Network Dynamics when Selecting Work Team Members

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Abstract When selecting work team members several behavioral components concur. In this chapter we summarizes our line of research on this topic; here, we articulate our results and provide suggestions for extending our analysis in order to shed light on the selection of work team members. First, a computational model – together with a theoretical approach and the results of two human experiments where subjects interact in a similar game – allows us to identify some of the most important determinants. Our results suggest that the occurrence of two factors is crucial: the presence of leaders as aggregators of knowledge and the presence of agents able to expand and improve their higher profit projects. Second, we explicitly assume the presence of formal leaders. By analyzing the results of this modified model, we shed light on the conditions which allow the emergence of effective leaders.

1 Introduction

Human interaction and group formation in the workplace is an important aspect in terms of performance and satisfaction and has been studied by several authors (for instance, [16]). In [14] it is claimed that the literature about intra-organizational network has largely ignored the literature about formal teams. In social network analysis various methods are available. Among 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.

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In [22] the Author presents a model of evolution of friendship network where the dynamics of the network structure is considered as the result of individual characteristics and of behavioral rules such as preferences for similar friends.

Previous work provides a description of the mathematical models for network evolution when ties are directed and the node set is fixed [1]. There, it is also shown that many of these models tend to an asymptotically connected network.

Some authors present an empirical study on group composition [10]. Their findings show that, when selecting group members, people are biased towards others of the same race, or towards others who have a reputation for being competent and hard working, or towards others with whom they have developed a strong working relationship.

The computational approach allows a sort of “What if” analysis, and simulation can be used to establish constructive sufficiency [21]. This may be helpful in complex models where analytical results may be difficult to obtain, and in which the consequences depend partly on random or pseudorandom processes. It may also be a source of other insights into the relationship between the assumptions and the consequences. Of course, the explanation has a greater impact when the relationship between the assumptions and the result is nonobvious, and is supported by empirical evidence.

This paper summarizes our line of research on this topic; here we articulate our results which were published in previous contributions and provide suggestions for extending our analysis in order to shed light on the selection of work team members. Our line of research is articulated in several stages. First, in [5] we proposed a theoretical model of social interaction for the study of network dynamics, then in [6] we analyze human subjects behavior when interacting in the proposed model. Finally, in [8], such behaviors were implemented to simulate the evolution of artificial agent populations in a similar context. From both the analysis and the comparison of these data two major issues emerged: the existence of leaders and their role in the interaction, which leads to a further stage of research, concerning the emergence of effective leaders. The results of this line of research were published in [7].

The structure of the paper is the following. In Sect. 2 the underlying theoretical model is presented and the unique Nash equilibrium and social equilibrium are provided. Section 3 displays the results obtained after the implementation of observed behavioral rules. Sections 4 and 5 are devoted to the proposal of our future lines of research on this topic, namely the role of communication among agents and its effectiveness, and a quantitative study of networks that takes into account a measure *ad hoc* of influence (i.e., leadership).

2 The Theoretical Model

The organization consists of n agents univocally identified by an index $i \in N = \{1,2,\ldots,n\}$. 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 Chap. II in [15].

Each agent can choose its partners from a subset $M \subseteq N$ of known people. Acquaintance 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 not necessarily a symmetric $n \times n$ matrix.

Agents can participate in at most two projects; in each of them two decisions have to be taken:

1. They must specify the designated members of the project.
2. They must specify the effort they will exert in a (repeated) public goods game.

We consider exclusively the projects where all participating agents, agree on the team composition. The team composition, together with the participants' efforts, constitute an *implemented project*.

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 on an n-member project we say they form a *size n clique* since in the graphical representation of matrix $\mathbf{W}$ they are depicted as a clique with n nodes.

Within each implemented project agents play a public goods game (for a survey on experimental research see [12]). The efforts of the participants are aggregated and used to produce a commodity with a production function f; the output is shared among the members of the team. We denote c_i agent i's cost of effort, and assume that greater effort means greater cost to the agent and increasing marginal cost. The payoff of agent i in project p can be formalized as follows:

$$\pi_{i,p} = \frac{f\left(\sum_{j \in T_p(i)} e_j\right)}{n} - c_i\left(e_i\right), \tag{1}$$

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 is a unique level of effort maximizing agent's payoff.
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 payoff increase with the number of members participating to the project.

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

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

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 payoff formulation, when everybody exerts the socially optimal effort, the individual payoff increases with the number of agents in the team.

3 The Results of the Computational Model

The second stage of our research consisted in performing some experiments where human subjects interacted on the game we presented in the previous section. The results of these experiment were presented in [6]. When considering the simulation stage, the first step consists in the implementation of some of the behaviors we observed in the human subjects. Our purpose is not to replicate the observed human behavior in experiments, but rather, 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 (Fig.1). 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 these lead 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, described as follows. 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 comprises both intragroup and intergroup levels of conflict and, for this reason, may be interpreted as a sort of generalized team game as studied in [3].

As mentioned, the computational model we consider is an *Agent Based Model* where the classes of the behavior of the agents have been obtained analyzing the results we acquired considering two human subject series of experiments. The first series consisted of 21 sessions each including about 93 individuals, while the second one consisted of 12 sessions with about 48 individuals (for a complete description of the experiment the reader may refer to [6], while for a discussion on the use of human subjects experiment the reader may refer to [4] and [7]).

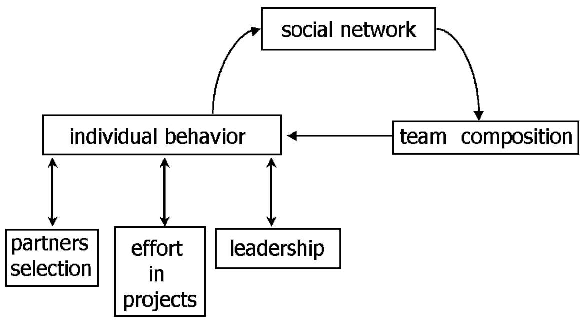

Fig. 1 Team composition as the result of individual behavior

While in the public goods game, agents are assumed to have the same role, in our human subject experiments some subjects took a different role. This is not surprising since, as it is well known, several aspects of human behavior cannot be completely explained in terms of rationality, see for instance, [11]. In particular some individuals took a leadership role within their group; this may be explained since in our interaction the agents were allowed to communicate and discuss the game before each repetition.

While several classes of behavior were implemented, those which resulted more interesting were the following:

- Agents considering the two best projects and expanding the second one either by adding one more subject or proposing a new project with at least one agent more than the second best project.
- Agents playing the socially optimal effort.
- Provided that the leader knows less than thirteen agents, when the first best project is not a size 7 clique or, the first best project is a size 7 clique but the second project is not, then it introduces all the agents it knows to one another.
- When the leader knows less than seven agents and the best project is not a size 7 clique or, the agent knows less than eight agents and the best project is a size 7 clique but the second best project is not, the agent expands the vector of its known agents in order to include all the agents that in the sociomatrix have a geodesic distance smaller than three; in a friendship relation this would simply mean that "the friends of my friends become my friends".

The results we obtain with our computational model are quite interesting. They are reported in [8] and for the sake of brevity cannot be reported here in full. Nevertheless, they can be articulated in diverse ways. A first important aspect is the role of communication and mutual acquaintance 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 that we considered, the importance of mutual acquaintance 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 fact, we compared the effectiveness of leaders in terms of number of links in the organization. According to our findings the number of leaders and their relative location is extremely important. In this sense the leadership role is necessary for a sort of implicit coordination of agents. In our model, leaders do not suggest projects, rather they act on the social network and may help the emergence of projects in the discussion phase. That is, social leaders are cardinal in stating the pace of a balanced expansion of the social matrix; essentially they control the combinatorial explosion while fostering mutual acquaintance among agents. Given the role of social leaders in group formation it is interesting to consider the model of group development by [19]. This model in its original form consists of four stages: forming, storming, norming and performing. While our model was not meant to replicate Tuckman's model, some considerations are in order. Firstly, we can interpret the role of social leader in sharing members' mutual acquaintance as a way

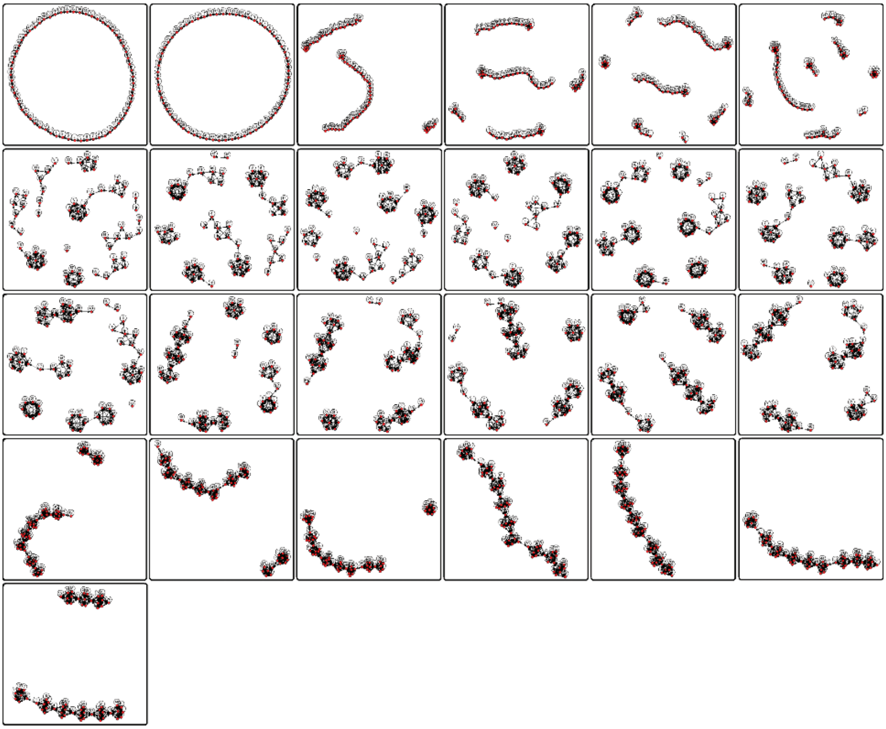

Fig. 2 Project network evolution in populations with 7-interval leaders and circle graph initial sociomatrix at turns 1–6, 10–60, 100–600, 1,000–6,000 and $10,000$

to reduce uncertainty in the forming stage when importance is placed on making acquaintances, sharing information and testing each other. Secondly, we can also observe a sort of norming stage as the group members exert the effort which is optimal to the group and do not free ride. As a final point, it must be observed that, since in our model the leaders were those agents that incentivized acquaintance among the others, they were not the agents with more connections. By contrast, the agents in the "influence area" of two leaders were those with more connections. Another interesting aspect is the comparison of the human experiment and the computer simulation. In Figs. 2 and 3 we present respectively artificial population evolution at turns 1, 2, 3, 4, 5, 6, 10, 20, 30, 40, 50, 60, 100, 200, 300, 400, 500, 600, $1,000$, $2,000$, $3,000$, $4,000$, $5,000$, $6,000$ and $10,000$ while human subject evolution is presented on the first 21 consecutive turns.

Finally, in Fig. 3, the project network evolution is reported for one of the human subject experiments we considered. In this case the reported turns are consecutive from the first to the last.

While 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, the network

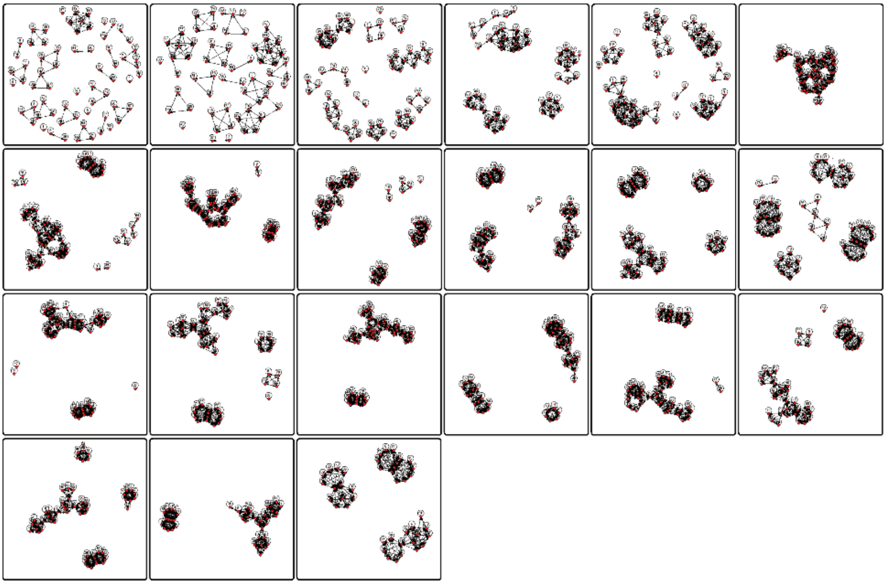

Fig. 3 Project network evolution for a human subjects experiment at turns 1–21

evolution is faster than in the artificial society; here size 6 weakly connected clusters are present on turn 2 while on turn 3 appear strongly connected clusters. Second, the human experiment took place on 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. The analysis of our simulations and the comparison to the human experiment behavior indicates several directions where to extend our research.

4 Modeling the Leadership Role

In this case we focus on the emergence of leadership when some of the observed behaviors (see [7]) are incorporated in a network. In the first stage of our research we consider a similar theoretical model with different stress on the leadership role. While in the network dynamics research we studied a sort of implicit leadership, the approach we follow in this research explicitly models the leader role. Analyzing the different interactions, we study under what conditions individuals may emerge as effective leaders.

In the following stage of our research the leader role will be introduced more explicitly in the network interaction. In other words, agents will be able to decide whether they want to be followers of a particular leader, find a different leader or even stand as leaders themselves. The approach we follow is the one outlined in [4] where gathered data and observations, when performing classroom experiments with human subjects, are used to model bounded rationality agents. The theory we build is a "Grounded theory" in the sense of [18], i.e., a theory that is derived from data systematically gathered and analyzed through the research process.

The different results we were able to observe, both in the human experiments and the simulations, are the further confirmation of interaction complexity in organizations. The simulation proved to be extremely important in analyzing the system behavior when some variables were fixed; this would be impossible when considering only human subjects, as many uncontrollable factors determine their decisions. In our approach we were interested in discovering under which conditions we could observe different leaders *emerge*. At the beginning of the interactions, in the human subject experiments leadership roles seemed to be distributed to the agents. In fact, in the human subjects experiments the number and composition of initial groups and leaders seemed to be the result of subject physical positioning during the experiment, and this was someway replicated in the computer simulations. So the question was to understand on what basis only few of them could emerge and survive during the repeated interaction. These leaders emerged in the sense that they could "keep followers". This point is interesting because somehow it links some aspects of leadership described in popular books ([17], for instance) to empirical evidence. Also comparing the results obtained with the human subjects experiments to the simulations provides some interesting suggestions, since in both cases leaders rewarding followers according to distributive justice would emerge; this kind of leader was named "Fair".

The interaction we used with the human subjects represented many of the elements of complexity theory per se. The computational model we present retains some of these elements. For example, with some classes of leaders, we can observe different final outcomes with small variations in the parameters, namely, the responsiveness probability and the initial number of leaders. This was particularly evident when considering either free riders or leadership styles different from Fair. In particular, while in the absence of free riders the only perceived inequity is leaders' distributive fairness, in a population with free riders further inequity is perceived. Both kinds of inequity cause some turbulence which, under certain conditions, does not encourage the emergence of the most suitable leader. Furthermore, unlike the computer simulation, the human subjects experiments do not produce single final leaders, which may suggest that the human subject responsiveness is not immediate. In addition, if we assume that in the human subjects experiments emerging leaders were those with larger groups, we can observe that the computer simulations are consistent with the empirical evidence, as in both emerging leaders have the larger groups. As a final point, recall that the underlying theoretical model leads to a unique final group, because of the higher individual payoffs. We did not implement agents having the maximization payoff as an objective, rather, following evidence in human subjects experiments, we chose to model sensitiveness to inequity. Yet, inequity minimization led chiefly to the maximization of the aggregate payoff, when fewer Fair leaders were present. The results of both the human subjects experiment and the computer simulation, showed how leadership emergence is a complex phenomenon, where many aspects and variables interact.

5 Introducing Explicit Agent Communication

While in the original paper the communication phase is modeled as a sort of brainstorming, in this research we are incorporating a model of communication among agents. The agent will be able to communicate about future projects and will be endowed with a sort of social cognition about what happened in the past. This way issues like free riding, commitment and reputation will be considered. In other words, the communication phase we observed in the human subject experiment will be modeled more explicitly. Many important matters will be tackled in this research. For instance, how can agents identify free riders? How can a bargaining process on the team composition end in reasonable time with a project? Furthermore, how can teams sanction free-riders or expel them from the project? The answers to these questions are still under study and are part of our further research.

6 Social Network Analysis

As mentioned in the results of the computational model for the artificial population we found that social leaders were not the agents with more connections. Rather, the agents in the "influence area" of two leaders were those with more connections. It would be interesting to understand the different roles agents play during the interaction simply by analyzing the social network.

In the artificial population analysis we introduced some measures for quantifying the evolution. The density of a graph – which is a recommended measure of group cohesion (see [2]) – is proportional to the number of links; these statistics seem appropriate for our analysis. In the first stage, we had to adapt density measure accordingly to our situation which consists of multiple projects and non-dichotomous networks. We actually considered modified density together with the number of components, which seems to be appropriate for our analysis. This way the different situations could be described as follows:

- Several links and several components indicate the presence of isolated *size n cliques*.
- Several links and few components indicate the presence of several connected *size n cliques*.
- Few links and several components indicate the presence of several isolated agents.
- Few links and few components indicate the presence of simple structures such as the circle graph or chains of agents.

While on the hand it would be interesting to refine the measures we used, on the other hand it would be appealing to find some network measure able to identify the leaders from the social network data without any knowledge of their actions. We are analyzing some of the network measures introduced in [20] in order to be able to identify the social leader simply by analyzing the network evolution over time.

Another aspect we are considering is the modification of network representation algorithm such as [13] in order to have an efficient graphical representation of the social network evolution over time. The first step has been to analyze and reimplement [13] visualization procedure as described in [9].

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