Bounded Rationality, Group Formation and the Evolution of Trust: an Agent-Based Economic Model

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ABSTRACT

It is possible to model trust as an investment game, where a player in order to receive a reward or a better outcome, accepts a certain risk of defection by another player. Despite having achieved interesting insights and conclusions, traditional game theory does not predict the existence of trust between players who are selfish and exhibit maximizing behavior. However, experiments with these games reveal the presence of trust in player decision making. The purpose of this paper is twofold. First, it aims to build an agent-based economic model to discuss the factors associated with trust in a population. Using the generative methodology proposed by Epstein, we introduce learning, natural selection and group formation to the model to verify their impact on the emergence of trust between agents. Second, since the experiments reveal that the participants took bounded rational decisions, the paper aims to show that in an agent-based model, bounded rationality can be modelled through an artificial intelligence algorithm, the Learning Classifier System (LCS). As a result, we have observed that natural selection favors more selfish behavior. In addition, learning and the forming of groups increased trust in our simulations and they were able to reverse selfish behavior when introduced along with natural selection. The level of trust that emerged from the model with these three features was similar to that observed in these experiments. Finally, it is possible to verify that the LCS was able to model bounded rational behavior in agents.

Keywords: Trust. Investment games. Bounded rationality. Agent-based simulation **.** Learning**.** Artificial Intelligence algorithm.

1. INTRODUCTION

Trust plays an important role in economic development by favoring economic transactions and making them faster and less bureaucratic. In economics, trust can be analyzed by a representative situation: transactions concerning a certain loan without any formal warranty between one individual, the Investor, and another, the Trustee. This good or amount lent increases the utility of the Trustee who, at a later time, returns to the Investor the good or amount lent along with a value that corresponds to a percentage increase in utility.

In traditional game theory where the players are assumed to be maximizing their payoffs, the Trustee has a dominant strategy that consists of keeping the good or amount lent by the Investor since this loan is informal and has no warranty. The utility is the value of that good or amount plus the increase in utility provided by it. Looking forward to the Trustee move, the Investor's strategy consists of not making any loan since any good or amount lent will be kept by the Trustee. This would be the prediction of the Nash equilibrium according to traditional game theory.

However, experiments made to empirically test the decisions taken by the participants in such games have shown that there are behavior features that interfere with this mechanism that lead to results that differ from those predicted by traditional game theory. These experiments have shown that even under conditions of anonymity and without any formal warranty, Investors make loans to Trustees who usually return some value to the Investors.

By altering some features of the framework of these experiments, such as the ties between the players or the information they have about past outcomes, researchers can explain which features may increase or decrease the level of trust between these participants, thus adding to our understanding of this behavior.

Building an agent-based model helps us see how trust can emerge from a simple set of assumptions and rules. It is also possible to understand how changes in these sets of assumptions and rules affect the emergence of trust between agents. While it is possible in experiments to analyze the characteristics of individuals and their influence on trust, simulations permit the analysis of more structural individual features such as learning, natural selection and group formation which are harder to analyze in experiments.

However, using an agent-based economic model presents a challenge in terms of modelling the agent's decision making in a way similar to the behavior observed in experiments. The artificial intelligence algorithm Learning Classifier System (LCS) has been chosen for this article due to its similarity to the bounded rationality theory that better describes people's decision making process.

This paper aims to construct an agent-based economic model[1] where the decisions are the same as in the experiments and, by doing so, add to the discussion of the features associated with the emergence of trust in a population. Also, it is possible to see that LCS can model bounded rational behavior in this type of model. This study is organized as follows: Section 2 details the concept of trust used and describes the framework of the investment game used in the experiments as well as the agent-based economic model. Section 3 describes the model we've constructed to analyze the emergence of trust. Section 4 describes the results and Section 5 offers our conclusions.

2. TRUST IN GAME THEORY AND EXPERIMENTS

Trust can be assumed to be an expectation of monetary gain or an increase in the utility of an agent whom we will term the Investor who acts in such a way that he or she is exposed to the risk of losing utility by the defection of another agent, namely the Trustee (Cox, 2004). By using games such as the investment game, one can gain insights about the features that relate to trust by comparing the expected behavior of a rational agent according to traditional game theory with the observed behavior of people who actually participate in the same game.

In the investment game proposed by Berg, Dickhaut and McCabe (1995), a group of Investors received \$10, consisting of ten \$1 bills, each. Then they had to decide individually how many bills to put in an envelope that would be given to the Trustees group and keep the remaining amount. Each individual of the Trustee group received an envelope with the amount sent multiplied by 3 also in \$1 bills. The Trustees then had to decide how many bills they would send back to the Investors they were paired with, keeping the remaining amount.

According to traditional game theory, using reverse order reasoning and assuming that players are maximizing their payoffs, the Trustees will choose to keep the entire amount they receive and not return anything to the Investor. Anticipating this decision, the strategy of the Investors is not to send anything to the Trustee. That is, the Investors do not show trust because they do not have any expectation of monetary gains by sending part of what they receive to the Trustees, exposing themselves to the risk of losses. So in this game played by

[1] The simulation model was built in NetLogo (Wilensky, 1999).

maximizing selfish agents, there would be no transactions and the players would end up with the amount designated at the beginning.

However, in experiments conducted by Berg, Dickhaut and McCabe (1995), Investors sent on average \$ 5.16 and \$ 5.36 depending on the type of experiment, with the values varying considerably among individuals. Trustees also showed reciprocity returning on average 28.0% and 33.1% of the amount received, with the values also varying considerably among them. These values are very different from those predicted by traditional game theory.

One approach to analyzing trust in games is agent-based simulation. It allows us to gain insights in terms of which factors contribute more to the emergence of trust between agents.

3. MODEL OF TRUST IN AN AGENT-BASED SIMULATION

The purpose of agent-based modelling is to understand the proprieties of complex social systems through the analysis of simulations. According to Axelrod (1997), agent-based modelling differs from the two standard methods of doing science: induction (discovering patterns in data) and deduction (providing consequences to a specific set of axioms). It starts with a set of assumptions that are used to generate simulations that can be analyzed inductively. This agents interacting locally can generate large-scale effects that are called "emergent properties" which can be surprising because of the difficulty of anticipating full consequences of even simple forms of interaction.

So building an agent-based model helps us understand how trust can emerge from a simple set of axioms and also how simple changes in these axioms affect or not the emergence of trust between agents.

This model is inspired by the work of Epstein and Axtell (1996) in which they create an artificial society through agent-based simulation and study how phenomena like inequality, migration, culture, war, markets, etc. appear through small alterations in the modelling of the environment and the agents.

3.1. BUILDING AN ARTIFICIAL WORLD

To analyze the emergence of trust through a set of axioms in a simulation model, it is necessary for the model's agents to face the same kind of decisions that the participants of the experiments did so that these decisions can be compared. So the environment of the model in which the agents will interact has been designed in a way that provides agents with choices that will result in payoffs if they are willing to run greater risks of defection by the other agents, that is, they will have to decide whether or not they trust the other agents.

The environment of the model consists of a 7 x 7 dimension board linked by the edges[2]. In this environment there are two types of food: fruit and boars. Each cell of this board has a given capacity in terms of fruit and boars, that is, some cells are more fruitful than others. Each cell's capacity in terms of fruit and also boars is randomly assigned in a uniform distribution between 0 and 20[3]. In the case of fruit gathering or boar hunting in a given cell, the amount gathered or hunted is deducted from that cell's stock. For each round that corresponds to one day in the simulation, there is a natural replacement of the stock of fruit and boars that grows until it reaches its capacity.

The agents in this simulation live in this environment. In the beginning of each simulation, 60 agents[4] are created and randomly placed in the environment. Each cell can host more than one agent, and it is possible that a cell has no agent at all. These agents have two main activities to feed themselves: they can gather fruit or hunt boars and should organize these activities throughout the hours they have available each day. Each agent has ten hours a day to dedicate to these production activities.

The activity of gathering fruit is individual. Each agent is dependent on himself or herself to accomplish this task. The agents have a limit of fruit that they can gather per round, due to the time spent on this activity. They gather the largest amount of fruit possible given their capacity to gather fruit and the stock of fruit available in the location which they have decided to explore. Each hour each agent can gather one fruit that has one calorie. All of the fruit gathered is consumed and their calories are appropriated by the agents and become part of their calorie stocks, which can grow without limit.

On the other hand, the activity of hunting boars is collective and needs two agents to be accomplished. Since the agents are slower than the boars, they cannot reach them directly. So they use a strategy in which an agent, the Leader, chases a boar and leads it to another

[2] The board is linked by the edges in a toroid shape. This shape is very common in agent-based model because it guarantees that every cell in the board has the same number of neighbors and no cell occupy a special position.

[3] With 49 cells in the environment, each one with a random amount of fruit or boars following a uniform distribution between 0 and 20, the total capacity of fruit or boars in the environment follows a normal distribution with a mean of 490.

[4] Based on the environment characteristics and the model rules, it is estimated that the carrying capacity of the environment is about 60 agents. With fewer agents, survival is easier and they reproduce more often. With more agents, survival is more difficult and they die more often. So the initial number of agents in the system

agent, the Killer, who kills it. However, the Killer has the advantage of having the option to keep all the kills and decides how many should be divided with the Leader. At the end of the transaction, each of these agents consumes their portion and each of them appropriates the associated calories. Each hour a pair of agents can hunt one boar which has three calories. As in the fruit gathering, each pair of agents hunts the largest number of boars possible given their capacity to hunt and the stock of boars available in the location where the Leader have decided to hunt.

One important characteristic of this model is that the Leader may decide for how long he or she will hunt boars and how long he or she will gather fruit and may spend all day gathering fruit, split the day between fruit gathering and boar hunting in any proportion, or spend all day hunting boars up to the limit of ten hours available for production activities. This decision is mandatory for the Killer who will have to follow the Leader's decision. Another important characteristic is that boars have more calories than fruit, so the decision to hunt boars is more advantageous for the pair of agents, but involves risks for the Leader.

The characteristics of the environment and the feeding activities have been designed so that they can fit in the same framework as the investment game. Each agent has 10 hours of production activities which is the same amount of money that the Investor receives in the investment game, that is, 10 dollars. At first all the time can be spent on the individual activity of gathering fruit, which results in 10 calories. In the same way that the Investor in the investment game can send any value between 0 and 10 dollars to the Trustee, the Leader in the simulation can switch any amount of the 10 hours of fruit gathering into boar hunting. This time spent in boar hunting results in three times more calories than in the fruit gathering, which resembles the multiplication of the amount sent in the investment game. That is, the Killer, who is equivalent to the Trustee, receives a larger amount of calories than would be obtained by fruit gathering. Like the Trustee, the Killer has to decide which part of the calories will be divided with the Leader in reciprocity for the trust shown. Table 1 shows the equivalences between the investment game and the simulation model.

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was set at 60 because in some simulations the process of reproduction and death of the agents was set off and this number of agents makes it possible to compare the different models.

Table 1 – Equivalences between the investment game and the simulation model

	INVESTMENT GAME	**SIMULATION MODEL**
Initial values (ag. 1)	10 dollars	10 hours
Agent 1	Investor	Leader
Agent 2	Trustee	Killer
1st move (agent 1)	Sends X dollars to Trustee Keeps $10 - X$ dollars	Hunts boars during X hours Gathers $10 - X$ fruit (calories)
Remuneration	X is multiplied by 3	X boars have $3X$ calories
2nd move (agent 2)	Keeps Y dollars $\in [0, 3X]$ Returns $3X - Y$ dollars	Keeps Y calories $\in [0, 3X]$ Returns $3X - Y$ calories
Final values (ag. 1)	$10 + 2X - Y$ dollars	$10 + 2X - Y$ calories

3.2. DECISION RULES, BOUNDED RATIONALITY AND THE LCS ALGORITHM

In this artificial world that we have modeled, the agents have to learn about the environment and decide how to behave in order to survive depending on whether they trust or not the other agents. As described above, a rational decision making process would lead to the values predicted by traditional game theory, but the behavior of people observed in experiments with investment games differs. So the agents' decision making rules have been designed according to bounded rationality and Simon's satisficing theory (1959, 1979).

According to Simon (1979), bounded rationality is a human characteristic that refers to the limits of our cognition. Our brain is more apt at pattern recognition than abstract reasoning. Through bounded rationality we can make faster decisions, and this has been crucial to our survival. So our decisions are based on pattern recognition and rules of thumb that change intractable decisions into tractable decisions.

Also, we don´t exhibit maximizing behavior. Instead we exhibit satisficing behavior. We establish a certain level of aspirations and when performance falls short of that level, search behavior is induced. At the same time, this level of aspirations adjusts itself downward (Simon, 1959).

One way to introduce decision making processes and bounded rationality into our simulation models is to use the artificial intelligence algorithm Learning Classifier System created by Holland (1975, 1996). In sum, this algorithm involves a pattern recognition process in terms of the environment and the use of a classifier system that associates patterns with actions. The LCS works in a very similar way to human inductive reasoning that associates patterns with decisions. That is, this classifier system works as a set of rules of thumb that map situations that the agent may encounter and determines the actions to be taken in every situation.

This classifier system uses a form of learning, namely reinforcement learning, in which rules that have been used and have led to positive outcomes are rewarded with a higher score and those which have led to negative outcomes are punished with a lower score. This score helps to choose which action is to be taken in future situations and also serves as the basis for the agent's experience in regard to each rule. On one hand, rules with high scores are good and should be maintained for future use. On the other, rules with low scores may be replaced by others that perform better in the future.

Another important characteristic of LCS is the genetic algorithm behind the classifier system. Eventually the agent tests new rules searching for new ways to interact with the environment. This process takes into account the score of each rule in the formulation of new rules. New rules are formulated through mutation or the crossover of rules with high scores. That is, in exploring new behavior, agents will base their selections on behavior that has been shown to perform well in the past. Over time these new rules will replace rules with low scores and bad or less effective behavior will slowly be abandoned by these agents.

The genetic algorithm behind LCS can be compared to Simon's satisficing process. Individuals whose performances fall short of their aspiration levels will induce search behavior. This search eventually may lead to more successful behavior which will help these individuals perform according to their aspiration levels and abandon bad behavior at the same time.

3.3. AGENT'S DECISIONS IN THE SIMULATION

In the simulation, the agents have to decide if they are going to gather fruit or hunt boars, but this decision has to be split into smaller decisions. For example, after deciding to gather fruit, agents also have to decide where to gather fruit and this decision has to be based on the way they understand the environment. And the way they understand the environment also depends on the attention they pay to the information they get from the environment.

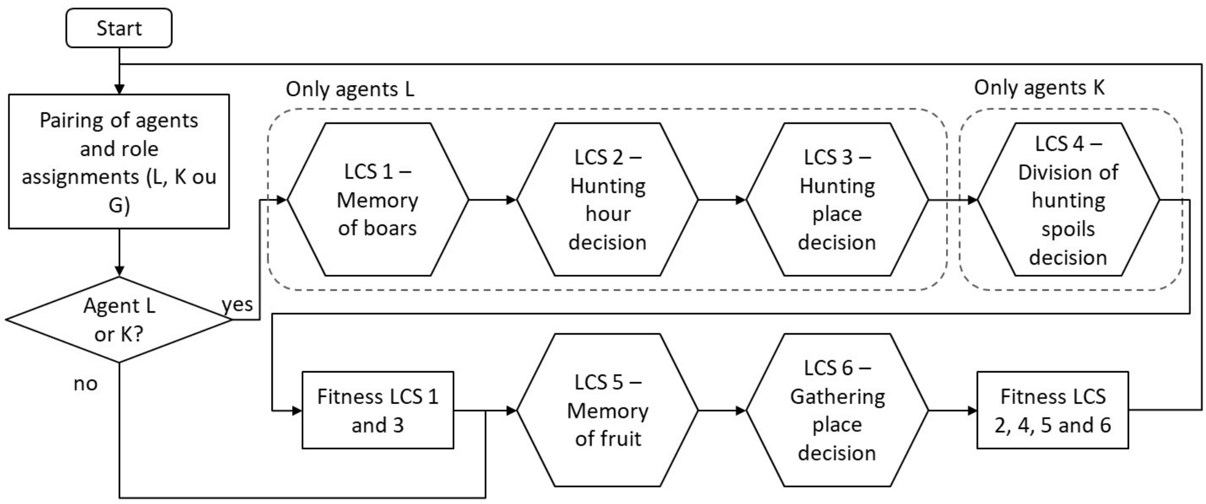
This process follows Simon's procedural rationality (1978). In complex decisions there is a considerable gap between the real environment where decisions take place and the environment as the agent perceives it. In an environment where the number of considerations that are potentially relevant to the effectiveness of a decision is large, only a few of the more salient of these considerations lie within the circle of awareness. In this context, rationality exhibits itself as a consequence of this perceived environment.

The agents in the model have a limited range of vision and can only see the amount of fruit and boars in the cell which they find themselves in or in adjacent cells. However, they have memories and can remember information about places they have previously seen, though the space available for memory is scarce.

So in the activity of fruit gathering, in order to decide where to explore, the agents first have to decide which places to pay attention to and then decide where to go. In this decision they also have to take into account places that they can no longer see. Agents can remember places that they have seen in previous rounds. Since memory is scarce, keeping information of places that are no longer visible means taking into account less information about places that are currently in sight in the decision making process.

It is also necessary to specify the decisions that the agents make and the process dynamics of the simulation. Figure 1 shows the flow of the decision making process and the order that these decisions take place.

Figure 1 – Flow of Decision Making Process in Simulation Model



Each round begins with agents being paired randomly and randomly being assigned the role of Leader (L) or Killer (K). In case of an odd number of agents, the agent who was not paired will be assigned as a gatherer (G). This process occurs at every round and agents can play different roles in each round. The roles assigned to each agent define their decisions for that round.

After the pairing, the decision processes begins, with agents L having to: 1) pay attention to the hunting conditions, that is, the number of boars in sight; 2) decide how many hours to spend hunting and 3) decide where to hunt. The information used in these decision processes and the fitness criteria used to evaluate each decision are summarized in Table 2.

After deciding the number of hunting hours and place, the hunt will be conducted and the results will be calculated. The results of the hunt will be the lesser of the number of boars in the hunting place and the number of hunting hours. Following the decision of the agents L and the hunt process, the agents K now have to decide what percentage of the calories obtained in the hunt will be sent to the Leader.

Since the fitness criteria of the decisions of hunting hours and division of hunting spoils take into account not only calories obtained from boars but also those obtained from fruits, it is necessary to wait until the fruit gathering ends to evaluate these decisions. So, after the division of the hunting spoils, only the decisions 1 and 3 are evaluated.

Table 2 – Information Used in the Decision Making Processes and Fitness Criteria

LCS	**Information used**	**Fitness criteria**
1 – Memory of Boars	Number of boars in adjacent cells	Hunting results
2 – Hunting Hour Decision	# boars / # fruit in memory; # boars in memory and history of past hunt division	Total results of the round – calories obtained from boars and fruit
3 – Hunting Place Decision	Memory of boars	Hunting results
4 – Division of Hunting Spoils Decision	# boars / # fruit in memory; hunting hours and history of hunting hours	History of total result – calories obtained from boars and fruit
5 – Memory of Fruit	Amount of fruit in adjacent cells	Gathering results
6 – Gathering Place Decision	Memory of fruit	Gathering results

The process continues with all agents having to: 5) pay attention to the gathering conditions, that is, the number of fruits in sight and 6) decide where to gather. The process is similar to the hunt. The number of fruit gathered is the lesser of the number of hours dedicated to the activity and the number of fruit at the location.

After this, the remaining decision rules can be evaluated and this round finishes and a new round starts.

3.4. GENERATIVE MODELS AND THE FEATURES ANALYZED IN THE EMERGENCE OF TRUST

As mentioned in section 3, the construction of this agent-based simulation model was inspired by the work of Epstein and Axtell (1996). The strategy they used was to build a simulation model with simple rules in terms of searching for food and survival and then introducing some features to evaluate the emergent proprieties that were caused by these rules.

According to the authors, modelling artificial societies allows us to "grow" social structures in silico demonstrating that certain sets of micro-specifications are sufficient to generate the macro-phenomena of interest. This way, through artificial society modelling it is possible to establish a strategy to analyze how some features can be sufficient to stimulate the emergence of trust between agents. This strategy consists of building a simple model, the Base model, where the agents are set up with random decision making rules. Since there is no pressure to adapt in this Base model, there tends to be perpetual random behavior and no changes in the agents' behavior. The features of interest: learning, natural selection and group formation are introduced into this model and their individual and collective impacts are then analyzed.

We will analyze the agents' behavior in terms of two production activity decisions: trust, represented by the number of hours that the Leaders decide to dedicate to the hunt and reciprocity, represented by the percentage of calories that the Killers decide to share with the Leaders.

The learning feature is the same as the one used in the LCS algorithm. Besides simulating human rationality through pattern identification in decision making, the LCS also has another characteristic related to learning, namely reinforcement learning. Through this mechanism, the more successful the rules used by these agents, the higher their fitness score. This makes them more likely to use them in similar situations in the future, and makes it more likely that they will serve as the basis for the formulation of new decision rules through mutations and crossovers. Similarly, less successful rules will decrease their fitness score and making it less likely that they will be used in the future and more likely that they will be replaced by other created rules.

The natural selection feature represents the agents' metabolisms that makes them die and leads to their removal from the environment if they cannot accumulate enough calories for survival. Metabolism is complemented by reproduction which replicates more when agents exhibit behavior that is better adapted to the environment. Reproduction is conditioned by a minimum amount of calorie stock and part of it is passed on to the offspring at birth. The amount of calories passed on is equivalent to half of the current stock, but this is restricted to a globally defined limit.

In reproduction, the agents also pass copies of their current decision rules to their offspring. However, after birth the offspring rules evolve independently accordingly to individual experience and are no longer related to their parents' rules.

The group formation feature is related to the concept of multilevel selection. According to this concept, altruism discourages inter-group selection but favors intra-group selection. That is, it can make individual survival more difficult because of other members of the group who are selfish, but if the group has a considerable portion of altruistic individuals, then this group may be more apt to survive than groups that do not have this altruistic characteristic.

So the emergence of trust and reciprocity is conditioned by the formation of groups in the simulation model. In the beginning of the simulation, each agent is randomly placed in a cell on the board. This cell becomes the agent's home. In the model with group formation, a group is defined as the agents who live in the same location and these agents are only paired with agents from the same group. Eventually (with a probability of 0.1% each round) an agent can migrate to another random position on the board, which makes it possible for the agent to join another group or even create a new one. In addition, at birth an offspring will be randomly placed in a cell on the board and will not necessarily live in the same place as his or her parent. In the model without group formation, the agents can be paired with any agent within the model[5].

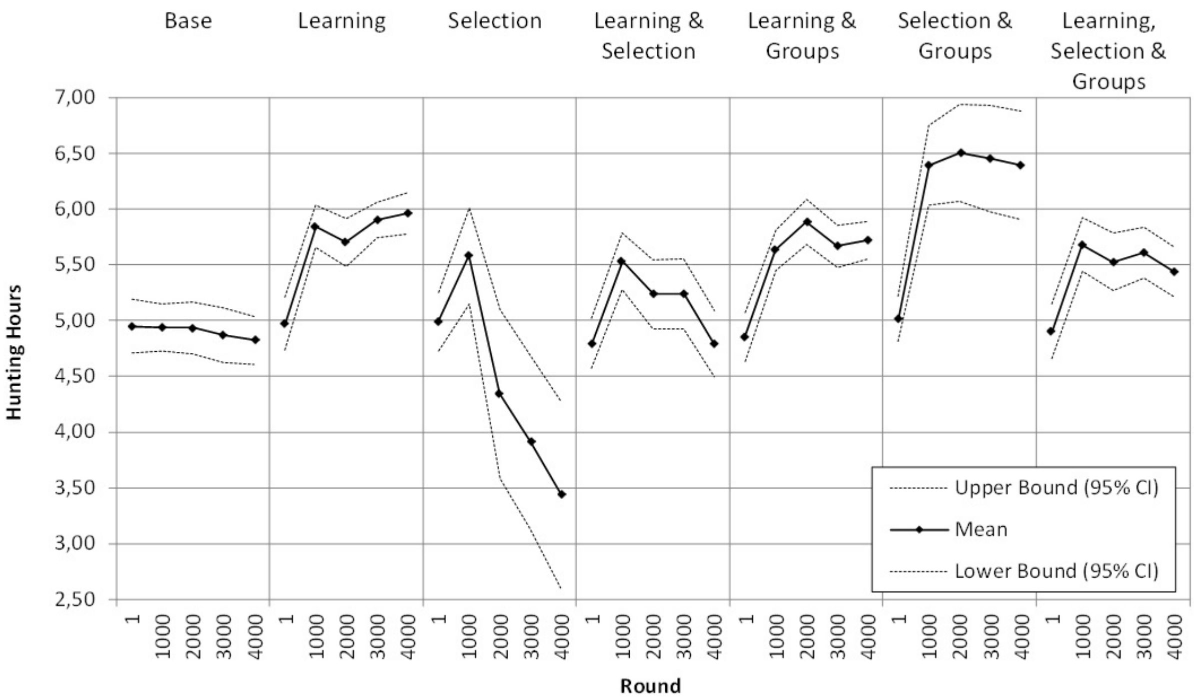
[5] Since the agents in the model with group formation are only paired with others within their groups, the number of groups with an odd number of agents is equal to the number of agents that are assigned the role of only gatherers in each round. To preserve comparability, in the model without group formation, the agents that are only gatherers are first randomly assigned based on the number of groups with an odd number of individuals and only after this are the other agents assigned their roles.

4. RESULTS

To analyze the simulation model, 50 runs of simulations were made for each type of model: 1) Base, 2) Learning, 3) Selection, 4) Learning & Selection, 5) Learning & Groups, 6) Selection & Groups and 7) Learning, Selection & Groups. Each simulation had 4000 rounds. For each simulation, the mean hunting hours decided by the Leaders and the mean percentage of the division of hunting spoils decided by the Killers were measured.

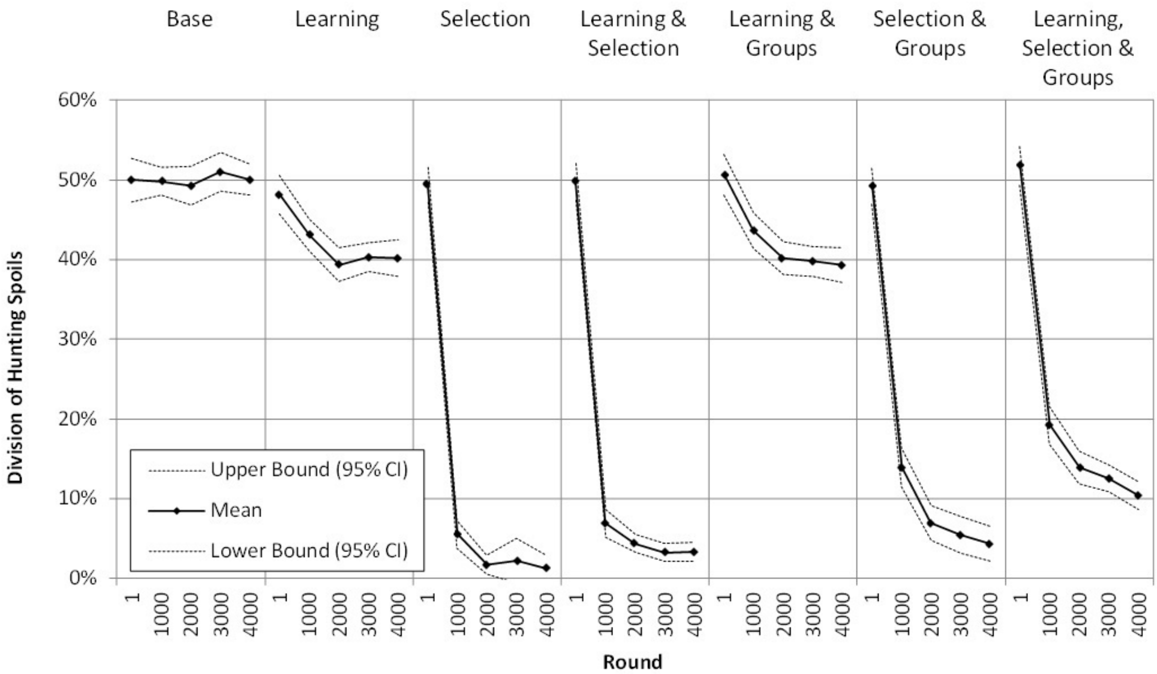
The results of the simulations can be seen in Graphs 1 and 2.

Graph 1 – Hunting Hours Decided by Leaders



Source: Simulation model.

Graph 2 – Percentage of Division of Hunting Spoils Decided by Killers



Source: Simulation Model.

It is possible to say that trust and reciprocity behavior is random in the Base model. The confidence interval of the hunting hours decided includes the value of 5 hours which is the mean of the available options and the confidence interval of the percentage division of the hunting spoils includes the value of 50%.

In the Learning model, it is possible to see a shift upward, in the direction of a more cooperative behavior, in the decisions of the agents L, reaching the average of 5.96 hours of hunting by round 4000. The decisions of the agents K, on the other hand, shifted downward, in the direction of a more selfish behavior, reaching on average 40.2% of the hunting spoils shared with the agents L by round 4000. The important observation here is that learning by itself is capable of making trust between agents emerge in simulations.

In the Selection model, the decisions of agents L shifted upward in the first rounds but changed direction by round 1000, showing a more selfish behavior as the rounds passed, reaching 3.44 hunting hours on average by round 4000. The agents K showed from the beginning a tendency to selfish behavior, reaching only 1.3% of division by round 4000. This value is very close to the rational behavior of the Nash equilibrium. This may have influenced the decisions of the agents L toward a selfish behavior.

Comparing the results of the Selection model with the Learning model, it can be seen that, on one hand, there is a tendency for the Killers to behave more selfishly and that selection exerted more pressure on them to behave like that. On the other hand, Leaders tended to be more cooperative in the beginning of both models. But selection also exerted pressure on the Leaders’ behavior to become more selfish, which did not happen in the Learning model.

The Learning & Selection model showed results similar to those from the Selection model, with agents being a little less selfish. Agents L spent on average 4.79 hours hunting and agents K shared on average 3.3% of the hunting spoils by round 4000. Learning in this case reduced the pressure exerted by selection for more selfish behavior.

The Learning & Group model shower results similar to those from the Learning model. By round 4000, agents L spent on average 5.72 hours hunting and agents K shared 39.3% of the hunting spoils.

The introduction of group formation on the Selection & Group model was responsible for a less selfish behavior from the agents L who spent 6.4 hours hunting on average by round 4000. Agents K were still very selfish sharing only 4.3% of the hunting spoils on average by round 4000.

Finally, in the Learning, Selection & Group model, group formation increased cooperation with agents L hunting for 5.44 hours on average and agents K sharing on average 10.4% of the hunting spoils by round 4000.

To sum up, selection tends to favor selfish behavior, while learning and group formation favor a more cooperative behavior.

4.1. VALIDATION WITH REAL DATA

The agent-based simulation model presents choices similar to those faced by individuals in the experiments proposed by Berg, Dickhaut and McCabe (1995). This enables us to analyze the results of the simulation and verify how close they are to those obtained in the experiments.

Berg, Dickhaut and McCabe (1995) conducted two types of experiments with investment games, one without social history where players didn’t receive any information about the decisions made by players in past games, and another with social history where players received a brief report about the results of the experiments without social history like the number of individuals per value invested, the average value returned and the average profit (the average value received minus the average value sent).

In the experiments without social history the average value sent by Investors was \$5.16 (SD = \$2.94) and the average payback of Trustees was 28.0% (SD = 28.6%) of the value received. Comparing the Investors' decision in the investment game with the decisions of the Leaders in the Learning, Selection & Group model (5.44 hunting hours, SD = 0.78), it is possible to accept that the difference between them is not significant (Welch test p-value = 0.602). However, comparing the Trustees' decisions with the decisions of the Killers (10.4% sharing of hunting spoils, SD = 6.0%) shows that the difference is significant (Welch test p-value = 0.001683).

The same can be observed when comparing the experiments with social history. The average value sent by Investors ($5.36, SD = $3.53) and the decisions made by the Leaders in the Learning, Selection & Group model are not significant (Welch test p-value = 0.9078), but the difference between the payback percentage of Trustees (33.1%, SD = 26.2%) and the Killers' decisions is significant (Welch test p-value = 9,646e-05).

Since there is no correlation between the decisions of the Leaders and the Killers in the model, it is possible to say that the modeling reflects the behavior of Investors as they occur in real experiments. However, in terms of the Killers, other features need to be developed in the simulation model to increase reciprocity at the end and make their behavior more similar to that observed in reality.

It is also important to notice that the LCS algorithm was able to model the rationality of the agents in the simulation so that they behave bounded rationally.

5. CONCLUSIONS

The strategy of this paper has been to use the generative model approach presented by Epstein and Axtell (1996) to build a simulation model consisting of a search for food based on simple rules: fruit gathering as an individual activity and boar hunting as a pair activity. The former results in fewer calories. The latter, on the other hand, is conditioned on the trust of one of the players. Based on this simple model, some features have been introduced: learning, natural selection and group formation and their individual and collective impacts have been analyzed.

Unlike the use of social norms such as inequality aversion or fairness in the utility functions to model the decision processes, these three features are not premises of their design but rather mechanisms by which the decision making process adapts and is formed. These mechanisms are responsible for the social dynamics that result from the interaction of the agents and this influences their decision processes. Of the three features analyzed, natural selection favors maximizing and selfish decisions, while learning and group formation favor more cooperative behavior.

When comparing the Learning, Selection & Group model with the real data obtained in the experiments, it is possible to accept that the difference in the trust behavior between the agents in the simulation and the players in the experiment is not significant. However, the difference in their reciprocity behavior is significant, with the agents in the simulation being more selfish on average than the players in the experiments.

Since there is no significant correlation between trust and reciprocity in the simulation model as well as in the experiments, it is possible to say that a simulation model with learning, natural selection and group formation can model the trust observed in experiments with investment games. On the other hand, reciprocity cannot be modelled this way and demands a more profound approach.

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