.02×10^3	<0.001
IM70	24.60	2.32	5.64×10^3	<0.001	IM70	23.87	1.44	5.00×10^3	<0.001
IM80	24.91	3.97	5.84×10^3	<0.001	IM80	26.37	2.82	6.54×10^3	<0.001
IM90	25.75	9.03	4.72×10^3	<0.001	IM90	32.39	7.51	9.64×10^3	<0.001
IM100	58.04	44.80	3.51×10^3	<0.001	IM100	60.81	37.11	1.13×10^4	<0.001

Table 5.39: Left: ER8, Matrix 2; Right: Grid, Matrix 2

Agent	C After C %	C After D %	G-test stat.	G-test p-val.	Agent	C After C %	C After D %	G-test stat.	G-test p-val.
BACTD0	68.55	31.21	2.85×10^4	<0.001	BACTD0	67.74	31.03	2.75×10^4	<0.001
BACTD1	64.96	29.68	2.53×10^4	<0.001	BACTD1	65.10	29.43	2.59×10^4	<0.001
BACTD10	60.37	24.74	2.54×10^4	<0.001	BACTD10	60.61	25.30	2.50×10^4	<0.001
BACTS0	69.44	69.56	0.31	0.575	BACTS0	69.38	69.53	0.48	0.489
BACTS1	62.89	63.42	5.67	0.017	BACTS1	62.13	62.90	12.01	<0.001
BACTS10	48.07	49.61	47.28	<0.001	BACTS10	48.30	50.46	93.30	<0.001
IM0	95.93	13.48	1.35×10^5	<0.001	IM0	97.54	10.51	1.48×10^5	<0.001
IM10	95.33	22.77	9.12×10^4	<0.001	IM10	91.01	11.61	1.43×10^5	<0.001
IM20	92.79	20.62	1.04×10^5	<0.001	IM20	86.65	10.64	1.29×10^5	<0.001
IM30	86.23	26.15	7.42×10^4	<0.001	IM30	69.66	8.13	6.77×10^4	<0.001
IM40	73.77	14.30	7.26×10^4	<0.001	IM40	52.03	2.93	2.73×10^4	<0.001
IM50	56.78	11.19	3.70×10^4	<0.001	IM50	34.82	2.08	1.07×10^4	<0.001
IM60	43.26	5.41	1.97×10^4	<0.001	IM60	34.97	2.57	1.12×10^4	<0.001
IM70	40.84	6.33	1.72×10^4	<0.001	IM70	32.04	3.40	9.87×10^3	<0.001
IM80	40.85	6.88	1.72×10^4	<0.001	IM80	28.24	4.32	7.61×10^3	<0.001
IM90	44.94	14.02	1.72×10^4	<0.001	IM90	30.33	10.50	6.74×10^3	<0.001
IM100	48.76	33.81	4.45×10^3	<0.001	IM100	53.23	35.96	5.96×10^3	<0.001

Table 5.40: Left: ER5, Matrix 3; Right: ER8, Matrix 3

Agent	C After C %	C After D %	G-test stat.	G-test p-val.
BACTD0	68.67	31.28	2.86×10^4	<0.001
BACTD1	65.13	29.35	2.60×10^4	<0.001
BACTD10	60.60	25.05	2.53×10^4	<0.001
BACTS0	69.71	69.71	3.16×10^{-5}	0.996
BACTS1	62.62	62.90	1.51	0.219
BACTS10	48.91	50.86	76.04	<0.001
IM0	98.60	9.49	1.40×10^5	<0.001
IM10	96.08	17.93	1.09×10^5	<0.001
IM20	90.91	20.05	1.04×10^5	<0.001
IM30	82.63	24.65	7.07×10^4	<0.001
IM40	74.67	15.49	7.26×10^4	<0.001
IM50	55.07	5.91	3.56×10^4	<0.001
IM60	40.92	2.50	1.55×10^4	<0.001
IM70	32.37	2.60	9.66×10^3	<0.001
IM80	34.02	3.96	1.13×10^4	<0.001
IM90	36.80	10.36	1.18×10^4	<0.001
IM100	57.74	35.43	9.99×10^3	<0.001

Table 5.41: Grid, Matrix 3

Cooperation Conditionality - Full Tables

Full tables for the conditionality portion of the MCC analysis of Section 4.2.4 are given here. For each table, we compare cooperation rates after being surrounded by a majority of either cooperators or defectors on the last turn. Shaded rows indicate that cooperation is higher near other cooperators than near defectors (i.e. conditionality is observed) and that the difference is statistically significant ($p < 0.05$). Captions give the network type and reward matrix associated with each table.

Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.	Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.
BACTD0	49.69	48.71	15.70	<0.001	BACTD0	48.97	48.71	1.13	0.288
BACTD1	28.53	29.34	6.38	0.012	BACTD1	30.78	29.85	6.38	0.012
BACTD10	24.02	25.10	9.03	0.003	BACTD10	21.76	24.57	34.80	<0.001
BACTS0	69.29	69.52	0.52	0.472	BACTS0	69.59	69.43	0.18	0.675
BACTS1	38.53	37.93	4.85	0.028	BACTS1	39.54	39.02	3.62	0.057
BACTS10	32.40	31.66	5.94	0.015	BACTS10	32.04	31.50	2.39	0.122
IM0	22.33	0.37	1.92×10^3	<0.001	IM0	6.75	0.01	8.58×10^2	<0.001
IM10	39.36	0.61	4.59×10^3	<0.001	IM10	14.13	0.05	1.67×10^3	<0.001
IM20	33.33	0.15	3.80×10^3	<0.001	IM20	16.48	0.10	1.75×10^3	<0.001
IM30	39.63	0.31	4.78×10^3	<0.001	IM30	24.46	0.25	2.42×10^3	<0.001
IM40	43.40	0.33	6.10×10^3	<0.001	IM40	33.89	0.32	3.86×10^3	<0.001
IM50	47.73	0.46	6.75×10^3	<0.001	IM50	35.49	0.49	3.72×10^3	<0.001
IM60	52.30	0.73	8.16×10^3	<0.001	IM60	42.51	0.74	5.17×10^3	<0.001
IM70	54.97	1.00	9.16×10^3	<0.001	IM70	48.64	1.32	6.05×10^3	<0.001
IM80	62.24	1.55	1.31×10^4	<0.001	IM80	55.37	2.39	9.58×10^3	<0.001
IM90	68.20	4.07	2.42×10^4	<0.001	IM90	59.26	5.41	1.31×10^4	<0.001
IM100	79.93	17.56	7.31×10^4	<0.001	IM100	73.78	27.05	4.12×10^4	<0.001

Table 5.42: Left: ER5, Matrix 1; Right: ER8, Matrix 1

Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.	Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.
BACTD0	50.27	49.91	1.78	0.182	BACTD0	48.96	49.91	14.84	<0.001
BACTD1	28.37	29.73	9.24	0.002	BACTD1	42.33	43.28	13.89	<0.001
BACTD10	24.93	24.57	0.31	0.578	BACTD10	34.06	37.86	1.91×10^2	<0.001
BACTS0	69.46	69.13	0.55	0.457	BACTS0	69.32	69.56	0.57	0.450
BACTS1	39.62	38.52	12.97	<0.001	BACTS1	56.80	56.34	3.37	0.066
BACTS10	32.62	31.49	7.59	0.006	BACTS10	42.29	41.49	9.72	0.002
IM0	0.58	0.00	62.71	<0.001	IM0	78.29	12.31	8.45×10^4	<0.001
IM10	7.77	0.03	7.96×10^2	<0.001	IM10	71.41	9.73	5.15×10^4	<0.001
IM20	16.20	0.07	1.55×10^3	<0.001	IM20	69.48	9.25	4.06×10^4	<0.001
IM30	21.53	0.15	1.98×10^3	<0.001	IM30	62.37	5.93	2.22×10^4	<0.001
IM40	28.48	0.32	2.60×10^3	<0.001	IM40	57.18	2.11	1.32×10^4	<0.001
IM50	33.81	0.45	3.27×10^3	<0.001	IM50	53.93	1.73	9.98×10^3	<0.001
IM60	42.83	0.72	4.55×10^3	<0.001	IM60	60.71	1.45	1.35×10^4	<0.001
IM70	48.93	1.19	5.46×10^3	<0.001	IM70	59.54	1.81	1.25×10^4	<0.001
IM80	54.78	1.99	6.67×10^3	<0.001	IM80	66.27	3.18	2.15×10^4	<0.001
IM90	61.25	4.56	1.21×10^4	<0.001	IM90	69.82	5.59	3.29×10^4	<0.001
IM100	75.92	21.30	5.17×10^4	<0.001	IM100	79.14	20.02	6.55×10^4	<0.001

Table 5.43: Left: Grid, Matrix 1; Right: ER5, Matrix 2

Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.	Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.
BACTD0	49.73	50.67	15.16	<0.001	BACTD0	49.65	49.09	4.50	0.034
BACTD1	42.96	44.80	53.76	<0.001	BACTD1	41.80	44.89	1.24×10^2	<0.001
BACTD10	34.68	36.52	38.31	<0.001	BACTD10	30.95	36.87	2.89×10^2	<0.001
BACTS0	69.70	68.66	8.11	0.004	BACTS0	69.46	69.83	0.74	0.389
BACTS1	57.86	57.22	6.09	0.014	BACTS1	57.29	56.82	2.78	0.096
BACTS10	42.09	41.79	1.30	0.255	BACTS10	41.22	40.91	1.16	0.282
IM0	70.90	9.13	6.96×10^4	<0.001	IM0	78.44	5.61	1.02×10^5	<0.001
IM10	64.57	4.72	3.52×10^4	<0.001	IM10	61.60	1.29	2.52×10^4	<0.001
IM20	54.14	3.22	1.27×10^4	<0.001	IM20	51.29	0.71	1.10×10^4	<0.001
IM30	55.14	4.78	1.14×10^4	<0.001	IM30	22.23	0.19	2.01×10^3	<0.001
IM40	42.95	1.01	5.05×10^3	<0.001	IM40	32.66	0.32	2.76×10^3	<0.001
IM50	46.80	1.87	5.55×10^3	<0.001	IM50	35.22	0.52	3.35×10^3	<0.001
IM60	48.99	1.76	6.30×10^3	<0.001	IM60	44.56	0.77	4.81×10^3	<0.001
IM70	53.21	2.12	8.02×10^3	<0.001	IM70	50.08	1.23	5.45×10^3	<0.001
IM80	55.81	3.67	9.25×10^3	<0.001	IM80	55.45	2.44	8.02×10^3	<0.001
IM90	60.06	8.08	1.29×10^4	<0.001	IM90	63.14	6.14	1.73×10^4	<0.001
IM100	73.70	27.46	4.02×10^4	<0.001	IM100	77.04	22.04	5.42×10^4	<0.001

Table 5.44: Left: ER8, Matrix 2; Right: Grid, Matrix 2

Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.	Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.
BACTD0	50.44	49.07	30.66	<0.001	BACTD0	48.88	49.42	5.02	0.025
BACTD1	46.40	45.90	3.88	0.049	BACTD1	45.46	45.69	0.85	0.358
BACTD10	37.36	38.96	35.79	<0.001	BACTD10	37.93	39.67	41.16	<0.001
BACTS0	69.49	69.33	0.25	0.620	BACTS0	69.40	69.58	0.24	0.624
BACTS1	63.35	62.29	14.71	<0.001	BACTS1	62.64	61.75	9.57	0.002
BACTS10	49.55	48.22	28.85	<0.001	BACTS10	50.14	48.69	36.14	<0.001
IM0	91.01	16.70	8.15×10^4	<0.001	IM0	92.02	16.15	8.74×10^4	<0.001
IM10	94.57	18.88	8.08×10^4	<0.001	IM10	87.96	8.40	1.37×10^5	<0.001
IM20	93.07	15.73	1.06×10^5	<0.001	IM20	86.94	8.41	1.36×10^5	<0.001
IM30	88.39	17.87	9.14×10^4	<0.001	IM30	76.53	7.59	7.33×10^4	<0.001
IM40	81.65	9.99	9.83×10^4	<0.001	IM40	67.41	2.63	3.14×10^4	<0.001
IM50	72.69	8.15	5.76×10^4	<0.001	IM50	55.94	2.08	1.08×10^4	<0.001
IM60	67.73	4.21	2.88×10^4	<0.001	IM60	58.78	2.29	1.40×10^4	<0.001
IM70	68.14	4.44	3.11×10^4	<0.001	IM70	59.32	3.02	1.43×10^4	<0.001
IM80	69.59	4.47	3.71×10^4	<0.001	IM80	59.07	3.87	1.26×10^4	<0.001
IM90	75.84	8.38	5.79×10^4	<0.001	IM90	62.99	8.93	1.87×10^4	<0.001
IM100	77.40	17.68	6.22×10^4	<0.001	IM100	72.65	23.41	4.47×10^4	<0.001

Table 5.45: Left: ER5, Matrix 3; Right: ER8, Matrix 3

Agent	C Near C %	C Near D %	G-test stat.	G-test p-val.
BACTD0	49.55	50.16	5.32	0.021
BACTD1	45.30	45.89	4.74	0.029
BACTD10	37.75	39.17	21.71	<0.001
BACTS0	69.72	69.47	0.31	0.578
BACTS1	63.00	62.09	7.82	0.005
BACTS10	50.28	49.19	17.33	<0.001
IM0	90.74	19.32	5.04×10^4	<0.001
IM10	94.41	12.46	9.84×10^4	<0.001
IM20	89.67	11.70	1.08×10^5	<0.001
IM30	84.37	16.09	8.83×10^4	<0.001
IM40	81.09	10.42	9.79×10^4	<0.001
IM50	72.78	4.61	4.57×10^4	<0.001
IM60	66.24	2.04	1.90×10^4	<0.001
IM70	60.84	2.21	1.17×10^4	<0.001
IM80	62.31	3.28	1.48×10^4	<0.001
IM90	66.64	8.22	2.41×10^4	<0.001
IM100	75.49	21.72	5.06×10^4	<0.001

Table 5.46: Grid, Matrix 3

Player Stratification - Full Tables

Full tables for the player stratification analysis of Section 4.2.5 are given here. For each table, we compare player binning according to the 5 groups of Grujić et al. [19]. Shaded rows indicate adherence to Equation 4.1. Captions give the network type and reward matrix associated with each table.

Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %	Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %
BACTD0	5.44	30.03	31.15	28.46	4.91	BACTD0	5.98	29.94	31.21	27.78	5.09
BACTD1	11.92	52.19	21.60	13.64	0.65	BACTD1	11.15	51.92	21.89	14.41	0.62
BACTD10	24.14	45.33	17.28	12.96	0.30	BACTD10	23.08	46.95	17.46	12.19	0.33
BACTS0	0.00	0.00	35.92	64.08	0.00	BACTS0	0.00	0.00	32.01	67.99	0.00
BACTS1	0.00	20.86	79.14	0.00	0.00	BACTS1	0.00	16.27	83.73	0.00	0.00
BACTS10	0.00	59.79	40.21	0.00	0.00	BACTS10	0.00	61.27	38.73	0.00	0.00
IM0	90.95	8.49	0.00	0.03	0.53	IM0	96.57	3.43	0.00	0.00	0.00
IM10	82.49	16.39	0.00	0.89	0.24	IM10	90.53	9.47	0.00	0.00	0.00
IM20	78.37	21.36	0.00	0.00	0.27	IM20	86.09	13.91	0.00	0.00	0.00
IM30	67.99	31.78	0.00	0.00	0.24	IM30	77.28	22.72	0.00	0.00	0.00
IM40	60.36	39.41	0.00	0.00	0.24	IM40	65.30	34.70	0.00	0.00	0.00
IM50	51.54	48.22	0.00	0.00	0.24	IM50	58.31	41.66	0.00	0.00	0.03
IM60	38.20	61.69	0.00	0.00	0.12	IM60	45.12	54.88	0.00	0.00	0.00
IM70	28.76	70.92	0.00	0.00	0.33	IM70	27.84	72.13	0.00	0.00	0.03
IM80	18.20	81.51	0.00	0.00	0.30	IM80	11.42	88.55	0.00	0.00	0.03
IM90	2.54	97.22	0.00	0.00	0.24	IM90	1.83	98.17	0.00	0.00	0.00
IM100	0.18	29.14	54.23	16.27	0.18	IM100	0.00	18.61	60.68	20.71	0.00

Table 5.47: Left: ER5, Matrix 1; Right: ER8, Matrix 1

Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %	Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %
BACTD0	5.30	28.99	31.36	29.76	4.59	BACTD0	5.65	29.14	31.54	29.20	4.47
BACTD1	11.45	52.43	21.07	14.64	0.41	BACTD1	5.21	37.49	32.90	22.31	2.10
BACTD10	23.93	45.62	18.08	11.89	0.47	BACTD10	5.62	46.42	29.26	17.46	1.24
BACTS0	0.00	0.00	33.73	66.27	0.00	BACTS0	0.00	0.00	33.58	66.42	0.00
BACTS1	0.00	18.20	81.80	0.00	0.00	BACTS1	0.00	0.03	94.50	5.47	0.00
BACTS10	0.00	60.56	39.44	0.00	0.00	BACTS10	0.00	7.63	92.37	0.00	0.00
IM0	99.79	0.21	0.00	0.00	0.00	IM0	33.08	20.68	6.12	32.84	7.28
IM10	94.14	5.86	0.00	0.00	0.00	IM10	26.09	46.72	17.54	9.14	0.50
IM20	87.66	12.34	0.00	0.00	0.00	IM20	22.10	54.20	19.70	3.73	0.27
IM30	79.97	20.03	0.00	0.00	0.00	IM30	18.43	73.14	7.19	1.04	0.21
IM40	67.22	32.78	0.00	0.00	0.00	IM40	26.01	73.55	0.09	0.00	0.36
IM50	59.67	40.33	0.00	0.00	0.00	IM50	24.59	75.15	0.00	0.00	0.27
IM60	43.46	56.54	0.00	0.00	0.00	IM60	22.96	76.66	0.03	0.00	0.36
IM70	30.62	69.38	0.00	0.00	0.00	IM70	16.69	82.99	0.00	0.00	0.33
IM80	19.38	80.62	0.00	0.00	0.00	IM80	5.36	94.47	0.00	0.00	0.18
IM90	5.33	94.67	0.00	0.00	0.00	IM90	1.27	98.31	0.18	0.00	0.24
IM100	0.00	28.67	59.17	12.16	0.00	IM100	0.21	21.69	57.72	20.03	0.36

Table 5.48: Left: Grid, Matrix 1; Right: ER5, Matrix 2

Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %	Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %
BACTD0	4.59	29.47	31.80	29.17	4.97	BACTD0	4.82	30.03	31.36	29.17	4.62
BACTD1	5.59	36.30	31.83	23.99	2.28	BACTD1	4.85	36.66	33.08	23.46	1.95
BACTD10	6.83	46.15	29.41	16.83	0.77	BACTD10	6.63	47.25	28.93	16.21	0.98
BACTS0	0.00	0.00	32.43	67.57	0.00	BACTS0	0.00	0.00	32.43	67.57	0.00
BACTS1	0.00	0.00	92.99	7.01	0.00	BACTS1	0.00	0.03	95.18	4.79	0.00
BACTS10	0.00	7.19	92.81	0.00	0.00	BACTS10	0.00	9.62	90.38	0.00	0.00
IM0	49.53	19.41	5.83	22.19	3.05	IM0	66.69	3.52	8.02	20.83	0.95
IM10	36.12	53.31	8.02	2.54	0.00	IM10	82.16	10.38	7.37	0.09	0.00
IM20	47.16	49.62	2.69	0.53	0.00	IM20	77.63	20.68	1.69	0.00	0.00
IM30	30.86	64.73	4.26	0.15	0.00	IM30	77.10	22.90	0.00	0.00	0.00
IM40	44.32	55.68	0.00	0.00	0.00	IM40	68.08	31.92	0.00	0.00	0.00
IM50	27.96	72.01	0.00	0.00	0.03	IM50	56.09	43.91	0.00	0.00	0.00
IM60	26.54	73.46	0.00	0.00	0.00	IM60	43.82	56.18	0.00	0.00	0.00
IM70	15.62	84.38	0.00	0.00	0.00	IM70	31.33	68.67	0.00	0.00	0.00
IM80	6.33	93.67	0.00	0.00	0.00	IM80	12.75	87.25	0.00	0.00	0.00
IM90	0.68	99.23	0.09	0.00	0.00	IM90	2.01	97.66	0.33	0.00	0.00
IM100	0.00	13.43	63.28	23.28	0.00	IM100	0.00	21.60	61.39	17.01	0.00

Table 5.49: Left: ER8, Matrix 2; Right: Grid, Matrix 2

Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %	Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %
BACTD0	5.77	28.55	31.57	28.88	5.24	BACTD0	5.27	29.97	31.60	28.58	4.59
BACTD1	5.92	33.08	32.34	25.56	3.11	BACTD1	5.30	34.29	32.19	25.74	2.49
BACTD10	6.27	43.99	28.43	20.06	1.24	BACTD10	7.16	42.25	28.88	20.18	1.54
BACTS0	0.00	0.00	33.25	66.75	0.00	BACTS0	0.00	0.00	33.14	66.86	0.00
BACTS1	0.00	0.00	72.46	27.54	0.00	BACTS1	0.00	0.00	76.18	23.82	0.00
BACTS10	0.00	0.47	99.32	0.21	0.00	BACTS10	0.00	0.47	99.23	0.30	0.00
IM0	11.42	7.22	4.35	60.89	16.12	IM0	8.93	5.86	1.48	73.02	10.71
IM10	3.55	2.57	5.83	80.74	7.31	IM10	18.34	13.67	14.23	49.76	3.99
IM20	4.76	6.48	13.73	71.21	3.82	IM20	18.79	22.43	20.03	38.37	0.38
IM30	4.32	10.33	25.65	58.28	1.42	IM30	18.17	53.91	17.54	10.38	0.00
IM40	9.35	39.91	33.58	16.69	0.47	IM40	29.17	64.62	5.71	0.50	0.00
IM50	3.91	70.00	25.53	0.38	0.18	IM50	21.51	78.49	0.00	0.00	0.00
IM60	8.91	87.40	3.46	0.00	0.24	IM60	16.51	83.49	0.00	0.00	0.00
IM70	3.34	95.21	1.18	0.00	0.27	IM70	10.44	89.56	0.00	0.00	0.00
IM80	2.69	93.91	3.20	0.00	0.21	IM80	4.29	95.71	0.00	0.00	0.00
IM90	0.92	84.44	9.64	4.79	0.21	IM90	0.33	99.44	0.24	0.00	0.00
IM100	0.24	38.67	52.25	8.73	0.12	IM100	0.00	34.88	50.86	14.26	0.00

Table 5.50: Left: ER5, Matrix 3; Right: ER8, Matrix 3

Agent	Pure D %	Mostly D %	Mixed %	Mostly C %	Pure C %
BACTD0	5.09	29.35	30.77	29.53	5.27
BACTD1	5.62	33.82	31.80	26.15	2.60
BACTD10	7.10	42.63	29.17	19.41	1.69
BACTS0	0.00	0.00	32.78	67.22	0.00
BACTS1	0.00	0.00	74.11	25.89	0.00
BACTS10	0.00	0.44	99.11	0.44	0.00
IM0	12.22	1.30	0.71	75.41	10.36
IM10	7.90	2.75	4.47	79.20	5.68
IM20	11.27	3.82	14.08	69.32	1.51
IM30	7.16	4.44	47.93	40.30	0.18
IM40	11.72	27.37	45.36	15.56	0.00
IM50	20.83	67.46	11.36	0.36	0.00
IM60	23.99	74.79	1.21	0.00	0.00
IM70	16.69	83.31	0.00	0.00	0.00
IM80	8.08	91.86	0.06	0.00	0.00
IM90	1.15	94.41	4.44	0.00	0.00
IM100	0.00	25.80	61.95	12.25	0.00

Table 5.51: Grid, Matrix 3