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Selecting team members: a computational model for studying network dynamics

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Abstract

In this paper we present a computational model of interaction between agents in order to participate to projects. We are interested in studying the effects of different behavioral components in terms of team selection, agent aggregation and performance of groups. Our theoretical approach is compared to the results of two human experiments where subjects interacted in a similar game. This comparison allows to identify some important behavioral components in the artificial agent interaction and team formation. The occurrence of two factors is crucial: the presence of leaders as aggregators of knowledge and a behavioral rule allowing the agents to improve their projects.

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1. Introduction

In firms and organizations most employees belong to some formal work groups and a great amount of literature was devoted to study groups and group productivity (for a first introduction see Diehl and Stroebe, 1999).

According to some recent contributions (Hinds et alii, 2000) people often play an important role, either direct or indirect, when choosing their working partners. For example in business organizations several recruiting committees are partially composed of prospective peers, furthermore when in groups the composition is inadequate the results may be at least suboptimal in terms of productivity. Since one of the determinants of work group performance is the group composition (for a review see Moreland and Levine, 1994), the ability to understand how people choose their group members is a crucial step in understanding what leads to the creation of successful groups. These factors may be extremely important for managers when assembling formal work groups.

Another broad field of research is social network analysis; in this area the research tradition in assessing the impact of a given network structure is well established and recently there has been a surge of interest in terms of social capital (Lin 2001).

Yet according to Lazer and Katz (2003) the literature about intra-organizational network has largely ignored the literature about formal teams. In social network analysis various methods are incorporated. Among the others, some important threads have included the development of mathematical tools (namely, graph theory) to characterize networks, and the development of statistical tools to analyze the interdependencies peculiar to networks (for an introduction see Degenne and Forsé, 1999).

Zeggelink (1995) presents a model of evolution of friendship network where the dynamics of the network structure is considered as the result of individual characteristics and behavioral rules such as preferences for similar friends.

Banks and Carley (1996) provide a description of the mathematical models for network evolution when ties are directed and the node set is fixed. They show that many of these models tend to an asymptotically connected network.

Hinds et alii (2000) present an empirical study on group composition. Their findings show that, when selecting group members, people are biased towards others the same race, others who have a reputation for being competent and hard working, and others with whom they have developed a strong working relationship in the past.

The computational approach allows a sort of "What if" analysis. According to Young (1998) simulation can be used to establish constructive sufficiency. This may be helpful in complex models where analytic results could be difficult to obtain, and in which the consequences depend in part on random or pseudorandom processes. It may also be a source of other insights about the relationship of the assumptions to the consequences. Of course, the explanation is even stronger if the relation of assumptions to result is nonobvious, and is supported by empirical evidence.

The approach we propose analyzes, through a formal model, the project network dynamics from the repeated interaction of individuals in teams. In particular we consider how the individual behavior in terms of partner selection, exerted effort and leadership may influence the team composition as summarized in Figure 1.

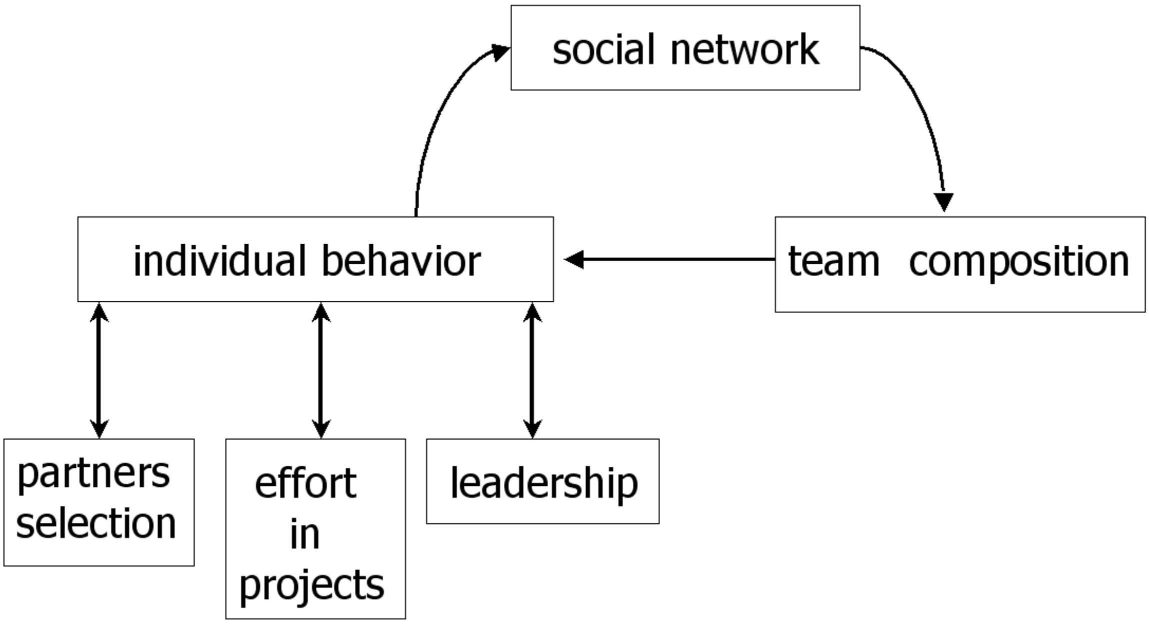

Figure 1 Team composition as the result of individual behavior

In our approach, we extend the formal analysis of the model considering both an experiment with human subjects and an Agent-based modeling (ABM) computer simulation. Our purpose is not to replicate the observed human behavior in experiments. Rather it is to use the empirical data to infer some of the implicit behaviors that generated them and model them in our artificial agents. The objective is to establish the constructive sufficiency of the model to produce behavior like that observed in human aggregation processes, such as the formation of partially connected cliques and leadership.

Human interaction and team formation is a complex phenomenon. To identify the different components we introduce a computational model of interaction and team formation among artificial agents. This way we are able to break down the agents' behavior in micro phases. We study the relative importance of each of these micro aspects of behavior when leading towards the emergence of some macro behaviors in the artificial society we consider. Our agents are all utility maximizers but, at the same time, they are heterogeneous in terms of behavioral rules. This is not a contradiction: they try to maximize their utility given the fact that, for example, they do may or may not free ride. We study how heterogeneity (in our sense individual attributes at the micro level) affects, at the macro level, the network structure and its dynamics. Finally, the task our agents are asked to perform incorporate both intragroup and intergroup levels of conflict and, for this reason, may be interpreted as a sort of generalized team game as studied in Bornstein (1993).

The paper is organized as follows. We present the theoretical model in Section 2. In Section 3 the computational model is described, while the knowledge issue and the different implemented classes of behavior are in Section 4. Section 5 collects and discusses the results and, finally, Section 6 concludes and gives some indications for further research.

2. The Theoretical Model

The organization consists of n agents univocally identified by an index $i \in N = \{1,2,...,n\}$. Agents interact forming projects in which at most m members can participate. In the artificial simulations and the human subjects experiments we fixed $m = 7$ (for an empirical motivation of this choice the reader may refer to chapter II in Miller and Rice, 1967).

Each agent can choose its partners from a subset $M \subseteq N$ of known people. Knowledge of agents in the organization is described using a sociomatrix $\mathbf{K}$. Each element k_{ij} of the sociomatrix $\mathbf{K}$ indicates whether agent i knows agent j : zero indicates that i does not know j; by converse, value one indicates that i knows j. We assume that each agent knows itself; as a consequence all diagonal entries are set to one. $\mathbf{K}$ is a not necessarily symmetric $n \times n$ matrix.

Agents can participate in at most two projects; in each of them their decision is two-fold:

1) they must specify the designated members of the project;
2) they must specify the effort they will exert.

We consider only *implemented projects*; they are defined as those where all participating agents agree on the project composition.

The relation "i works with j in an implemented project" defines a non-dichotomous symmetric matrix $\mathbf{W}$ where element $w_{ij} \in \{0,1,2\}$ is defined by the number of projects in which agents i and j work together. Matrix $\mathbf{W}$ defines the project network; when n agents work together in a n-team project we say that they form a n-*clique* since in the graphical representation of matrix $\mathbf{W}$ they are depicted as a n-clique.

Within the implemented projects the agents play a Public Good game. The efforts of the participants are aggregated and are used to produce a good with a production function *f*; the output is shared among the members of the team[3]. We denote c_i agent *i*'s cost of effort, and assume that greater effort means greater cost to the agent; we also assume that the marginal cost of effort is increasing. The profit of agent *i* in project *p* can be formalized as follows:

$$\pi_{i,p} = \frac{f\left(\sum_{j \in T_p(i)} e_j\right)}{n} - c_i(e_i)$$

where e_i is agent i's effort and $T_p(i)$ is the set of partners of agent *i* in project *p*. We assume that: 1) there exists a unique level of effort maximizing agent's profit; 2) there exists a unique Nash equilibrium e^N; 3) when all the agents exert the same effort, both the optimal effort e^N and the optimal profit are increasing in the number of members participating to the project.

In order to keep the math simple we considered in our experiments and simulations the following profit formulation:

[3] Team members may share even only a part of the output. It must be noted that the output each agent receives depends on the aggregate effort.

$$\pi_{i,p} = \frac{\left(\sum_{j \in T_p(i)} e_j\right)^2}{n} - e_i^3 \qquad (1)$$

In this case it is easy to prove that $e^N = 2/3$, and that the socially optimal effort for a n-team is $e_n^S = 2n/3$. With this profit formulation, when everybody exerts the socially optimal effort, the individual profit is increasing in the number of agents in the team.

In the two human experiments we performed, the subjects were asked to play the described game with profit formulation (1) for respectively 21 and 12 sessions. Before each session subjects were allowed to discuss each other for about ten minutes, then subjects were asked to provide two project proposals. Each project proposal consisted in the list of project participants and the individual effort the subject was willing to exert. After each session a public updated table of subject's individual and cumulated payoff was given. The full analysis and discussion of the human subject experiments is beyond the purpose of the paper and is not given here.

3. The Computational Model

In the agent based simulation we consider, each turn is divided in three phases. First, the agents propose and discuss the project. Then, some agents may decide to try to expand the sociomatrix in order to increase the probability of obtaining a larger consistent project. Finally, agents propose the two best projects that emerged in the discussion and the game is played.

3.1. Communication and discussion among agents

We could observe in the human subjects of our experiments that some individuals performed an essential role in terms of coordination of partners: often they suggested the effort and the team composition. Some of these subjects were able to find the socially optimal effort as a function of the number of team members, and suggested it to their teammates. Replicating the optimal effort in the following turn was something that spread quite immediately among the subjects. By contrast, the process of selecting the team composition was more complex. We could observe before each session of the experiment some subjects spending a considerable amount of time selecting their teammates.

Our first approaches in modeling the team selection with artificial agents simply choosing randomly their projects were disappointing in terms of results. The behavior of our artificial society was quite different from both what we expected and what we observed in human subjects. Nevertheless, these approaches allowed us to identify some important aspects to be considered.

When agents choose their projects randomly, the probability of obtaining a seven-member project is very low, because they must know each other and the number of possible projects each subject may propone is very high.

In fact, assume a population of n individuals knowing each other. We denote with r the number of team members. If $r \leq n$ teams of different dimension can be formed, up to r-member teams. For sake of simplicity we call an r-member team an *r-clique*. Therefore, the number of projects that can be obtained with exactly r individuals (i.e., the number of r-cliques) is equal to the binomial coefficient $C_{n,r}$. In Table 1 we show how many r-cliques, with r=2,…, 7, are possible in a population of n individuals.

n	2-cliques	3-cliques	4-cliques	5-cliques	6-cliques	7-cliques	Total
7	6	15	20	15	6	1	64
8	7	21	35	35	21	7	127
9	8	28	56	70	56	28	247
10	9	36	84	126	126	84	466
11	10	45	120	210	252	210	848
12	11	55	165	330	462	462	1486
13	12	66	220	495	792	924	2510

14	13	78	286	715	1287	1716	4096
15	14	91	364	1001	2002	3003	6476
16	15	105	455	1365	3003	5005	9949
17	16	120	560	1820	4368	8008	14893
18	17	136	680	2380	6188	12376	21778
19	18	153	816	3060	8568	18564	31180
20	19	171	969	3876	11628	27132	43796

Table 1 The number of possible projects in a population of *n*-individuals.

Comparing the figures in Table 1 allows to understand how the sociomatrix can play an important role. In fact, in an *n*-agent society where all the agents know each other, the probability of obtaining 7-cliques is very low since in such a society the number of projects each agent can propose is $(n^6 - 15n^5 + 115n^4 - 405n^3 + 964n^2 - 660n + 720)/720$. For example, even in the simple case of a 7-agent society, each agent can propose 64 different projects, and, if they are equiprobable, the probability that the seven-agent project is implemented is $1/2^{42}$.

In our model we implemented the discussion and proposal of projects, allowing each agent to propose up to 50 projects and having agents to choose the best feasible common project. This is a sort of brainstorming process in which agents propose whatever comes into their mind. The agents rank their feasible projects assuming that agents exert the socially optimal effort. This kind of ranking obviously takes into account the number of team members since in discussion it is dominant for the agents claiming to play the socially optimal effort.

3.2. Individual Diversity in Social Interaction and Leadership

According to their behavioral class and to the validated projects emerged during the discussion among agents, some of them may decide to act on the sociomatrix. In other words we consider agents that may decide to introduce their acquaintances to others and/or expand their own sociomatrix including all the agents known by their acquaintances. The social interactions have effect on the following turn. At the moment we do not consider situations in which leader may bargain with other agents on the team composition because, even with simple kinds of social interaction so far implemented, the model is extremely interesting. Furthermore, it would be rather difficult to determine exactly how many bargaining interactions the agents are allowed to have.

3.3. Game Interaction

According to the results emerged in the communication phase, each agent proposes the two best projects. In this phase agents may decide whether to play the socially optimal effort as in the communication phase. In our simulations, at the moment, agents do not free ride, but it is immediate to implement such a behavior. Then profits are computed and payoffs are given to agents.

4. Classes of Behavior and Structural Properties of the Sociomatrix

Given the complexity of the model, the behavior of artificial populations depends on four dimensions, namely: the *initial sociomatrix* form*,* the *team selection behavior* of agents, the *effort determination behavior* of agents, and the *social leadership behavior* of agents.

4.1 Initial Sociomatrix

As discussed in Section 3.1 the number of known agents is crucial in terms of the ability to select work groups with several agents. This has been modeled using a dichotomous sociomatrix describing the knowledge relation between agents. If agent i knows agent j the entry k_{ij} of the sociomatrix $\mathbf{K}$ is one. While usually diagonal elements are undefined we assume that each agent knows itself. Obviously sociomatrix $\mathbf{K}$ is square and not necessarily symmetric.

Our agents are assumed to be located on a circular universe. At the beginning of each simulation the mutual knowledge between agents may assume different forms. Specifically, we consider the following cases.

Total mutual knowledge. Every agent knows each other. In this case sociomatrix $\mathbf{K}$ is unitary.

***n*-neighbor knowledge.** Each agent knows just n neighbors on each side, therefore the sociomatrix we consider is close to a $(2n+1)$-diagonal matrix. For 1-neighbor knowledge only 2-cliques are possible while, in order to have 7-cliques, we need 6-neighbor knowledge. In this case each agent knows 13 individuals.

Block diagonal structures. These are ad hoc sociomatrices we considered in order to study the emergences of symmetric project implementations. For example, in a 21-agent population we considered two particular forms of sociomatrix (Figure 2) in order to have all the agents implementing two 7-clique projects.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
5	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
9	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
10	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
12	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
16	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
17	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
18	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
19	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
20	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
5	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
6	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
7	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
9	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
10	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0
12	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0
13	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0
14	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
16	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
17	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
18	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
19	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
20	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
21	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1

Figure 2 Two initial sociomatrices for a 21-agent population.

Previously observed sociomatrix. It is possible to assume as initial sociomatrix any previously saved one. For example it is possible to start with the final sociomatrix that emerged during another simulation.

4.2 Team Selection Behavior

Since, as we saw in the previous section, the combinatorial aspects of the team selection process must be carefully considered in order to have agents converging towards large projects, we developed different approaches in modeling this aspect of behavior.

1) Random number of members with random teammates. The number of team members is a random number in the range 1-7. The agent randomly selects its teammates from the agents it knows.
2) Fixed team number of team members.

Both these behaviors proved to be extremely ineffective in producing teams with a large number of members. Thus, we discarded them in our simulations.

3) Consider the project with the largest number of members and expand it keeping the same agents, and adding one more new agent. Since in the game played with our human subjects they were allowed to propose at most two projects, in our artificial agents we have them to consider their two most profitable projects that emerged in the discussion or in the previous phase.
4) Consider the two best projects and expand the first one either adding one more subject or proposing a brand new project with at least one agent more than the first best project.
5) Consider the two best projects and expand the second one either adding one more subject or proposing a new project with at least one agent more than the second best project.

The behavioral rules allowing agents to keep their best projects and to expand them proved to be extremely important in the simulations. These kinds of rules allowed, for example, the emergence of strong connections between agents.

4.3 Effort Selection Behavior

The behaviors we implemented in terms of effort selection are, at the moment, extremely sketched:

1) play the Nash effort i.e., free ride when the number of team members is greater than one;
2) play the socially optimal effort;
3) play a fixed effort.

In the experiments we observed, the human subjects almost always exerted the socially optimal effort. As a consequence, we consider agents belonging to class 2) for what it concerns the effort selection. Furthermore, this choice allowed separating the free rider issue from the choice of the teammates. This limits in no way the other potential aspects of behavior that can be studied since free riding and other behaviors can be introduced.

4.4 Social Leadership Behavior

Assume that agents are located on a circle and know just their closest neighbors; in this case only 2-clique projects are possible. Then, some of them may wish to act on the social network in order to allow the selection of larger projects. Specifically, we considered the following actions in order to expand the sociomatrix:

1) when the second best project does not use all the known agents and the agent knows less than thirteen agents, then it decides to introduce each other all the agents it knows;
2) when the first best project does not use all the known agents and the agent knows less than thirteen agents, then it decides to introduce each other all the agents it knows;
3) provided that the agent knows less than thirteen agents, when the first best project is not a 7-clique, or the first best project is a 7-clique but the second project is not, then the agent decides to introduce each other all the agents it knows;

4) when the agent knows less than seven agents and the best project is not a 7-clique, or, the agent knows less than eight agents and the best project is a 7-clique but the second best project is not a 7-clique, the agent expands the vector of its known agents in order to include all the agents that in the sociomatrix have geodesic distance smaller than three[4].

The details in which the described behaviors differ may have a huge impact in the expansion of the sociomatrix. Given the combinatorial intractability of the project selection process, it is extremely important to carefully balance the sociomatrix expansion with the number of members of implemented projects.

5 Results

Comparing the human subjects experiments and the first computer simulations we performed, several important aspects emerged.

While human subjects exhibited a tendency to aggregate and form 7-cliques, the artificial agents had great difficulty in forming even 4-cliques. In a situation with a population larger than twenty agents, where all agents know each other, the combinatorial problem discussed in Section 3.1 can prevent the emergence of 7-cliques. This situation may be described with the sentence "to know everyone is to know no one". For these reasons the initial sociomatrix is rather important. While with an initial sociomatrix where agents know just few others the team selection process can converge rather quickly, not the same holds when agents can choose their teammates from several others.

Another important aspect to be considered is that agents must be able to remember the projects that were more profitable and someway try to improve them.

[4] In a friendship relation this simply would mean that "the friends of my friends become my friends".

5.1 Expanding Project Agents Population

The results obtained from populations entirely consisting of class 3) team selection behavior are quite interesting. While, at first sight, a population in which agents implement this behavioral strategy and do not free ride should reach the situation in which agents have projects with as many as possible components, our simulation does not show this result. To understand why this does not happen it is sufficient to consider a population consisting of just five agents. Assume that for three of them the most profitable project is to work together, while the remaining two agents form a 2-clique as illustrated in Figure 3.

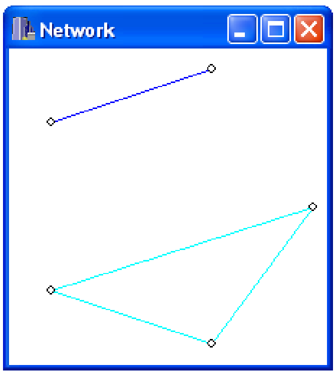

Figure 3. Final project configuration in a five-agent population.

Then for the 3-clique agents the only way to expand their project is to include the same agent selected from the remaining two agents, and have this one to propose a project in which it includes all of the 3-clique agents. This is impossible since each agent's strategy is just to expand by one its best project.

Nevertheless, a population consisting entirely of agents with this team selection behavior displayed interesting properties in terms of random graphs. Given a fixed set of n distinguishable vertices, random graphs theory considers, among other spaces, the space $\mathcal{G}^n$ of sequences of random graphs. Any element of $\mathcal{G}^n$ is a graph process, a nested sequence of graphs $G_0 \subset G_1 \subset ... \subset G_N$, with G_t having precisely t edges. With this population we obtain a sequence of graphs such that the subsequence of graphs at times $t \equiv 2(\text{mod}\, 3)$ is nondecreasing, that is:

$$G_2 \subseteq G_5 \subseteq G_8 \subseteq \ldots \subseteq G_{3k+2} \subseteq \ldots \subseteq G_T$$

5.2 The Role of the Sociomatrix

To understand how the initial form of the sociomatrix plays a role on the projects we performed simulations with a fixed size population and different initial sociomatrices. The results proved that, while certain forms of the sociomatrix may allow the formation of 7-cliques, this result could not always be observed due to the combinatorial issues discussed in the previous sections. For example, we considered a 21-agent population with the two different initial sociomatrices depicted in Figure 2. In both situations it is possible to have the optimal configuration where each agent implements two 7-cliques projects. Yet, while with the first initial sociomatrix the final configuration may occur in a few iterations, with the second the optimal configuration is much less probable.

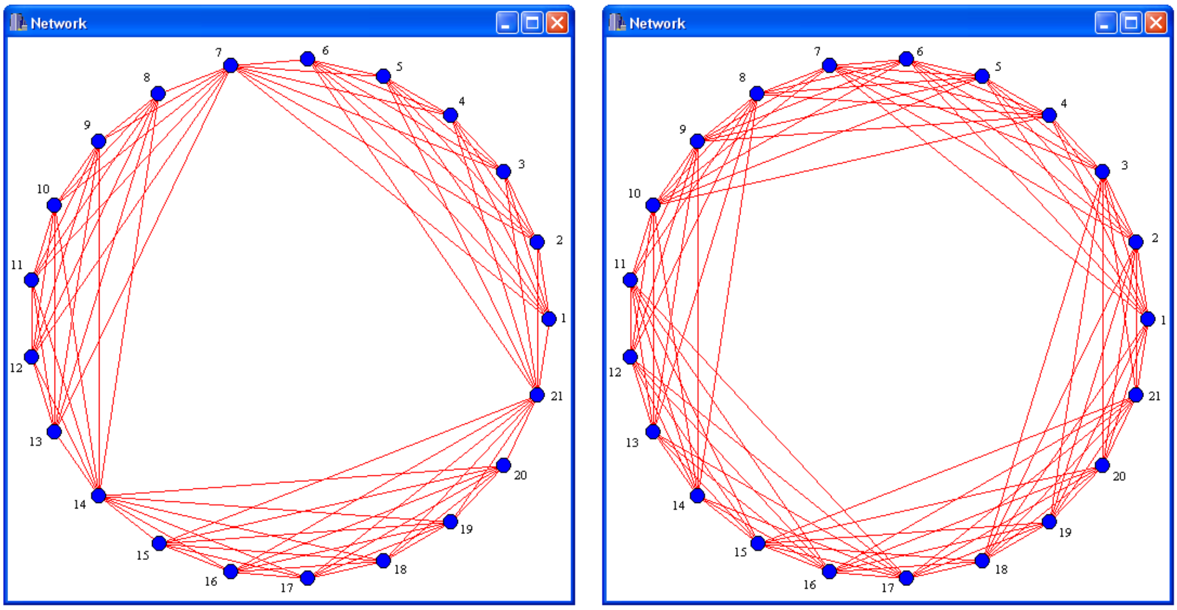

Figure 4 Two project final configurations in a 21-agent population.

This difference can be explained in terms of number of agents known by each agent in the two sociomatrices and the probabilities of agreeing on the same projects. For example consider agent 8. In the first case it knows eight agents and can choose from seven 7-clique projects, while in the second case it knows eleven agents and can choose from two hundred and ten 7-cliques projects. When combining the number of projects each agent can choose from, it is immediate to understand why in the second case the probability of having all agents agreeing on a same 7-clique project is so low.

Comparing our simulations results to the human subjects experiments it was evident that some agents assuming an active role were in order.

5.3 Population with Leaders

Finally, we explore the effects of leaders in a population consisting of agents with team selection behavior 5) and, at the beginning, knowing just their two closest neighbors. When no agents acting as leader are present, obviously the population keeps on proposing and playing 2-cliques forever since no one acts on the sociomatrix.

We compared the evolution of the implemented projects depending on the number and position of agents acting as leaders. In our comparisons we measured the number of links, the number of connected groups and classified the structures emerging in the simulations.

Here we describe each structure and their occurrence both in the artificial and human societies.

Chain of agents. The agents in this structure implement projects just with their closest neighbors. This structure does appear consistently neither in our artificial simulation nor in the human experiment results.

Closed chain of agents. This structure, which is close to the previous, occurs when also the first and the last agent implement a common project. It happens at the beginning of simulations when considering the 1-neighbor initial sociomatrix.

Isolated *n*-cliques. This structure occurs when *n*-clique projects are implemented and they are not connected at all.

These elementary structures combine in different ways depending on the number of projects the agents implement. While we could observe **chain of agents connected to *n*-cliques** only in the computer simulations, both in our simulations and human subjects experiments we observed **weakly connected clusters**, and **strongly connected clusters**. The occurrence of these structures gives a qualitative idea of the network evolution. For example in both human subjects experiments and computer simulation a high number of links and the occurrence of few strongly connected clusters indicates that agents are cooperating in large projects.

We performed simulations with a fixed size population consisting of 63 agents with initial 1-neighbour sociomatrix. The agents we considered, played the socially optimal effort, class 2) in terms of effort selection behavior, and expanded their projects according to class 5) as it concerns their team selection behavior. In this population we introduced agents assuming class 4) social leadership behaviors in different proportions. For sake of simplicity we assumed a circular world with agents identified by progressive numbers. In the 7-interval leaders the agents behaving as leaders were 1, 8, 15, 22, 29, 36, 43, 50 and 57. While in the 6-interval leader they were 1, 7, 13, 19, 25, 31, 37, 43, 49, 55 and 61. As a consequence, for the 6-interval and 8-interval the leaders were not equally spaced. We also studied leaders randomly scattered in the population.

Observing the final form of the sociomatrix we found that leaders were not the agents with more connections. By contrast, the agents in the "influence area" of two leaders were those with more connections. As a consequence, for these agents the combinatorial problem of selecting the project was particularly relevant. Another aspect we observed was that having too many leaders could not help the formation of 7-clique projects, since leaders tend to increment the social network of the agents they influence. By contrast, too few leaders may not be sufficient to build a connected enough social network.

The last experiment we performed is the following. We observed the final sociomatrix in a 7-interval leaders population. We started another simulation with no leaders, taking as initial sociomatrix the one observed at the end of the simulation with leaders. This way one of the effects of having leader in the population had been already incorporated: the sociomatrix is already expanded. While theoretically this sociomatrix is necessary to obtain the same outcome of the simulation with leaders, the results were quite different. In Figure 5 and 6 we can observe the two evolutions at different times. Both figures refer to turns 1, 2, 3, 4, 5, 6, 10, 20, 30, 40, 50, 60, 100, 200, 300, 400, 500, 600, 1000, 2000, 3000, 4000, 5000, 6000 and 10000. This time choice allows observing both the short term and long term evolution.

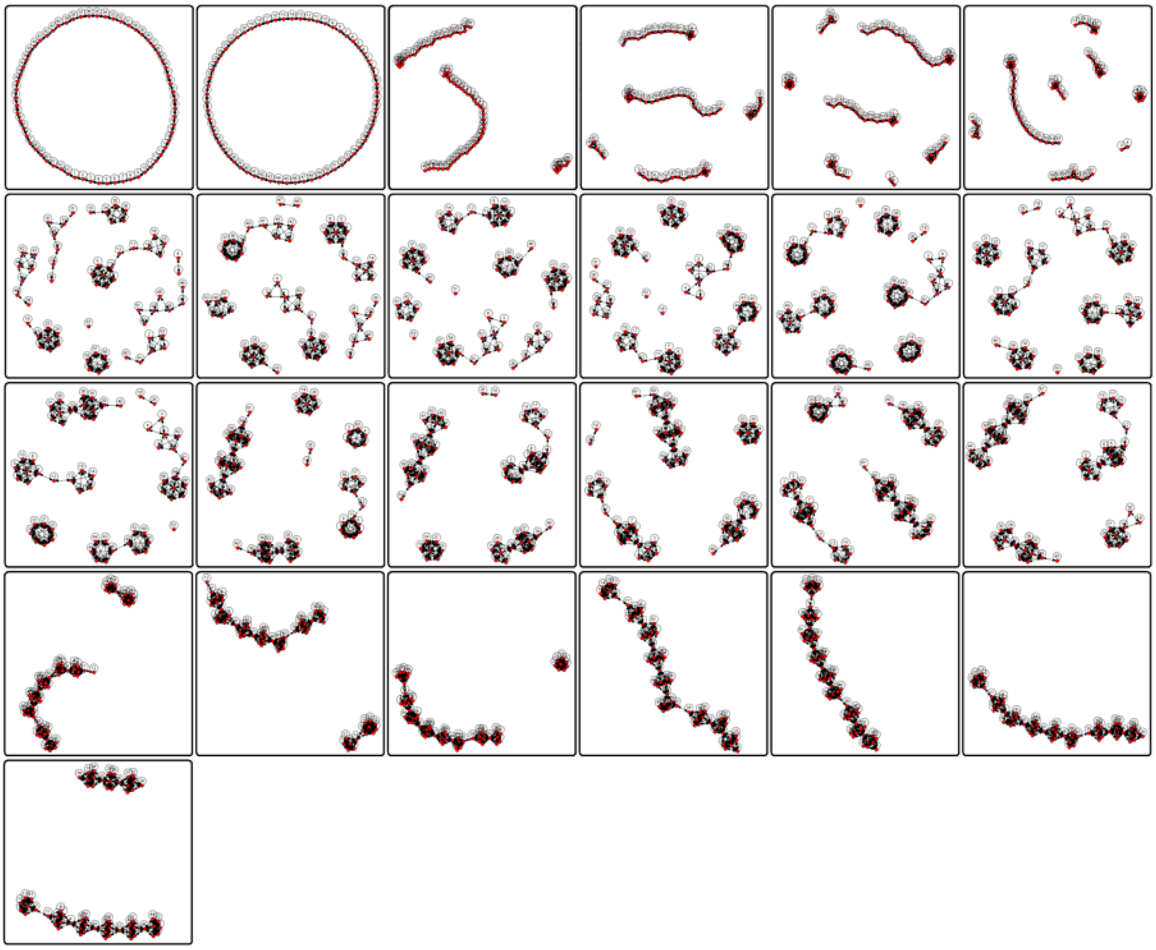

Figure 5 Project network evolution in populations with 7-interval leaders and 1-neighbor initial sociomatrix.

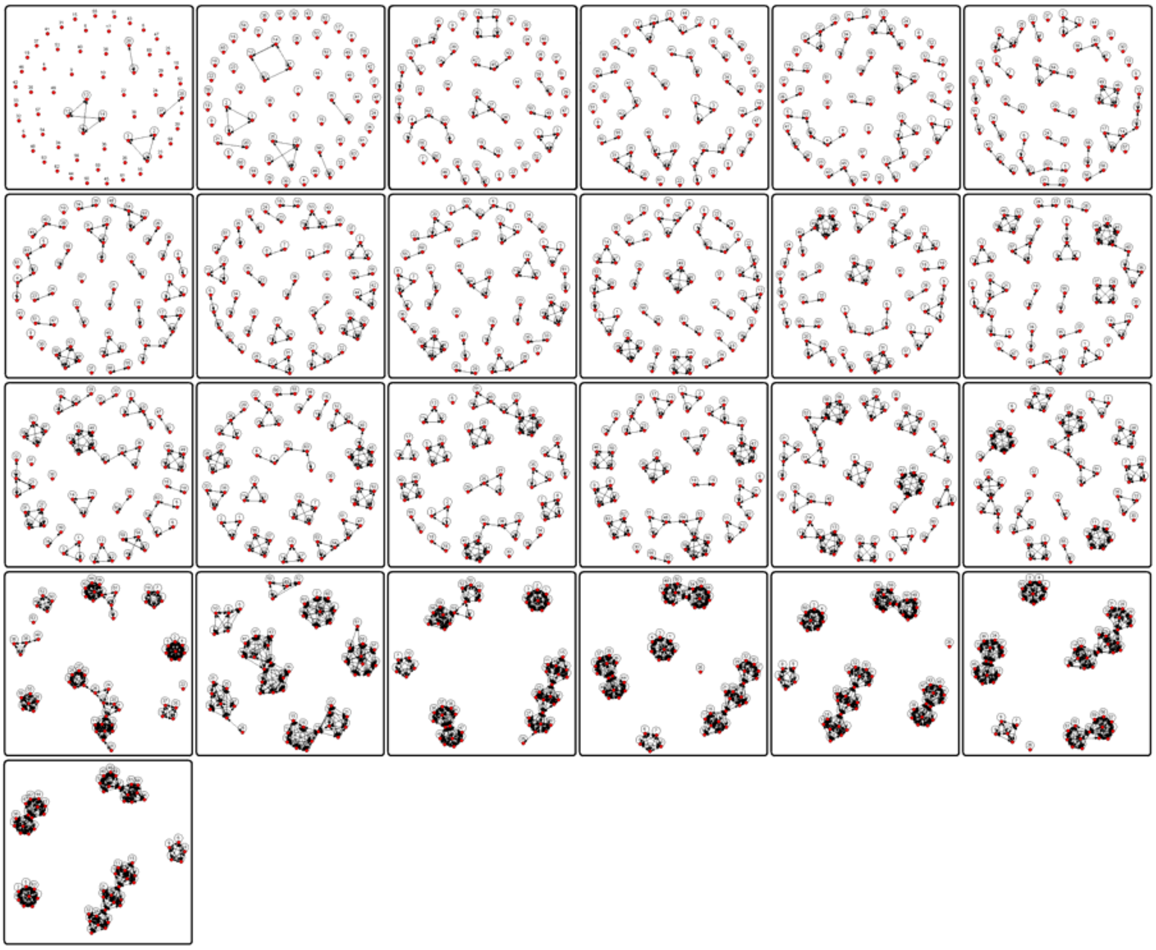

Figure 6 Project network evolution in populations with no leader and previous case final sociomatrix as the initial one.

The different aspects so far discussed are particularly evident comparing these two experiments. For example, in the no leader case at the beginning many agents do not even form the 1-clique project. This is due to the large number of agents they already know since then. By contrast, with a 1-neighbor initial sociomatrix, the agents start implementing projects with their neighbors. Furthermore, it can be observed that in case of no leaders the network evolution is much slower: while in the 7-interval leaders population weakly connected cliques with at least 5 agents in each cliques appear at about turn 30, for the no leader population their occurrence is not before turn 600.

By these results it is evident the threefold role the leaders have. First, they increase the social network of other agents making possible projects otherwise impossible. Second, they try to obtain a sort of balanced growth in terms of social network. Finally, they help in selecting one of the equilibria that, given a sociomatrix, are theoretically possible.

In the following figures we report the network evolution in terms of number of links and connected components for the different experiments we consider: 6, 7 and 8-interval leaders, no leaders and randomly located leaders in the proportion of one out of seven. Several structural and locational properties of networks are discussed in the literature (for a review see Wasserman and Faust, 1999). While most of the measures are devoted to consider simple graph, the relations analyzed with the model we consider are represented as complex multigraphs. Since to the best to our knowledge we are not aware of group cohesion measures for multigraphs and the density of a graph, which is a recommended measure of group cohesion measure (see Blau 1977), is proportional to the number of links, this statistics seem appropriate for our analyses. The artificial population data are the mean of five independent replications; we decided not to consider many more replications since the results were quite stable and the time for each replication was long (about 5 hours on a Pentium 4 CPU 2.80 GHz, Ram 512 MB).

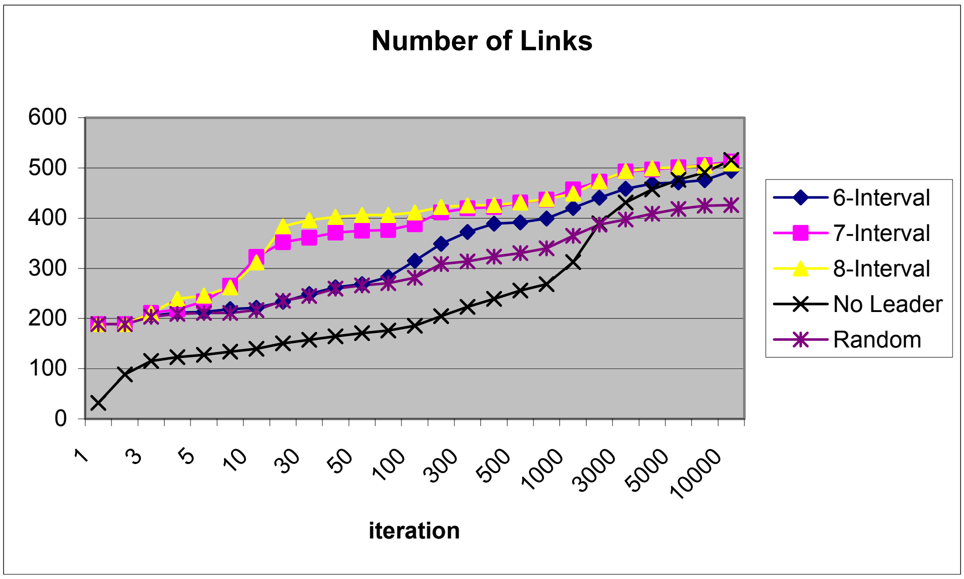

Figure 7 Number of links in different populations.

Both in terms of links (Figure 7) and non-trivial network components (Figure 8) 7-interval leaders seems to be the best configuration for leaders, even if at the beginning having 8-interval leader seems slightly more effective. This may be explained considering how leaders act in expanding the sociomatrix of the population. Having at the beginning too many leaders can hamper large group formation. A further consequence is that the optimal number of leaders is not constant over time. Finally, considering the no leader case it is evident that leaders in any configuration seem to be essential, at least at the beginning, to foster the number of links.

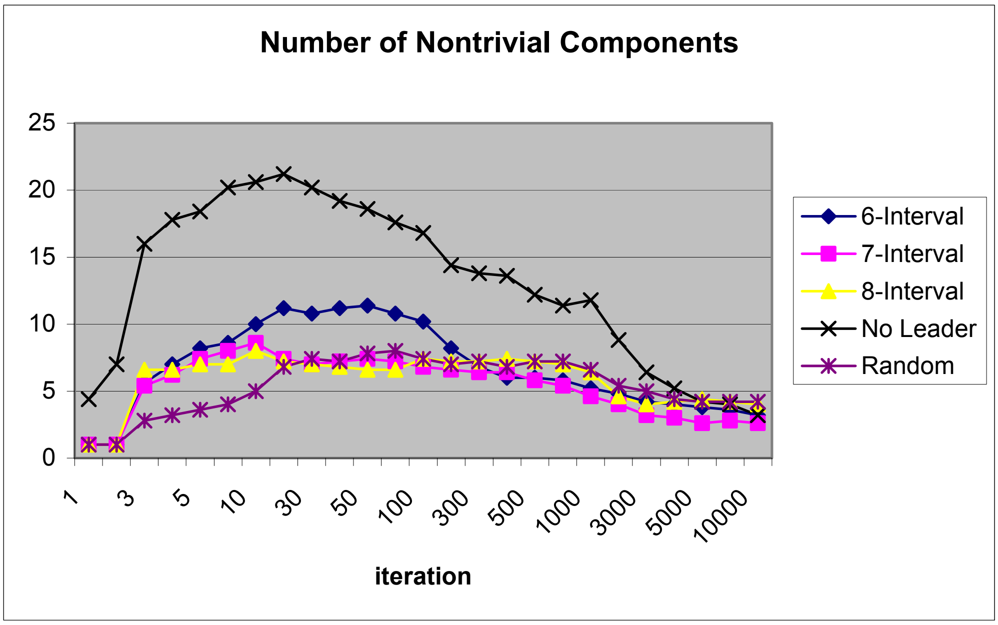

Figure 8 Number of nontrivial components in different populations.

Considering the number of components in the network it is possible to observe the role played by leaders. This is evident even considering the trivial components, i.e. the isolated agents, as shown in Figure 9.

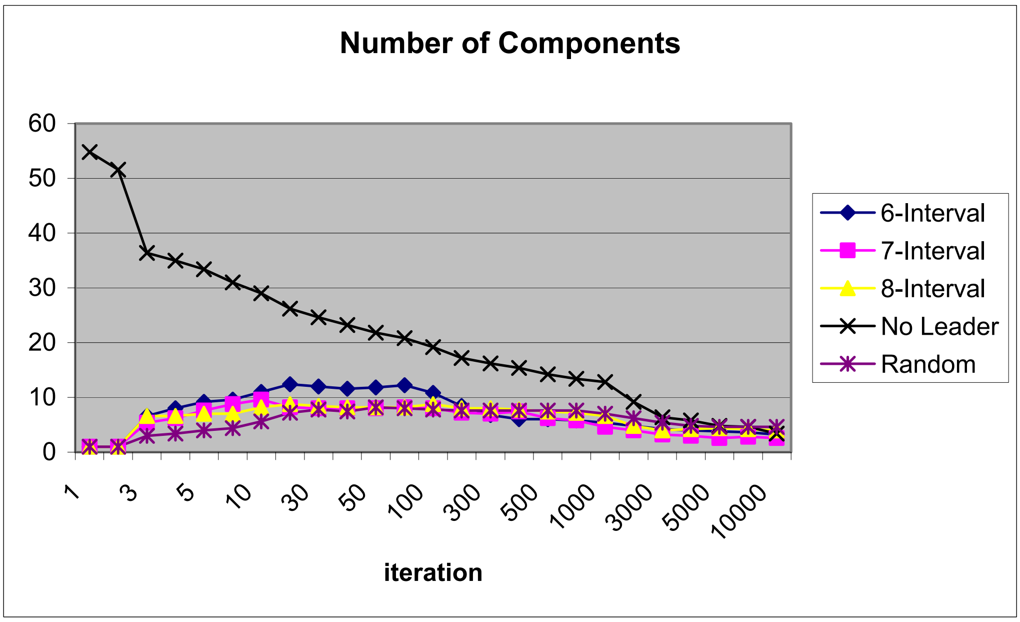

Figure 9 Total number of components in different populations.

Finally, in Figure 10, the project network evolution is depicted for one of the human subjects experiment we considered. In this case the reported turns are consecutive from the first one to the end of the experiment.

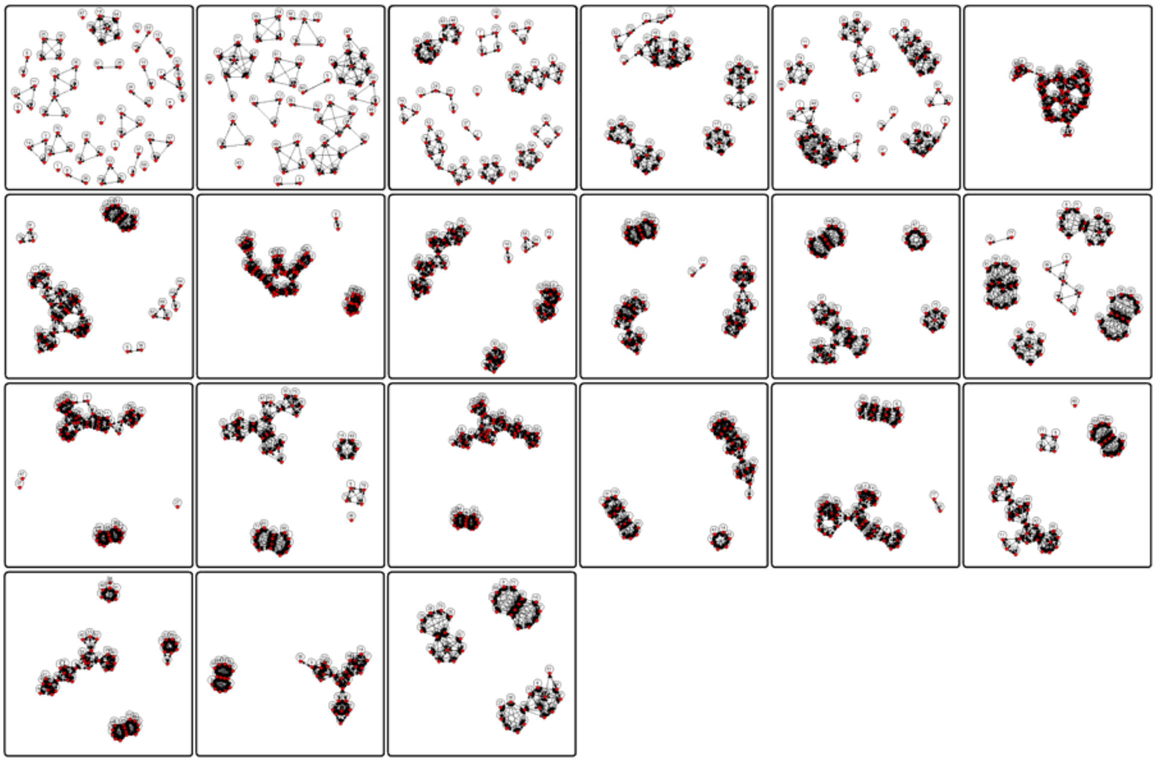

Figure 10 Project network evolution for a human subjects experiment.

With human subjects we found the same tendency to aggregation as in the artificial experiments. Nevertheless two important differences must be observed. First, since the project selection process among humans is more interactive and effective than the simple model of communication we implemented in the artificial agents, the network evolution is faster than in the artificial society. Second, the human experiment took place in different dates and we had the no-turn up problem: not all of the subjects turned up at each session of the experiment. This may explain the project network disaggregation: subjects had to continuously adapt their projects according to the contingent situation.

6. Conclusion and Further Research

Group composition has dramatic effects in terms of performance. When considering optimal allocation of human resources in firms this aspect must be carefully considered. The computational model we present in this paper allows to shed light on some aspects of the dynamics of choosing group work members.

A first important aspect is the role of communication and mutual knowledge between potential group members. While our model was not intended to capture the individual communication between subjects, even in the much simpler model of project discussion we considered, the importance of mutual knowledge and agent coordination in choosing the project to implement is relevant. For example, our model explains both the difficulties in large groups with no leaders and the problems emerging when too many leaders are present. In this sense the leadership role is necessary for a sort of an implicit coordination of agents. In our model leaders do not suggest projects, rather acting on the social network they may help the emergence of projects in the discussion phase. Particularly important is the number of leaders and their relative location: we compared the effectiveness of leaders in terms of number of link in the organization. Finally, it must be observed that, since in our model the leaders are those agents that incentivize knowledge among agents they are not those with most connections.

While the presence of social leaders is necessary for the emergence of structures similar to those observed in the human experiment results various other aspects need to be carefully examined. An important role in our analysis was played by human subjects' behavior. While we did not mean to replicate the human experiment dynamics, this analysis allowed us to focus on some simple patterns of behavior and to incorporate them in the simulation.

In further research we will extend the analysis on the human subjects results and will introduce new classes of behaviors in the computer simulation such as free-riders and other opportunistic behaviors.

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