The role of emotional traits in the evolutionary dynamics of Multiplayer Ultimatum Game

MSc Thesis
Extended Summary

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***Abstract*—From the beginning of times, cooperation among individuals exists and is indeed necessary for the well being of a population, in order to survive and prosper. However, justifying the emergence and maintenance of cooperation remains a huge interdisciplinary endeavor as cooperation involves a costly act. Many studies have been made with the purpose of explaining the emergence of cooperation among pairs of individuals, and within populations. In this context, however, the evolutionary role of individual's emotional states remains elusive. Fairness is an example of cooperative gesture in which individuals often sacrifice gains in name of equality. Shame and honor seems to have big influence in leveraging fairness among individuals. To understand better this influence we enlarged Multiplayer Ultimatum Game by including emotional traits (MUGE). We run a set of computer simulations to analyze the evolutionary dynamics of this game. We concluded that feeling shame is more effective than feeling honor, in context of extinguishing unfairness in the population. However, in case of groups which systematically reject offers, so called unsuccessful games, the impact of shame or honor is invisible. We show that performance of benefit of honor increases if proposers competition exists.**

I. Introduction

In our competitive world the simple emergence of cooperation is a riddle to biologists. It is known that natural selection implies competition and therefore opposes the evolution of cooperation. But the cooperative behavior is widespread across the human population and in other species, even if the collaboration between individuals appears to be irrational. Most human collective endeavors entail high levels of cooperation, from collective group hunting [1] to global warming [2] [3]. What drives this cooperation?

At all times exists a tension between what is best for the population and what is best for the individual. It is clear that the population does best if everybody cooperate. But for each individual there is a temptation to defect, i.e., inverse of cooperation, since defection maximizes ones gain regardless of other's choice. Cooperation happens when an individual concedes a benefit to another, paying an extra cost of doing it. But the evolution is based on a fierce competition between individuals, as a fight to discover who is the fittest. Yet we observe cooperation on many levels of biological organizations. What induce people to be more cooperative? There have been put a lot of effort in explaining how cooperation emerge and why cooperation creates better societies, but what about emotions?

In our daily life each of us experience a wide spectrum of emotions. Sometimes, emotion can provoke unwanted behavior but in specific situations, an emotion can help to decide how to react. Thus, emotions are interpreted by humans all the time. Emotions are also related to the cognitive process. A decision of an individual can be influenced by an emotion, thus a single emotion can influence a person's perception. Emotion gives information both to the person experiencing it and to the person who is observing the person experiencing it. By reading emotional state of another person we can identify the actions tendencies that the individual may have at the moment. In conclusion, the information provided by individual's emotions is normally used in cognitive and reasoning process. Particularly interesting emotion is shame and in situations of negotiation, shame, which may be seen as a social and moral emotion, emerges when a blameworthy action is made. In addition, shame can be viewed as a social punishment. Some experiments show that players in Public Goods Game are willing to pay to punish uncooperative behaviours [4]. Moreover, shameless individual is more likely to act selfishly if the probability of being punished is low. This emotion can drive cooperation and can help alleviate the tragedy of the commons [5] [6], which is a dilemma arising from the situation in which multiple individuals, acting independently will ultimately deplete a population resource. These two concepts, shame and cooperation, are very related since one may help another to emerge, respectively.

A. Games of life

Game theory is a mathematical formalization of social interaction and strategic behavior. In other words, it studies the strategic decisions and the outcomes of individuals when interacting with each other. This framework was presented by Neumann and Morgenstern [7]. Later this framework was improved by John Nash who also introduced the concept of Nash Equilibrium [8], the situation when both players choose a specific strategy and will not gain more by choosing another strategy, regardless of the decision of the other player. Nash equilibrium is used as a tool to predict the outcome of social interactions. One configuration of a conflicting situation between collective and individual interests, addressed in this

thesis, is the Ultimatum Game (UG). In its simplest is setup, a first player receives a sum of money and proposes how to divide the sum with a second player. The second player may choose to either accept or reject the proposal, if the second player accepts, he keeps the offer and the proposer retain the rest. If second player rejects the offer, they both get nothing. This game evaluates for how fair an individual may be. The simple meaning of "fair" is an transaction in which the surplus is equally divided.

So far we presented the riddle of cooperation, a basic framework to study social interaction and strategic behaviour, alongside with the famous Prisoner's Dilemma. The space of strategies in Prisoner's Dilemma is discrete and it boils down to Cooperate or Defect. However, we would like to study a scenario in which individuals are given more flexibility to choose their strategies, so we are able to order those strategies and properly apply a reward and punishment (honour and shame).

The focus of this study consists of two components, we want to study cooperation in artificial society together with shame and honor as possible influence on fairness. Previous mentioned bargaining games are all played only by two players but we want a some kind of multiplayer game to have a set of played strategies that can be ordered. To do this we will be using a game called Multiplayer Ultimatum Game which is a multiplayer version of Ultimatum Game previously mentioned. This game is played in groups and strategies are continuous, so we are able to order a set of played strategies by the group. In each group one of the agents propose an offer and the rest of the group votes, either accepts or rejects the offer, this game is described with more details in the next chapter. The second component requires agents to have shame and honor present in them and this is exactly what we did in this study, we developed a new interaction paradigm to study those emotional traits: we call it Multiplayer Ultimatum Game with Emotions or MUGE. Having this two components we want to answer questions like: does shame and honor can leverage the fairness among agents ? what are the levels of shame and honor are necessary to stabilize the cooperation ? To answer those questions we build a computer simulation to analyze the evolutionary dynamics of this new game.

II. Related Work

In the past were largely studied mechanisms [9] [10] by which is possible for the cooperation to emerge in large population of agents. To model such population of agents, we may call it artificial society, it is necessary to define a set of rules. A single agent has his own strategy and after each interaction with other agent he earns an payoff. This payoff is used in the imitation process, so called evolution process, each agent will update his strategy by mimicking the strategies of other agents with bigger payoff, called fitness. Through time artificial society evolve and new agents will appear, changing the course of the evolution. This is the basic framework of Evolutionary Game Theory (EGT). Many interesting experiments were made around the topic of emotions. Shame is the focus of this work since it can be compared to the social punishment. Next we will explain the crucial role of (EGT) to study the evolution of those artificial societies, we also introduce the Multiplayer Ultimatum Game.

A. Promoting cooperation mechanisms

A lot of work about specific mechanisms, by which cooperation can emerge, was made [9] [10]. To explain the emergence of cooperation some other assumptions have to be made in order to help stabilize the cooperation strategy. There are five mechanisms specified [9] that allow to populate population with cooperative individuals. Kin selection happens when one individual only cooperate with other agent, if they are relatives and the benefit from this relation is in mutual interest to both of them. The relatedness between them is defined as the probability of sharing a gene, the more related both individuals are the higher is the probability, thus the higher the payoff will be if they cooperate [11]. Thus said, we can conclude that this mechanism is very simple and it works, but it can not explain the cooperation among individuals or even between different species, so this theory is a little unsatisfactory, which lead us to direct reciprocity. It is very probable that one individual will interact with another entity many times, certainly one will remember the actions of other individual from the past interactions, and will use this information to decide which strategy to use when interacting with that specific individual later again. This is the basic idea behind the reciprocity, reliance on repeated interactions between the same two individuals. However, previous mechanisms did not cover all kinds of interactions, besides interacting with relatives or with individuals with whom you already interacted, also exists another kind of interaction in our society, a kind gesture. Often we help strangers who are in need, which can not pay back. And this phenomenon is called indirect reciprocity [12]. In this type of interaction exists always a donor and a recipient, the donor decide whether cooperate or not with the recipient. The only benefit that the donor can gain from this cooperation is a rise of his reputation. The interaction is observed by a smaller group of individuals who might inform others of his kind action. Reputation allows evolution of cooperation by indirect reciprocity. But once again, this theory is not complete because the population is not structured and everyone cannot meet everyone. In the real world one person interacts with limited number of persons, real world is not well mixed population because it is highly structured, which leads us to think that the emergence of cooperation might be related to the structure of the population. More recently, a set of remarkable discoveries at the realm of network science [13], [14], [15] has shown how real social networks portray patterns of interactions that largely transcend geography, and differ from the spatial lattices discussed above. Indeed, most social networks show a marked heterogeneity both in terms of the number interactions of individual has and on individual's influence on others [14] [13]. Surprisingly, such real structures are the ones that lead to highest levels of cooperation [16], [17] [18], providing additional clues on the roots (and evolutionary advantages) of such social structures in the living world. So far we talked about Game theory and mechanisms to promote cooperation, in this study we need a better framework to analyze how strategies evolve and change over time in a population.

B. Evolutionary dynamics

Long story short, Guth [19] studied new bargain game called Ultimatum Game. This game is played by only two players, one of them is called a Proposer, the type of player who makes an offer to another player with the purpose to split some amount, of money for example, between them. The Proposer is free to choose any amount. The second player is called a Responder who has the power to decide one of two things, either he accepts the offer because he feels that the split is fair, in this case Responder receives the offer and the Proposer receives the reminder of the amount, notice that, both of them are aware of the amount being split. The second choice the Responder has is to reject the offer than they both get nothing. Each one is trying to maximize his payoff: the Proposer saving the biggest slice to himself and the Responder trying to earn something, in alternative to nothing. Cannot get simpler than this. As one may notice the only way for the Responder to maximize his winnings is to accept every offer greater than 0, but unfortunately if the Proposer finds out the Responder's strategy he will use this information to lower his offer [19], slightly above 0, just enough for the Responder to accept it. Game Theory predicts this outcome as rational choice of one player over another.

C. Evolutionary Game Theory

The purpose of imitation in "games of life" is simple, if your "winnings" are low just imitate the better player. This basic idea of evolution of strategies over time and their imitation led us to (EGT). It is very similar to the Game Theory but introduces a new complexity because the games now will be played many times within a population, and answer questions of how one player can maximize his payoff without knowing the other agent's strategy. Many experiments shows that humans do not behave rationally [20]. In each game a player gain a certain payoff. We can associate the payoff of a player with his reproductive fitness, thus the idea of EGT used to comprehend evolution. Players who receive bigger payoffs are considered more fit and will reproduce more often. The idea of reproducing stands behind the idea of producing more agents look alike and also makes other players desire to imitate your behavior. This is the idea behind Evolutionary Game Theory. In a population, strategies that do well reproduce faster and other strategies are outcompeted. Simple rules can generate complicated behavior of the population. In this thesis, we study population's behaviour from a new proposed game called MUGE. The rules are the same as in Multiplayer Ultimatum Game (MUG) but with addition of emotions such as shame and honor. In every round, if the game is successful, the proposer who proposed the smallest offer to the group, a negative cost of shame, in space $[0.0, 1.0]$, is added to his payoff. The player who proposed the highest offer receives an extra positive benefit of honor to his payoff, in space $[0.0, 1.0]$. Putting it simple, the "bad" players are punished and "good" players are rewarded.

III. Role of emotions

In previous sections I presented a set of mechanisms that promote cooperation in a population. We also presented a EGT which is the main framework used in this study to comprehend players complex behavior in MUGE. We must not forget the behavioral game theory, that each individual has many different unique features, like emotions. Emotions affect how we feel, how we think and what we do. There have been done interesting work about the power of expression of moral emotions and a brilliant experiment with a group of students who played the PGG with the idea of exposing the best and the worst players in order to study shame and honor.

A. Expression of moral emotions

The affective domain is very broad subject to study and very interesting one. Sometimes we don't even notice this but our behavior towards other people changes according to our partners facial expression. We basically "read" each other. For instance, anger can communicate that the person is not satisfied by perceived deliberate harm or unfair treatment to him. Or shame, which can convey regret for doing something wrong, feeling guilty for your actions which could affect others in a bad way. A lot of work has been made in this field, seeking to explain human behavior when exposed to expressions of moral emotions. An experiment was made [21] which consisted in engaging people in negotiation game and social dilemma with virtual humans that either perceived to be agents or avatars, i.e., agent is controlled by computer and avatar which can show facial expressions, is controlled by humans. But the players did not know that their opponent would be always a computer agent who could display facial emotions. This experiment showed that the players showed less anger towards avatars then to computer agents, this shows how moral emotions have a great impact on people's decisions [22], [23], the more computer agent expressed joy the more the participant was willing to cooperate. As it was mentioned in the introductory chapter main focus of this study are shame and honor in MUG, which is a multiplayer version of standard UG consisting of one Proposer and $N - 1$ Responders, N is the size of the group. The Proposer makes an offer and the rest of the group votes, if the number of positive votes is higher or equal to M, the acceptance threshold, than the offer is accepted and is split among all Responders, thought the Proposer receives $1 - p$, p being the Proposer's offer. We would like to answer the question whether shame and honor could lead to greater cooperation and fairness, or not. We may consider shame and honor as some kind of punishment and reward.

To answer that an interesting experiment was made [5] to study the conflict between group and self-interest using PGG. A group of 6 students had to play 12 rounds of this game, each player started with an equal amount of money and in every round each player donated some amount of his total money to the public pool, at the end of the round the amount in the pool is multiplied by two and is split equally among all players. If a player dose not contribute he will not lose money rather on contrary he will receive his share any way because other players contributed. A full group of non-contributors does not increase their initial capital but the group of contributors do, they double it every round. And here we have a social dilemma called conflict of interest between the group and the individuals. What special about this experiment is that after tenth round the two participants who were least generous were exposed, they had to stand up, walk

to the board and write their name under sentence "I donated least". The same treatment received the two players who donated the most after tenth round, but they had to write their name under sentence: "I donated the most". The rest of the player remained anonymous through the game. Contributions to the public goods were almost 50 percent higher than in experiment where all players knew that they would remain anonymous over all 12 rounds. More tests were made with different levels of exposure which led to conclusion that the higher level of anonymity the lower contributions are made, and higher contributions to the public goods with lower level of anonymity. As mentioned before each individual has his own concept of fairness, in bilateral negotiation games humans typically accept offers with p≈0.4 ($p \in [0, 1]$), which is almost half. Will this number maintain if the number of responders increase to two or three? This question was answered [24] by an interestingly well done experiments which consisted in playing UG but with the addition of responder competition (RC) and proposer competition (PC). By competition means to add one or more player to the group of responders or proposers. This little change has a very large impact on accepted offers and proposed ones. Introducing RC to the ultimatum game, by adding one more responder, provokes a large decrease in mean accepted offers, reduces their average gains from trade by 42 percent to almost 20 percent. In PC, a competing proposer will tend to offer more because he is afraid that his offer will be smaller then his competitor, thus will not be accepted an he will gain zero. In our work the number of Proposers dose not change over time, what dose change are the agent's strategies. This is the basic version of the MUG. This work proposes a new framework to work with, which includes two emotional states: shame and honor, two of them might be compared to the punishment and reward. All details are grouped in the following chapter. Essentially we study an evolutionary game theoretical model that combines the interplay between group interactions and individuals with emotions to justify the evidence of fairness.

IV. Model

To investigate human emotional features of shame and honor a computer simulation was build. Since we want to prove that human decisions and behavior can be altered by his personal emotions while playing a game with a group, we developed MUGE. This version is a successor of Multiplayer Ultimatum Game [25] in which a Proposer makes an offer (p) to the group, with the imposition of $0 < p < total\_amount$, and his offer will only be accepted if the number of acceptances remain above or equal to predefined threshold (M). In case of success, the Proposer will receive a payoff of $1 - p$ and the Responders will share the p among them equally, more precisely $\frac{p}{N-1}$ for each Responder, where N is the group size. Notice that in a simple Ultimatum Game [19], in which only two individuals play the game, we are unable to capture the effect of shame and honor. For that matter, in MUGE we simulate shame and honor by adding an extra cost or reward to the player's payoff in case that his proposal stands out by being the lowest or the highest. The topic of emotions is very complex in a way that it is very hard to model them computationally. In this study we simplified the two basic emotions to their core: shame is seen as a social punishment and honor is seen as social reward. We rely on an extremely simple definition of these emotions however, we show that they are enough to drive the individual behaviours within a multi-agent system in which multiple agents interact. Therefore this simulation is expected to capture the consequences of the extra cost to the "bad" guys and small benefit to the "good" guys, shame and honor respectively, in the overall process of strategy adoption. Next we present the formal definition of the MUGE together with an example of the game itself.

A. Rejection threshold

As mentioned before, two kinds of players exist: the first is called Proposer who makes the offer to the group and the second is called a Responder who accepts or rejects the proposed offer. A specific number of Responders must accept the offer in order to the group of Responders split the proposed value, number of positive votes must exceed or be equal to the acceptance threshold M. This threshold ranges from 1 to $N-1$ where N is the size of the group. In this study, we examine two extreme cases of M, when $M = 1$ and $M = N - 1$. In case of $M = 1$, only one positive vote is enough to turn this game into a successful one, for split of offer to be made. It has been proven [26] that a Proposer will not care about increasing his proposed value, on the contrary, he will lower the value until it become small but still accepted by at least one Responder. In case of $M = N - 1$, all Responders must accept the Proposer's offer in order to have a successful game. This is tricky situation since the Proposer must please all the Responders. The study focused on two extreme cases and not all spectrum of M, because the intermediate values of M are simply the interpolation of two extreme cases of M. This was proven in the study [25] of MUG and came to conclusion: the higher M is, the fairer offers tend to be. Since our game MUGE includes M we only focused on the minimum and the maximum value of M because of mentioned reasons. Indeed, the scope of the present work is to analyse the effects of shame and honour on the evolution of fairness and not the specific interplay between these traits and the full range of M.

B. Splitting the goods

The game is played by an arbitrary number of players each with his individual strategy. Therefore to differentiate them each player receives a payoff correspondently to his actions. The average payoff of an agent is calculated by earned payoff, in case of successful games, while proposer plus when the same agent becomes a Responder, divided by the number of games. Shame and honor are expressed as an extra cost and benefit to the agent's payoff, if the player i proposes the smallest p value compared to other $N - 1$ players, a negative cost to his payoff is added, serves to promote sense of shame on this player. In the other hand, if the player i offers the biggest p value then he will receive an positive extra benefit to his payoff, serves to promote sense of honor. If more than one players have the same p value, either the cost or benefit is split among those few players. The expression for the average payoff of the agent i over all possible games is the following:

$$\pi_i = \alpha_i \Big[(1 - p_i) - Cs_i * f_c(p_i, \min_{l=1, l \neq i}(p_l, \ldots, p_N), false) + Bh_i *$$

$$f_c(p_i, \max_{l=1,l\neq i}(p_l, \ldots, p_N), true)\Big] + \sum_{i=1,i\neq j}^{N-1} \frac{p_j * a_j}{N-1} \quad (1)$$

where π_i is the average payoff of agent i, p_i is the offer of agent i, a_i can assume values 1 or 0, 1 if the proposed offer of agent i is accepted, 0 otherwise. Cs_i is the extra negative cost of shame to the agent's payoff , Bh_i is the benefit of honor towards agent's payoff, and finally the sum of payoff earned by the player while being a Responder over all possible proposals made by agents in the group. The f_c (equation 2) compares the proposed value of the agent i with the minimum proposed values from all other players, in case of player i being the one who proposed the smallest p, function f_c returns 1 and this triggers the cost of shame (Cs_i). The same logic is applied to the benefit of honor if the agent proposed the biggest p.

$$f_c(p_i, p_k, condition) = \begin{cases} 1, & \text{if } false \text{ and if } p_i < p_k \\ 1, & \text{if } true \text{ and if } p_i > p_k \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The values of cost of shame and the benefit of honor ranges from 0 to 1, in intervals of 0.1. By framing this cost/benefit between 0 and 1, we are able to have values that compare well with the possible proposals by Proposers, which also range between 0 and 1. This way, cost/benefit of shame/honor can be understood as a negative/positive payoff component written relatively to the maximum possible proposal.

C. Strategy revision

In Multiplayer Ultimatum Game, the more rounds they play the more experience they gain thus the payoff of each agent gets more distinctive over time. Some agents get higher payoffs because of their unique strategies which are defined by p and q. In this simulation there are two possibilities for an agent to update his strategy, by imitating another agent with better fitness or by mutating, which produces a completely new strategy and unique in all population. Both possibilities are explained in more detail next.

1) Mutation: The process of mutation generates a different agent, alter completely his previous strategy. The range of different strategies is in space $(p, q) \in [0, 1] \times [0, 1]$. Genetic variation is useful because it helps to create a change in the population over time. The process of natural selection can lead to significant changes in overall population, in a couple of generations. Therefore, in every generation two agents are picked randomly, focal agent A and agent B. First, the focal agent will try to mutate by generating a random number (rnd) from range [0,1] and compare it to the probability of mutation ($P[mutation]$), if $rnd < P[mutation]$, the focal agent proceeds and executes the mutation. He erase his previous strategy and creates a new one, by generating randomly new p and q value. This feature helps to explore new behaviors in the population. Second agent dose nothing, he is only picked in the case if the focal agent dose not mutate and proceeds to the imitation, which requires a second agent.

2) Imitation: Imitation is a form of social learning that leads to development of a culture and similar habits among them. In this process one agent do not need genetic inheritance to be able to imitate another agent. Copying behavior can be done just by the observation of the another agent's behavior. In our simulation exists few steps before the imitation may occur. First two random agents are picked from the population, one focal agent (agent A) and second agent (agent B). Therefore, each of the two agents play 10^3 games, in order to gain a good and distinct payoff, which later translates to the agent's fitness. A game consists of a group of N agents and each of them proposes his offer to the group, one at the time, while others agents vote. Notice that agent A and B never play in the same group and in each iteration a different group of size $N-1$ is generated. In order to focal agent A imitate the secondary agent B, first is calculated the probability of the imitation, ($P[imitation]$) itself, this is done by equation 3:

$$\frac{1}{1 + \epsilon^{\beta(f_x - f_y)}} \quad (3)$$

where f_x is the fitness of the focal agent A and f_y is the fitness of the secondary agent B. The constant β is the strength of imitation, the bigger it is more the imitation will depend on the fitness difference [26]. A random number ($rnd2$) is generated from space $[0, 1]$, if $P[imitation] > rnd2$, the imitation will occur, otherwise the focal agent A will keep his old strategy. While the focal agent A imitates the strategy of agent B, by copying the p and q values, it might happen a slight perturbation due to errors in perception and observation, thus the new $\acute{p}$ and $\acute{q}$ value of agent A, new strategy parameters, will be given by equation 4 and 5:

$$\acute{p}_A = p_A + \varepsilon \quad (4)$$

$$\acute{q}_A = q_A + \varepsilon \quad (5)$$

where $\xi_p(\varepsilon)$ and $\xi_q(\varepsilon)$ are uniformly distributed random variables in the space $[-\epsilon, \epsilon]$. This small feature is a key to explore bigger spectrum of possible strategies and also models a some kind of blur in the step of imitation, like in real world people when imitating other people.

V. Evaluation

Having presented a detailed overview of our new model MUGE we proceed to the computer simulation's results. In standard MUG, over time, the p value decreases in case of M=1, because only one Responder is necessary to seal the deal and split the offer [25]. Thus, Proposers get greedy and offer less and less over time maximizing their share of the deals. The purpose of MUGE is to test where new means, such as shame and honor, can increase the offers and thus create fair individuals. In this section, we present the results of computer simulations that test the effect of shame and honor on fairness. Honor adds an extra positive benefit to the payoffs of players who make the higher offers. Shame deduct from the agent's payoff, agents which make small offers, the cost of shame. Since we have two types of emotions, we experimented both of them in different setups: with only one type of emotions present or with both at the same time. Since the players gain payoff if the game is successful (i.e., the number of acceptances is equal or higher then M) we also tested the effect of those emotions in cases when the game is not successful. This enables us to understand the circumstances in which this types of emotions are more suitable to increase fairness. All tests includes two extreme cases of M, the rejection threshold,

	Successful game	Unsuccessful game
Shame	M = 1,4	M = 1,4
Honor	M = 1,4	M = 1,4

Table I: Test combinations for shame and honor separated.

	Successful game	Unsuccessful game
Test 1	Honor	Shame
Test 2	Honor + Shame	NONE

Table II: Test combinations for shame and honor combined.

when $M = 1$ and $M = N - 1$, where N is the group size. In the next section, we briefly explain how we proceeded in these simulations and the results are presented and discussed.

A. Tests Scenarios

The computer program to run the simulation was written in C++. In MUGE, each agent is defined by the p and q value, (p,q) $\in [0, 1]$, representing a strategy adopted by the agent.We start with a population of agents, each of them with a random p and q value. The simulation proceeds by picking, randomly, two players from a population. Before any game is played, the first agent will try to mutate by the probability of 0.01. In case of success he dose not play games with other groups, he just changes his strategy to new random p and q value. Next, two random agents are picked again. In case that a mutation does not occur, the simulation proceeds and each of those two agent play 1000 rounds of the game, always with random opponents and never together in the same group. This enables, for both of them, to experience distinct situations. Along those games, each agent receives a payoff according to his actions, after 1000 games (that we call it iterations) the fitness of each agent is calculated. After this, the focal agent will update his p and q value, as a result of a learning process, or cultural adaptation [27]. The focal agent will copy the second agent's strategy, the p and q value, with a probability given by a function previously introduced (equation 3). In this equation, which is the intensity of selection, the β is set to 10 (see chapter IV). If the imitation occurs, the second agent's p and q values are copied to focal agent. Additionally, error of perception is also added to those values. This error is located between -0.05 and 0.05 and it is added to the copied values, yet we always guarantee that p and q remain within 0 and 1. The process of updating occurs for $2 * 10^4$ time steps. This defines a run. The stationary state of one run is calculated using the average of the last $6 * 10^3$ time steps. Each simulation has 40 runs and average value from this 40 runs is used in our plots which defines the resulting population's mean p and q value.

As mentioned at the beginning of this chapter, we focused in studying each of the emotions separately first. Besides that, we also played with the rule of how the punishment is applied (or reward is awarded). There are two situations: apply only when the game is successful or unsuccessful. Just to remember, the game is called successful when the offer is accepted and split among Responders is made.
As a summary of our scenarios for testing emotions separately is presented in table I. After this, we tested shame and honor combined but also with different rule setup. Table II represents all combinations we tested. Each case was tested with $M = 1$ and $M = 4$, in case of $N = 5$. Next we present the results.

B. One emotion at the time - Successful games

In the first test, shame cost is associated with the punishment of a player in case of his offer being the smallest among other Proposers from the group. We can observe from Figure 1 and 2, by augmenting the shame cost from zero to one, the p value grow up. Overall growth of p is explained by the fact that Proposers with the lowest offer try to compensate lost points (shame) from their payoff, by imitating, probably, the second placed Proposer with the second lowest offer, just to not be the "worst" player again. This causes a chain reaction which leads the p to the high values.

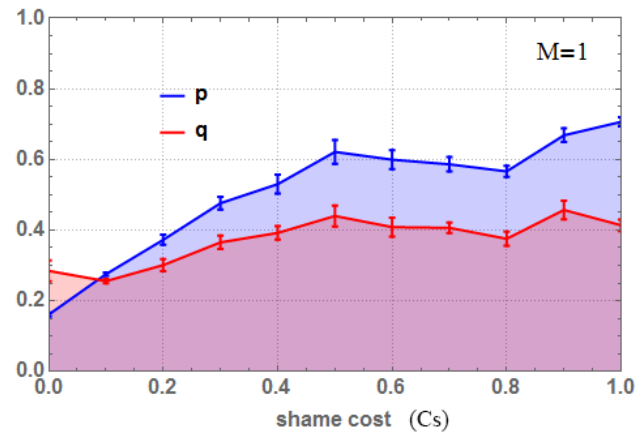

Figure 1: Result of varying **shame cost** attributed to agent's payoff in case of **successful games**, in well-mixed population, in case of $M = 1$.

Besides shame, we also simulated MUGE with the benefit of honor. The Proposer who offers the biggest slice from his pie receives an extra benefit to his payoff. The effect of honor is weaker, if compared to the shame (Figure 3 and 4). The purpose of honor would be to combat the selfishness in the group and augment fairness. Yet, we are not targeting the real bullies of the group, i.e., those who propose less, but instead offer extra benefit to the righteous players. Since the greedy players who propose small offers are not punished, the value of p do not change in case of $M = 1$. Yet, benefit of honor can augment p if the M is big, in case $M = 4$, because there is a proposer competition, the proposer's offers already high and equal, thus, the extra benefit helps to distinguish between the fair proposer.

After this we can assume that shame is more powerful weapon against unfairness than honor in case of successful games. Shame can speed up the increase of mean p value in the population. We also learned that the benefit of honor has a bigger affect on mean p when the M increase. With this two emotional threats (shame and honor) we can induce new behaviour. What if we invert the scenario and apply emotions in unsuccessful games? Next we address the answer to that.

C. One emotion at the time - Unsuccessful games

In the previous section we revealed results from a computer simulation in which we applied shame cost and benefit of

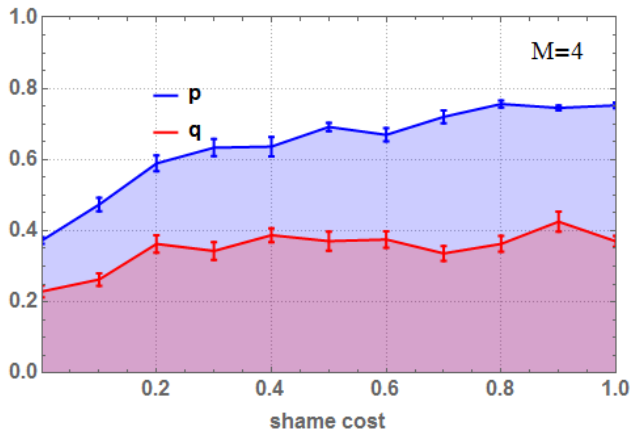

Figure 2: Result of varying **shame cost** attributed to agent's payoff in case of **successful games**, in well-mixed population, in case of $M = 4$.

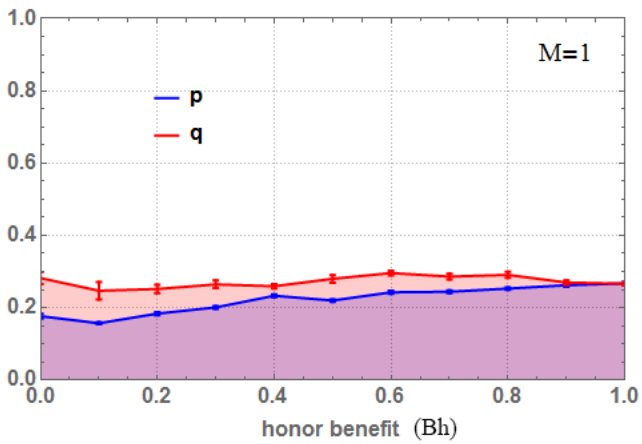

Figure 3: Result of varying **benefit of honor** attributed to agent's payoff in case of **successful games**, in well-mixed population, in case of $M = 1$.

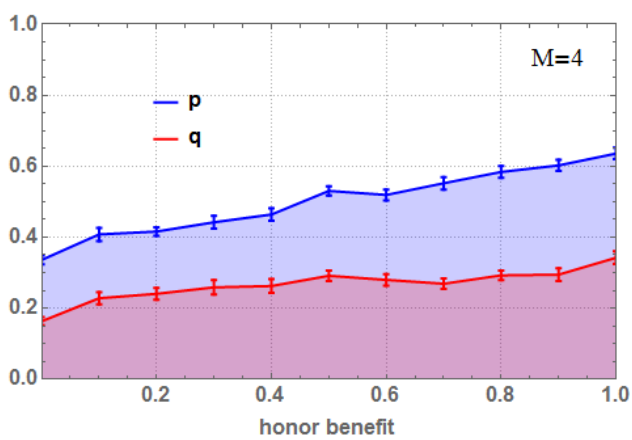

Figure 4: Result of varying **benefit of honor** attributed to agent's payoff in case of **successful games**, in well-mixed population, in case of $M = 4$.

honor, separately, to a specific player in a successful game, therefrom we were curious about what could happen in unsuccessful games. From our observation after testing this hypotheses, we concluded that the punishment must be made when the actions took effect on the group, i.e., in successful games only. From zero to one of, cost of shame or benefit of honor, the mean p value of population does not alter. And also concluded that benefit of honor is not effective in cases of unsuccessful games.

D. Shame and Honor combined

In previous section we tested a big variety of combinations with shame and honor. Some of them returned expected results others were surprising but explainable. Therefore from previous tests we learned that adding benefit of honor to unsuccessful games is a disaster for fairness but contrarily, effect appears in successful games. We also concluded that shame in successful games is a great weapon to combat unfairness. This section presents two more tests and in each of them the shame and honor is combined. This way, we wanted to know what happens when both shame and honor are introduced, when games are successful.

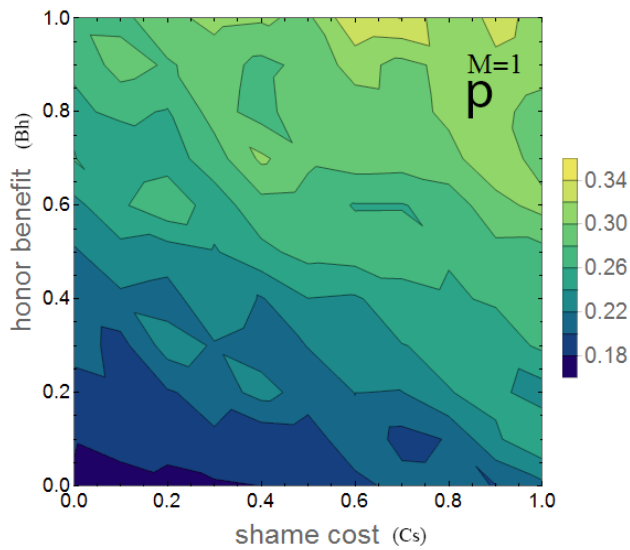

Figure 5: Result of varying **benefit of honor** attributed to agent's payoff in case of **successful games** and **cost of shame** in case of **unsuccessful games**, with $M = 1$, in well-mixed population.

If we think about these two emotions a little, we may agree, without knowing previous results, that it would be logical to apply cost of shame (punishment in this simulation) if the game was unsuccessful because we are trying to give a lesson to the greedy players, we would like to keep the players splitting the goods but educate the worst players, thus education could be done when Proposer and Responders disagree. Seems logical to apply shame when game is unsuccessful. On the other hand we have the benefit of honor, only the fairer players are among who should receive a reward for being who they are. This thinking led us to simulate MUGE with both emotions but benefit of honor

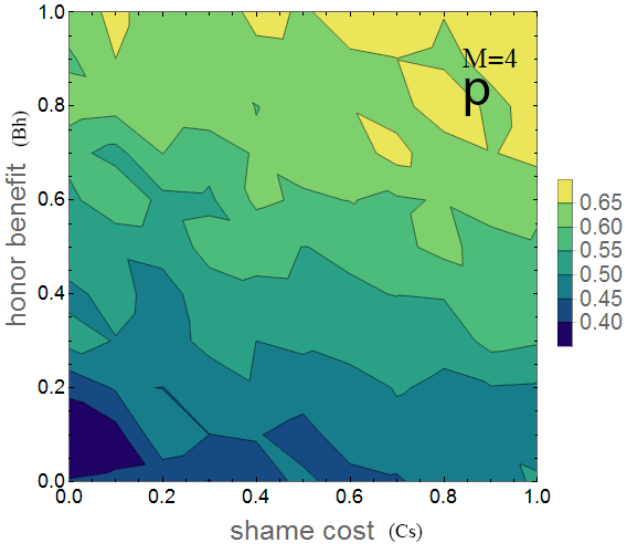

Figure 6: Result of varying **benefit of honor** attributed to agent's payoff in case of **successful games** and **cost of shame** in case of **unsuccessful games**, with $M = 4$, in well-mixed population.

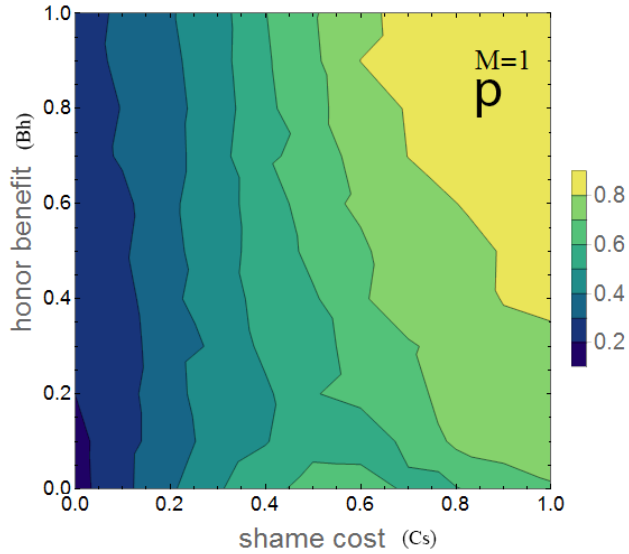

Figure 7: Result of varying **benefit of honor** and **cost of shame** attributed to agent's payoff in case of **successful games**, with $M = 1$, in well-mixed population.

applied only if the game is successful and cost of shame only when the game is unsuccessful. Figure 5 reveals that this combination of benefit of honor and cost of shame is not the ideal because the p value do not grow much, minimum is $p = 0.18$ and maximum is $p = 0.34$, in case of $M = 1$. This results were expected because we already learned that cost of shame in unsuccessful games has poor performance. In case of $M = 4$, Figure 6, we received better results because the p value reached 0.65. Big M brings proposers competition therefore benefit of honor only improves the mean offer. From previous test we concluded that punishing players in unsuccessful games has little benefits, more profitable is to honor the "good" players. The pace of planting fairness into the population with honor benefit is not that fast as shame in successful games, and to prove this we performed a new test which unifies both emotions quiet good.

In this test, both emotions, honor and shame, were applied only when the game was successful. The maximum proposed p value achieved was 0.8, the main influence to this growth is the cost of shame while benefit of honor did not performed that well as cost of shame, in case of $M = 1$ (Figure 7). In case of $M = 4$ (Figure 8), we achieved the best results. Important factor in this test is the M value, since it is $M = N - 1$, i.e., maximum it could be, the benefit of honor has great impact on p values, in this situation.

E. Discussion

Our study focused in detecting the effectiveness of shame and honor in MUGE. Next we will be discussing our results. We draw a simple table (Figure 9) which contains a resume of our first round of tests, in which shame cost and benefit of honor were testes separately. A line pointing up means that a combination of specific M and specific emotion had a growing effect on fairness, related with high average values

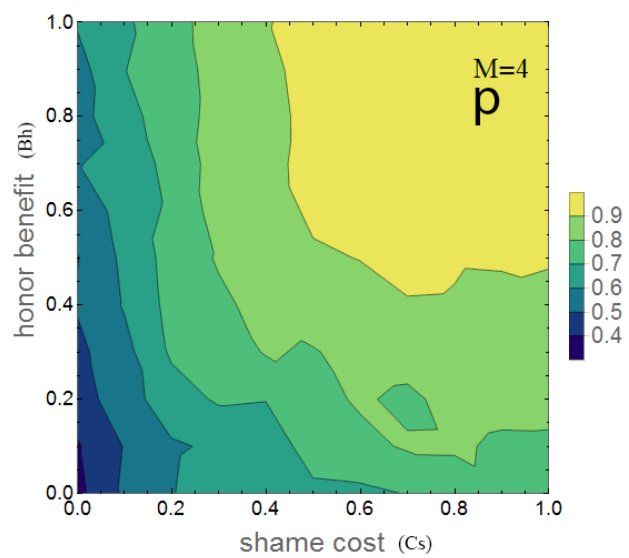

Figure 8: Result of varying **benefit of honor** and **cost of shame** attributed to agent's payoff in case of **successful games**, with $M = 4$, in well-mixed population.

of p. The cells containing horizontal lines represent no growth whatsoever.

In the second round, we tested how both emotions, shame and honor, performed together. There were two cases, in first the benefit of honor was given in successful games and cost of shame was deducted from the agent's payoff in unsuccessful games. In the second case we applied honor and shame in only successful games.

From this tests we concluded the following:

- **Attributing Shame and Honor when the offer is rejected has a dual and conflicting effect**: (1) Shame

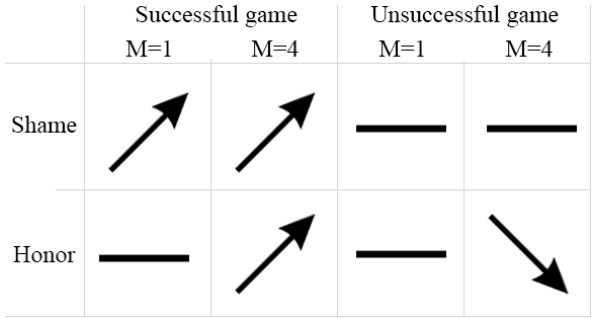

Figure 9: This table represent all combination of **shame cost** and **benefit of honor** tested in our simulations, concerning the fairness of proposed values.

and Honor act in order to give advantage to high p values but (2) offers are tendentiously rejected only when values of p are low. Thus, are both favoring and harming high values of p.

- **The effect of Honor is lower than the effect of Shame** because Honor benefits directly high values of p and Shame directly harms low values of p. When M is low, high values of p are disadvantageous because both high and low p values conduce to approved offers and, naturally, low p values are beneficial to Proposers as they allow them to retain more payoff (they gain $1-p$, when a proposal is accepted); Honor is unable to prevent this relative beneficial effect of low p values, when M is low. Yet, shame directly affects low p values.

- **Performance of benefit of honor increases as the M increases**, in cases of $M = N - 1$ we observed a great impact on group fairness by just adding benefit of honor to successful games (Figure 10).

VI. Conclusion

This study is an attempt to study why and how emotions affect individual's decision in a situation of bargain game. To answer that, we used EGT as a framework to study behavioral evolution in the context of a new game called Multiplayer Ultimatum Game with Emotions, which is very similar to the Multiplayer Ultimatum Game, but contains the new feature of adding shame or honor to the agent's payoff function. Shame and Honor may be viewed as an additional punishment and a reward, respectively. That will be used to deduct or reward points to the agent's payoff, which ultimately will modify the final agent's fitness. Therefore, the question that motivated this work was "Does shame and honor affect fairness, in a context of group bargaining?". To answer that, we performed a set of computational simulations in order to observe the evolution of individual behaviour while agents interact, having the feeling of shame and honor present. In this chapter we conclude our work by listing our contributions and finally giving some insights about future work.

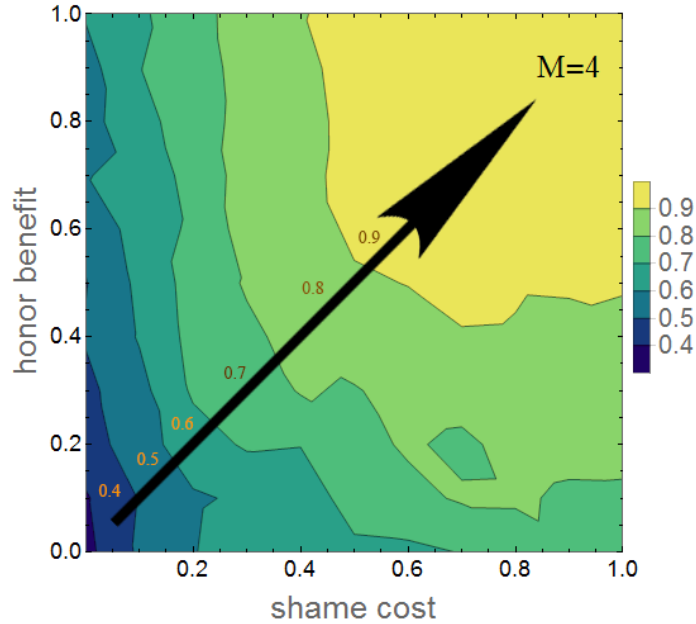

Figure 10: Mean p values as result of applying **benefit of honor** together with the **shame cost** in successful games, in well-mixed population with M=4, $N = 5$

A. Contributions

In this section we present a summarized contributions and main conclusions acquired from this study. For more detailed conclusion is advisable to consult the Chapter 3 and 4. There are two major achievements: 1) we first formalized a new interaction paradigm to study the effect of emotional traits (shame and honor) on group bargaining and 2) we developed a system in which agents from an artificial society, besides having a strategy to play with other agent, also receive the effect of shame or honor. We also implemented a computational model to study the evolutionary dynamics of the above mentioned game. This computational model brings new horizons of possibilities and the results from those simulations revealed many interesting properties. The model is flexible enough to implement more complex behavioral features to study.

After simulation results we concluded three things. The first one, the most visible, is that when honor and shame are included always that a proposal is accepted, we show that shame has a higher effect than honor. The simple explanation is that shame targets the greedy players from the beginning, contrary to honor, and the process of enhancing fairness is faster because of that. The second thing we noted was that when including Honor and Shame solely when offers are rejected, it has no (or counterproductive) effect. The effect of Shame and Honor is only useful to apply in successful games. And for last we concluded that Honor has greater effect in extinguishing unfairness if the M is big.

B. Future Work

After we revealed the outcome of adding shame and honor to the agent's state, new ideas emerged that could be a clue to

be explored in the future work. We will consider the following five future work ideas:

- **Wider application of shame and honor** As one may notice, at each game we punished or rewarded only one agent. The exposure of just one agent might not be enough to comprehend how really shame and honor affect overall decisions. This could be overcome, by applying shame and honor to two or more players, instead of just one as it is done in current model.
- **Additional mechanisms** In some experiments with real people [5] the level of exposure of players, like showing his or hers contribution to the group after the game, contributes to the emergence of cooperation. If greedy players are exposed to the group, the feeling of shame makes them change their mind, forces to start contributing more than before. Besides shame or honor, we are in the presence of concept of reputation, the result of social evaluation of player by his opponents. Besides reputation, we could use a set of mechanisms which promote cooperation (see chapter III) such as kin selection, direct and indirect reciprocity, network reciprocity to study behavioral interaction with this mechanisms.
- **Structured populations** We could elaborate on the connections between agents. In this scope, agent are nodes in a network and they only interact with a limited number of neighbors (the ones connected to the agent by links). In real world, we do not interact with everybody, and this leads us to assume that our social networks are one of many factors that define our behaviour.
- **Experimental validation** Studies like this should be well grounded with the experimental data. For this study, main goal would be to track person's emotions while she plays the bargain game. This could be achieved by filming the face of the person and later analyze her emotional expression, or we could distribute a questionnaire about person's internal feelings, at the end of the game.
- **Different emotional traits** It would be interesting to simulate different emotions, it would require to find what values to use, how those emotions could be expressed in the payoff equation 1 and finally analyze how they change the behaviour.

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