Influence of Opinion Leadership and Communication in a Minority Game: an Agent Based Simulation

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Abstract

In the present work we built a simulation in which a some reactive agents at each step take a binary; the agents in the minority win and get a payoff. The Minority Gamem in its original formulation, states that there is no communication among the agents involved in the simulation; the idea in this paper is to introduce in the model a sort of a social network, in order to see how the links among certain agents can change the results of the simulation. We also introduced some special agents, that we defined "opinion leaders", giving the role they have in the simulation. We investigate on how the introduction of these particular agents change the behaviour of the aggregate system.

Introduction

The Minority Game (MG) is a simple, generalized framework, belonging to the Game Theory field, which represents the collective behaviour of agents in an idealized situation where they have to compete through adaptation for some finite resource.

Game Theory is a distinct and interdisciplinary approach to the study of strategic behaviour. The disciplines most involved in game theory are mathematics, economics and the other social and behavioural sciences. Game theory (like computational theory and so many other contributions) was founded by the great mathematician John von Neumann. The first important book was The Theory of Games and Economic Behaviour, which von Neumann wrote in collaboration with the great mathematical economist, Oskar Morgenstern. Certainly Morgenstern brought ideas from neoclassical economics into the partnership, but von Neumann, too, was well aware of them and had made other contributions to neoclassical economics.

The key link between neoclassical economics and game theory was and is rationality. Neoclassical economics is based on the assumption that human beings are absolutely rational in their economic choices. Specifically, the assumption is that each person maximizes her or his rewards - profits, incomes, or subjective benefits - in the circumstances that she or he faces. This hypothesis serves a double purpose in the study of the allocation of resources. First, it narrows the range of possibilities somewhat. Absolutely rational behaviour is more predictable than irrational behaviour. Second, it provides a criterion for evaluation of the efficiency of an economic system.

If the system leads to a reduction in the rewards coming to some people, without producing more than compensating rewards to others (costs greater than benefits, broadly) then something is wrong. Pollution, the overexploitation of fisheries, and inadequate resources committed to research can all be examples of this. In neoclassical economics, the rational individual faces a specific system of institutions, including property rights, money, and highly competitive markets. These are among the "circumstances" that the person takes into account in maximizing rewards. The implications of property rights, a money economy and ideally competitive markets is that the individual needs not consider her or his interactions with other individuals. She or he needs consider only his or her own situation and the "conditions of the market." But this leads to two problems. First, it limits the range of the theory. Where-ever competition is restricted (but there is no monopoly), or property rights are not fully defined, consensus neoclassical economic theory is inapplicable, and neoclassical economics has never produced a generally accepted extension of the theory to cover these cases. Decisions taken outside the money economy were also problematic for neoclassical economics.

Game theory was intended to confront just this problem: to provide a theory of economic and strategic behaviour when people interact directly, rather than through the market. In game theory, "games" have always been a metaphor for more serious interactions in human society. Game theory may be about poker and baseball, but it is not about chess, and it is about such serious interactions as market competition, arms races and environmental pollution. But game theory addresses the serious interactions using the metaphor of a game: in these serious interactions, as in games, the individual's choice is essentially a choice of a strategy, and the outcome of the interaction depends on the strategies chosen by each of the participants. On this interpretation, a study of games may indeed tell us something about serious interactions.

In neoclassical economic theory, to choose rationally is to maximize one's rewards. From one point of view, this is a problem in mathematics: choose the activity that maximizes rewards in given circumstances. Thus we may think of rational economic choices as the "solution" to a problem of mathematics. In game theory, the case is more complex, since the outcome depends not only on my own strategies and the "market conditions," but also directly on the strategies chosen by others, but we may still think of the rational choice of strategies as a mathematical problem - maximize the rewards of a group of interacting decision makers - and so we again speak of the rational outcome as the "solution" to the game.

While the MG is born as the mathematical formulation of “El Farol Bar” problem considered by Arthur, (1994), it goes way beyond this one, since it generalizes the study of how many individuals may reach a collective solution to a problem under adaptation of each one’s expectations about the future. In Arthur, (1994) the “El Farol Bar” problem was posed as an example of inductive reasoning in scenarios of bounded rationality. The kind of rationality which is usually assumed in economics – perfect, logical, deductive rationality – is extremely useful in generating solutions to theoretical problems, but it fails to account for situations in which our rationality is bounded (because agents can not cope with the complexity of the situation) or when ignorance about other agents ability and willingness to apply perfect rationally lead to subjective beliefs about the situation. Even in those situations, agents are not completely irrational: they adjust their behaviour based on what they think other agents are going to do, and these expectations are generated endogenously by information about what other agents have done in the past. On the basis of these expectations, the agent takes an action, which in turn becomes a precedent that influences the behaviour of future agents. This creates a feedback loop: expectations arise from precedents and then create the actions which, in turn, constitute the precedents for the next step.
The original formulation of “El Farol Bar” problem is as follows: N people, at every step, take an individual decision among two possibilities. Number one is to stay at home; number two is to go to a bar. Since the space in the bar is limited (finite resource), the time there is enjoyable if and only if the number of the people there is less than a fixed threshold (aN, where a<1). Every agent has his own expectation on the number of people in the bar, and according to his forecast decides whether to go or not. The only information available to the agents is the number of people attending the bar in the recent past; this means that there is no deductively rational solution to this problem, but there can be plenty of models trying to infer the future number according to the past ones. The other very interesting aspect of the problem is that if most agents think that the number of people going to the bar is > aN then they won't go, thus invalidating their own prevision. Computer simulations of this model shows that the attendance fluctuates around aN in a (aN,(1 - a)N) structure of people attending/not attending. The “El Farol Bar” problem has been applied to some proto-market models: at each time step agents can buy (go to the bar) or sell an asset and after each time step, the price of the asset is determined by a simple supply-demand rule.
The MG has been first described in Challet and Zhang, (1997) as a mathematical formalization and generalization of “El Farol Bar” problem. It is assumed that an odd number of players take a decision at each step of the simulation; the agents that take the minority decision win, while the others loose. Stepping back to “El Farol Bar” problem, we can see it as a minority game with two possible actions: a1 = 1 (to go to the bar) and a2 = -1 (not to go to the bar). After each round, the cumulative action value A(t) is calculated as the sum of each value given to the single actions. The minority rule sets the comfort level at A(t) = 0, so that agent is given a payoff -ai(t)g[A(t)] at each time step with g an odd function of A(t).
While the mechanism behind the constitution of an opinion in the human beings is beyond the purpose of this work, here we want to analyze how a social network interconnecting a community of agents playing a MG can influence their choices and, in particular, how it could determine changes of their own original opinions. We also introduced some special agents, that we defined “opinion leaders”, giving the role they have in the simulation. In the real world, opinion leaders are key people who are recognized as influential and charismatic members of a community or communities. These individuals are seen as models whose opinions and behaviours are likely to influence the opinions and behaviours of a target population; in our model these agents’ opinion has an higher weight compared to the others’. We investigate on how the introduction of these particular agents change the behaviour of the aggregate system.
The tool we used to get analytical results for our experiments is computer simulation; modelling is a way of solving problems that occur in the real world. It is applied when prototyping or experimenting with the real system is expensive or impossible. In this particular case, simulation is a great tool for reproducing experiments in “what-if” scenarios, i.e.: by changing a parameter at a time, what happens to other values and to the aggregate trend?

Communication by Social Network

The “El Farol Bar” problem, as well as the Minority game in its original formulation state that there is no communication among the agents involved in the simulation; the idea in this paper is to introduce in the model a sort of a social network, in order to see how the links among certain agents can change the results of the simulation. A social network is defined as “a set of nodes - e.g. persons, organizations - linked by a set of social relationship - e.g. friendship, transfer of funds, overlapping membership - of a specific type” (Laumann, et al., 1978).
In our case the minority rule will be very easy: a set of N agents will have to choose between (-1) and (1). Who is in the minority (denoted with n < N) wins and gets a payoff equal to N/n: the fewer agents stay in the minority, the higher the payoff. Also the social network involved will be quite simple, just linking an agent to others with a relation limited to the possibility of asking a question: “will you choose (-1) or (1)?”. Not all the agents will be connected, though, so that some of them will have to make a prevision just considering the past few results, exactly like in the original MG.
Any kind of network can be described in terms of a graph, composed of nodes and a set of lines, edges, joining the nodes. In a mathematician's terminology, a graph is a collection of points and lines connecting

some (possibly empty) subset of them. The points of a graph are most commonly known as graph vertices, but may also be called nodes or simply points. Similarly, the lines connecting the vertices of a graph are most commonly known as graph edges, but may also be called arcs or lines. The study of graphs is known as graph theory, and was first systematically investigated by D. König in the 1930s (Gardner, 1984). Graphs come in a wide variety of different sorts. The most common type is graphs in which at most one edge (i.e., either one edge or no edges) may connect any two vertices. Such graphs are called simple graphs and are the ones we'll use in our analysis. The edges of graphs may also be imbued with directedness. A normal graph in which edges are undirected is said to be undirected. Otherwise, if arrows may be placed on one or both endpoints of the edges of a graph to indicate directedness, the graph is said to be directed.
In our work the graph used to represent the social network linking the agents together is bi-directed, i.e. each edge points on both directions as once. This seems realistic, since we can imagine our network as a group of friends, or in general people who know each other. If A knows B, then it's quite obvious that B knows A in turn; we don't voluntarily consider those situations in which a subject disseminates his opinion to others and isn't touched by their decisions (e.g.: advertisement, political campaigns, and so forth). That's because we suppose that this sort of dissemination comes "a priori", i.e. before our analysis starts; we are now interested in studying how a set of agents mutually connected into a network can influence one another and come to a final overall result. In Remondino and Cappellini (2005), we examined the aggregate results of how a social network could change the way agents form they own opinion, in a MG context. Now we go further, by introducing the concept of "opinion leader" into our simulation framework.

Opinion Leaders – Decisional Power

In the attempt to create a realistic situation we thought of introcucing some very special agents in our simulation. While normal agents change their mind according to a simple percentage rule, according to how many of their neighbours have the same opinion, and influence in turn the other ones with the same system, Opinion Leaders (OLs) have an higher weight about influencing other agents and are tougher in changing their own mind.
An OL is a person who is considered a credible source of information for others on a specific topic and who is sought out for that information.
OLs are influential because they have certain characteristics which make them attractive to others. They may be funny, intelligent, good looking, creative, or a combination of these and many other qualities. Whatever the reasons. OLs play a very important role in the community because their behaviors and values are emulated by others. The influence of each opinion leader might be limited to his or her own social network, or it may extend across many networks.

Peer OLs are key people who are recognized as influential and charismatic members of a community or communities. These individuals are seen as models whose opinions and behaviors are likely to influence the opinions and behaviors of a target population. An OL is a member of the community who is particularly popular or respected by other members of the community. An OL may be viewed as representing his/her community in the entertainment field, sports, government/politics, academia, business, popular culture, community work, and so on.
The key characteristic of an OL is that he or she is trusted to evaluate new information in the context of (local) group norms. The other main features of a person considered as an OL are that (s)he must be:

- Sensitive to local environment and group's norms
- Approachable and have good listening skills
- Perceived as clinically competent and caring
- Perceived as excellent evaluators

It's important to notice that OL not necessarily are in official positions or early adopters or not even innovators in their choices. That's why to identify them usually it's necessary to use sociogram techniques and surveys. It's therefore evident that OL play a very important role in the formation of trends and decisions in a society; we decided to implement some agents with the role of OL in our simulation in order to see how they can change the aggregate trend in a MG with communication.

Model Description - Implementation

In this section we will describe how the model was implemented in the simulation framework; we first descrive the model without OLs, then, in detail, how OLs are modelled and what are the differences among them and the other agents.
At the beginning of the simulation, during the setup, a simple world populated by N agents is created. These agents can be considered as the vertexes of a social network and the links among them (relations) as the edges. The network is directed and every arc is composed by two edges with opposite directions. Every agent has a list of F (friends) other agents (called friendsList) to whom he can ask. This list is composed by the neighbours, i.e. the vertexes linked to the examined vertex (the agent).
The neighbourhood is intended as a sociological, and not only physical, closeness. According to (Laumann et al. 1978) we describe the relations between our agents as friendship. This social relationship is characterized by a random creation but is also very stable in short/medium term. Our links are directed and bi-directional, as the friendship is.
Here follows a brief description of the simulation process:

• At the beginning of each simulation step, every agent has its own forecast. The forecast is absolutely random between two choices –1 and +1.
• The decision taken by each agent (before communicating with others) is denoted with a "certainty index" equal to 1 (100%).
• Now an agent is randomly chosen. He starts asking to the first in the list; if this one has the same prevision, then the certainty index is increased by a value of 1/F, while if the prevision is different, than the certainty index is lowered by 1/F
• After having asked a statement to all the friends in his list, the agent takes the final decision: if the certainty index is equal or greater than 1, then the decision will be the original one. If it's lower than 1, then the decision will be the other possible one
• Another agent is then randomly chosen, and so on (the same agent can't be chosen twice during the same turn). Note that an agent that's been asked can still change his mind, basing on the agents he will in turn ask.

Before starting the simulation, we can change two core parameters: the number of the agents involved and the number of the links among the agents. Here we examine three runs of the simulation, one with 1000 agents and 500 total links (an average of one link every two agents); the other one with 100 agents and 500 links (an average of five links for every agent) and the last one with 100 agents and 4950 links (a fully connected network). In every run we iterate the minority game for 1000 times.
The model could be considered as some groups of friends that must choose between two alternatives: pub and disco. They communicate the selected choice to their friends, elaborate them and then take a final decision.
The OL is a minority agent with different thresholds. The basic idea is that OL influence more people and besides he must be quite sure about his/her decision. You can imagine (s)he as an advocate or a supporter of a certain social or political cause.
During agents creation we select the two with maximum number of links. We force their opinions to be opposite, so that they become advocates for the two opposite causes in the game (binary choice). We also change the weight related to OL ideas, doubling or decupling the original value.
Could an opinion leader change his own opinion? Yes he can, but usually this should be less frequent than for "normal" agents. At every step (s)he can randomly change opinion with a probability of 5‰, or if 87.5% (certainty index > 1,75) or more of his/her "friends" have taken his/her same decision (this is an higher value when compared to the 50% + 1 of the normal agents, certainty index > 1).
In the output graph we can read the time on x-axis (1000 or 500 iterations of the game), and we plot two lines: the red one (the lower one in the graphs) depicts the decisions changed while the blue one (the upper one) is for unchanged decisions. In y-axis we read the number of decisions (changed or not) the scale (10^1, 10^2, 10^3) depends from agents number.

Results with no OL

We choose as standard example a world of 100 agents and 500 relations (figure 1), in which an average of 65 out 100 preserve their original decisions. In a second run we imagine a different situation, in which the agents have many more relations among them: an average of fifty for every inhabitant (figure 2). A simple common sense rule states that the more relations, the higher is the probability to change opinion. This example proves the rule to be right and our model to be consistent with real world results; we can now try a counter example, i.e. a poor relations world, as the one in figure 3; one thousand inhabitants with a total of just five hundred relations.

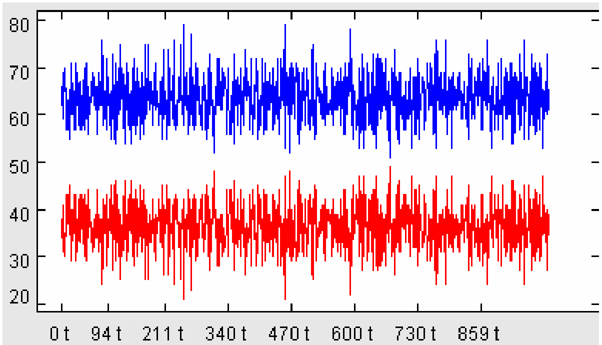

Figure 1: 100 agents and 500 relations

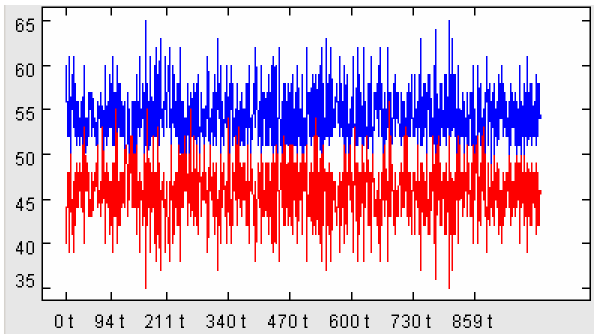

Figure 2: 100 agents and 4950 relations

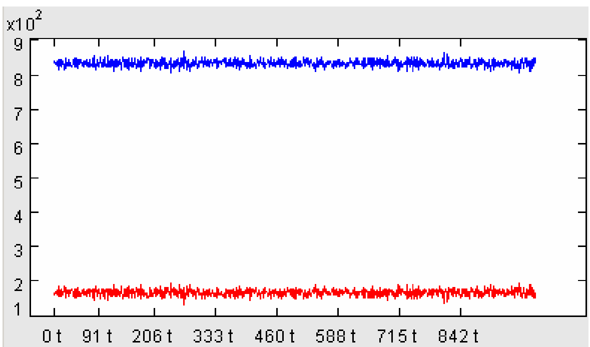

Figure 3: 1000 agents and 500 relations

In figure 3 we can observe that less than 20% of the agents changed their opinion; this is a very similar situation than in the original MG with no communication at all.

Results with OL

An example is a network layer of ten vertexes and fourteen edges, as shown in figure 4. In red and green you have the minority agents as described before, in blue the OL that choose -1 as the greens and in yellow the other one.

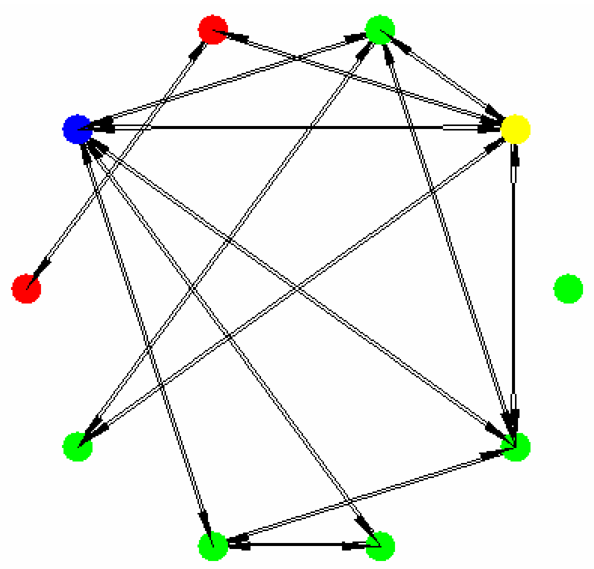

Figure 4: The network layer: 10 agents and 14 relations

The OL opinion has a weight double than the others'. It's extremely interesting to observe the graphs of total opinions (figure 5) and of OLs' opinions (figure 6).

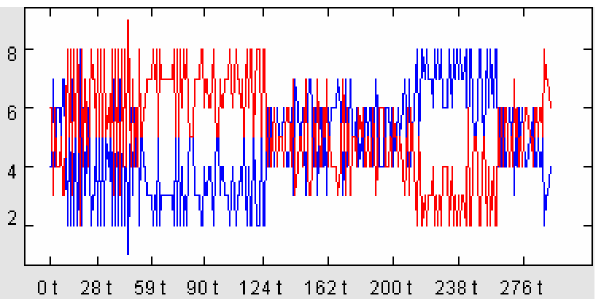

Figure 5: 10 agents and 14 relations: agents choices

We prefer to preserve both the minority rule (except for the very high boundary), and a very rare random event. We conserve the initial paradigm and give to the model more realism. E.g. In politics you can image a common situation of two main parties of which OLs are supporters with different ideas. But in a dictatorship or in a period of "revolution" during which political positions aren't emerging, you can have that the OLs support the same ideas, or that both change continually their opinions.

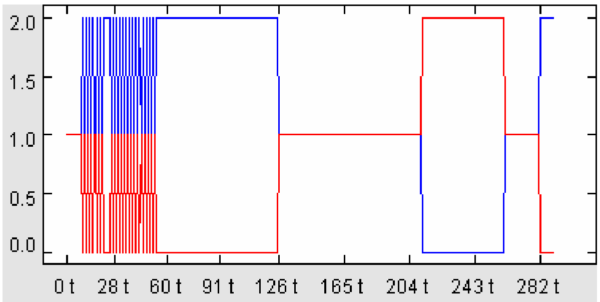

Figure 6: 10 agents and 14 relations: OLs choices

The correlation of the two series is 90,6%. So, in a small community a person with many relation can change the aggregate "mood". This correlation could be an effective measure of OLs' influence on the population.
There are three main stylized structures/behaviours.
From period 10 to 50 (the revolution/anarchy) you have a highly coordinated situation in which both OLs and almost 80% of the agents (eight out ten) adopt the same idea. That implies an opinion switch the next turn.
On the contrary, from period 126 to 210 (the plain democracy), the OLs upheld different opinions, then other agents are splitted between the two ideas.
Finally from period 210 to 260 and from 50 to 126 (the dictatorship), you can observe the polarization of the agents at the opposite of OLs common ideas.
In a network with more vertexes the OLs influence decrease quickly.

Local Minorities

Kauffman (1969), firstly described a disordered dynamical system that consists of N Boolean variables or spins stable related each other (Kauffman Networks) used by gene regulatory systems, (but also for spin glasses, evolution, social sciences, economics and finance). Each gene changes its status (active or not) depending on some other's signals. Paczuski et al (2000) used that structure introducing a Minority Game with personal limited information resources, but with a global reward mechanism.
Kalinowski et al. (2000) described a model in which agents who are placed in a circle are able to cooperate due to self-organization. The term "Local" was introduced by Moelbert and Los Rios (2002). They depicted a one-dimensional or square lattice with communities of 3 or 5 individuals, each one interacting with two (four) nearest neighbours.
All those works are based on a bounded communication and they are generally closer to a Small Worlds like scenario. They show that space correlation becomes important. We implement this local

communication among agents, but also introduce another level of information: every agent issue a statement before acting and the decision is subsequently based on that. At this moment we still don't consider the possibility to lie in the declaration.
Johnson et al. (1999), while describing an evolutionary version of the minority game (EMG), found that the introduction of partial information, instead of global and diffuse news, force agents to take a decision basing on inductive - rather than deductive - thinking. The result is a self-segregation of individuals.
Kirley (2004) extended this research in order to introduce small world connections in it. This spatial approach and a small degree of disorder lead to an improvement of system efficiency: the agents can coordinate more effectively their behaviour.
Local Evolutionary minority games (LEMG, Burgos et al., 2004), used an approach similar to Moelbert and Los Rios (2002) introducing a Local perspective in global EMG model. They found also a dependence on network structure and a likeness with particular spin systems.
Finally Namatame and Sato (2004) found coherent and systematic behaviours, and a macroscopic pattern arising the strategic interaction of local rules.
In literature we find a distinction about Local and Global models. A Local model contains the Global one as a particular case, in which the neighbourhood is composed by all individuals (Burgos et al., 2004).
The greater advantage in using Agent based models is to examine the dynamics of a system at a micro level, while the behaviour at the macro level is the aggregation of the micros.
We introduce here the concept of Local Minority; the same concept was referred to as "relative minority" in a previous work (Remondino, Cappellini 2004). A Local Minority is a group of individuals in minority in a (partially) close subset of the population. They can also not represent a global minority.
In Figure 4, you can observe a population splitted into a chain of triplets (subsets of three individuals). Their rewards depend on choices of neighbours only. In this configuration every agent could potentially be in one of the minorities. In fact 5 out 7 agents are in different local minorities.

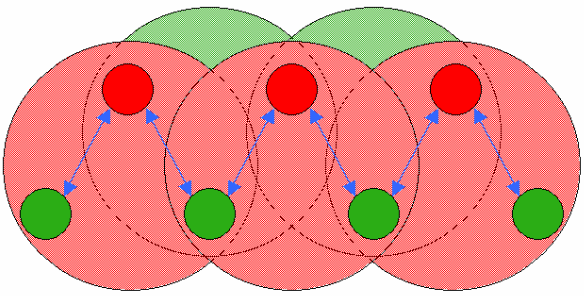

Figure 7: local minorities

As a metaphor for local minorities we can go back to a particular case of the MG, the Bar Problem quoted before. In that framework we can represent local minorities by imaging that in the same pub there are many different rooms, with different features; for instance one of them could have live music, the other one could be a smoking room, while the last one can be a no-smoking area. Of course each of them has a limited capacity so that the time in there is enjoyable only till a certain threshold. So, it's advisable that the total amount of people is divided into local minorities (rooms), so that the time there is fine for many of them. This perspective drives us towards some important consideration:

• The centrality of an exam at micro (meso) level of agents communities, instead of one of the total population, to understand the system dynamics.
• It respects a bounded (partial) knowledge of the world. Is this an egoistic view? Is it important to be happier than my neighbours?
• Could this be an useful framework to study "word of mouth" or NIMBY (Not In My Backyard!) problems?
• The cumulative rewards for the individuals in minority (minorities) could be higher than the half of the number of agents: this means than more than one half of the population (the majority) is included in the local minorities.

Conclusion and Future Directions

In our work we created an agent based simulation of a classic Minority Game, that's a framework in which an (usually) odd number of players must take a binary decision and who's in the minority wins. We introduced two original elements in our simulation: a social network, connecting some of the agents, and two particular entities, that we called "Opinion Leaders". The communication is a very interesting part of the simulation, useful to see how agents behave when they know the opinion of some of their neighbours. In particular, it proves a common sense rule, that's the more relations, the higher is the probability to change opinion.
In the real world an OL is a person who is considered a credible source of information for others on a specific topic and who is sought out for that information. In our simulation the agents defined as OLs are somehow special, in the sense that their opinion is "stronger" than the others', and is less subject to external influences. We tested that in a small community, a person with many relation can change the aggregate "mood". This correlation could be an effective measure of OL's influence on the population. By observing the results, we introduced a stylized political metaphor, by identifying periods of "revolution/anarchy", "democracy" and "dictatorship" in the aggregate trend of decision making. This is, of course, just one of the many possible interpretations of our model; for instance we can think of OLs as the testimonials for some advertising campaign or advocate for a social cause, and so on.

In future works we plan to introduce more OLs, and more than two decision poles.

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Alessandro Cappellini was born in Turin, Italy. He studied Economics at the University of Turin, where he obtained his Master Degree in July 2003, with a Thesis in Mathematical Economics concerning stocks market simulation with artificial and natural agents. He started attending a PhD (ending in 2006) on simulation at the University of Turin. His main research interests are Computer Simulations and Experiments applied to Finance, Economics and Social Sciences. He is also interested in behavioural finance, and is a founder member of the Italian behavioural finance association ("A.I.FIN.C"). Nowadays he works in Analysis and Strategic Planning bureau of Sanpaolo IMI.