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How Network Visibility and Strategic Networking Leads to the Emergence of Certain Network Characteristics: A Complex Adaptive System Approach

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Abstract: Person-to-person interactions within an organization form a network of people. Changes of the structural properties of these networks are caused through a variety of dynamic processes among the people. We argue in this paper that there is a feedback loop between individual actions and the network structure. Therefore, a proper interaction model is needed to explain the emerging structural changes among networked individuals. According to our proposed interaction model, which is based on a complex adaptive system approach, changes in the network properties are consequences of four factors: (1) the initial underlying network structures; (2) the process of network growth; (3) the adoption of strategic responses to what other individuals do in the network; and (4) the network visibility. The experimental results show that all of these factors have influence. If the process of network growth triggers strategic responses of all direct neighbors, we observe a heavy drop in the average shortest path length between the individuals. The value of the average shortest path length shrinks to three, even independently of the visibility of the global network topology. We observe the same trend for the clustering coefficient. Fluctuations in the clustering coefficients are not significant, if visibility of the network topology is set to a high value. However, in the presence of only small number of strategic responses and a high network visibility, a short average shortest path length and a high clustering coefficient can be observed.

Keywords: Co-Author Model, Strategic Behavior, Utility Maximization, Network Growth Models, Complex Adaptive System Approach, Agent-Based Modeling and Simulation.

JEL Classification Numbers: A13, C02, C15, C63, C73, D85.

1. Introduction

Social networks are everywhere. Changes of the structural properties in social networks are caused through a variety of dynamic processes among the constituents of such networks [13, 16, 17]. The focus of the previous studies on stochastic network formation models have been on capturing the main characteristics of real world networks. An interesting observation for most of the studies has been that a certain type of network follows special network characteristics. This network analyses are independent of capturing the causes of the observed features. They only try to map network features with basic topological formation models and their inherent characteristics (e.g., random network formation model with its short average shortest path length but low clustering coefficient [2, 5, 12]). These network formation models have been proposed to produce a desired network structure [21].

The topological formation of different network models presented in literature, such as the Erdos-Renyi random graph models, the Watts-Strogatz small-world model, and the Barabási-Albert scale-free model, do not consider the interaction between the network topology and the strategic choices of the players that are located in the network. Currently, those topologies are only explainable by the type of averaged behavior of actors, which are mainly random or follow a preferential attachment rule [1, 4, 16, 17, 18, 27]. The existing strategic network formation models can also generate network structures from scratch (e.g., from isolated nodes to dyads and stars) with simple payoff functions [7, 8].

These network formation models fail to model that networked individuals usually focus on their own networking outcome. Therefore, it is acceptable to consider humans as opportunity seeking actors, who act strategically to maximize their utilities from their network connectivity [8]. A proper interaction model is needed, to explain the emerging network characteristics.

Furthermore, due to this situation, it can also be assumed that the network structure is permanently changing. By looking further into changes in the structural properties of a network, it might be possible to relate them to strategic interactions of individuals [8].

A study of the network dynamics among actors of a network requires considering additional parameters. For example, it requires an in-depth understanding of the economic behaviors of network members and the social system, within which the social interactions are performed. The behavior of network members will be the ultimate feedback to the network. A study of network dynamics in this manner requires a complex adaptive system approach. The clustering coefficient and average shortest path length can be considered to be the emerging characteristics of the network. We aim to capture these changes of those characteristics, as the agents in the network interact in an apparently not random way but according to a proper incentive model.

Therefore, in this study, we design an interaction model, which describes four factors that impact individual interactions. The four factors are: (1) the initial underlying network structures; (2) the process of network growth; (3) the adoption of strategic responses to what other individuals do in the network; and (4) the network visibility. Based on this interaction mode, it is expected that the utility gain of an individual can be captured and the emerging structural changes among networked individuals can be explained.

The main idea behind the proposed interaction model is that people agree to communicate with each other and establish links among themselves, knowing that their time is limited but obtaining some benefit. In detail, the first and second factors are necessary for generating the network. Independent of the method of network growth, the growth triggers strategic responses of existing network members. The strategic response of individuals is based on their observation of the process of network growth and is intended to maximize the payoff. Consequently, the third factor also plays an important role in the network characteristics. Limitation in having a perfect visibility of the global topology of the network also imposes restrictions on the network members. It limits the chance of selecting the best candidate for maximizing the utility.

Based on these arguments, we formulate the following research question: Based on our interaction model, what is the impact of a utility maximization process on the emerging network characteristics?

To answer this research question, we create a network formation model based on our proposed interaction model. We consider an initial underlying network structure at startup to depict a population of individuals. The network growth part of our interaction model captures the fact that new individuals are ready to enter the network and, consequently, increase the network size. Whenever the network size increases, existing individuals within the network perform strategic behaviors to maximize their payoffs.

To quantify the effect, we use an agent-based modeling approach. With the help of agent-based modeling, we can capture the dynamics among the individuals within the network. The individuals are assumed to use the co-author utility function [8].

The experimental results illustrate that the four factors of our interaction model strongly influence the emerging network characteristics. If the process of network growth triggers strategic responses of all direct neighbors, a heavy drop in the average shortest path length among the networked individuals can be observed. The value of the average shortest path length shrinks to three, regardless of the visibility of the global network topology. Similarly, fluctuations in the clustering coefficients are not really significant, if the network visibility is set to a value higher than 2. However, in the presence of only a small number of strategic responses and high network visibility, we are able to observe short average shortest path lengths and high clustering coefficients. This result corresponds to definition of small-world networks.

There have been a few studies in literature, which linked small-world properties within a network to system performance [34, 35, 36]. A noteworthy aspect of our study is that it examines certain network characteristics from the view point of an actor's perception of self-success within the network. That is to say, if individuals within the network care more about their own success, we can expect the emergence of networks, which do not follow small-world properties. It is also to be noted that a study on how the average shortest path length and the clustering coefficient impact the networking outcome has been conducted [37, 38].

The remainder of this paper is organized as follows. The above-mentioned principles and concepts are explained in Section 2. Section 3 briefly explains our model. The experimental results, which are presented in Section 4, are the basis for the discussion and conclusion in Section 5.

2. Theoretical Background

The background to this paper is related to two branches of literature, namely stochastic network growth models and strategic network growth models [38].

The first branch of literature comprises studies about network topology formations, which can be generated with stochastic network growth models. Examples of those networks are random networks, scale-free networks, and small-world networks. The models are based either on random growth [1, 2, 3] or on preferential attachment growth [4, 5, 6].

The second branch of literature analyzes the strategic interactions of individuals in networks. An individual obtains a utility due to its interaction with other individuals in the network. The utility is defined through a payoff function and can be used to measure the social welfare. An overview to social and economic networks is given by Jackson [7, 8, 24]. The decision can also be based on degree centrality [28, 29, 30, 31, 32] or closeness centrality [23, 25, 26, 27]. The effects of individuals' interactions in networks are discussed in the context of network games [9, 11], public good provision [10], bargaining and power in networks [7], and reliability [22]. Among those strategic network growth models, there is the co-author model that will be used in this paper.

3. Proposed Model

3.1. Concept

Changes in the utility of individuals in a network are consequences of four factors within our interaction model: (1) the initial network structures; (2) the process of network growth; (3) the adoption of strategic responses to what other individuals do in the network; and (4) the network visibility. The key features of our interaction model with respect to the complex adaptive system approach are adaptation and feedback loops. This combination of features distinguishes our contribution in this paper with previous works in this area.

To formalize our interaction model, we consider a set of nodes $N = \{1, 2, \ldots 3\}$ and a set of M potential candidates for each node i through whom the utility maximization process is possible. A utility maximization process can be considered as a node's strategic response (i.e., a new link establishment that provides the node with the highest utility) to link establishment behaviors of other network members. Among those M potential candidates, node i prefers the one, which maximize its utility. The pseudo-code of our interaction model and its detail description are given in Algorithm 1.

3.2. Strategic Response of Individuals

For expressing strategic responses of nodes, the network needs to be expressed as a graph $G = \{N; L; U_i\}$. It specifies the actor set $N = \{1, \ldots n\}$, the link set L, and the utility functions $U_i: G \rightarrow \mathbb{R}$ for each actor $i \in N$.

```
Given graph G = {N; L; U_i}   // N is the set of n nodes, L is the set of links, and U_i : G → ℝ is the utility
    function for each node i ∈ N
Ask Nodes Update [utility]   // Update utilities of all nodes before network grows using U_i
For counter = 1 To P Do   // Set P to the number of nodes to be created
    Create-new-node m
    If M_ng = "Strategic Growth" Then
        Ask Node m [Create-link-with node j]   // Where max_j (U_m (G + jm)) > U_m (G)
    If strategic_response="One" Then   // Only one strategic response for a direct neighbor of node j is
    triggered
        Ask One-of-link-neighbors-of node j [   // Selection of node i from neighbors of node j
            Create-link-with node q ∈ B^K[i]   // Where q≠i and iq∉ L_i(G) and max_i (U_i (G + iq)) > U_i (G)
        ]
    If strategic_response="All" Then   // A strategic response for all direct neighbors of node j is triggered
        Ask Link-neighbors-of node j [   // Selection of all node i from neighbors of node j
            Create-link-with node q ∈ B^K[i]   // Where q≠i and iq∉ L_i(G) and max_i (U_i (G + iq)) > U_i (G)
        ]
    Ask Nodes Update [utility]   // Update utilities based on recent changes to the network structure using
    U_i
Report Clustering_Coefficient  // Clustering coefficient of the network
Report Average _Shortest _Path _Length // Average shortest path length of the network
End For
```

Algorithm 1. Pseudo-code of the network formation model based on the proposed interaction model.

A strategic response of actor i is defined as the establishment of link iq as the best response to actor j's strategy with two conditions:

- Actor q belongs to the *distance-k ball* of i, denoted by $B^k[i]$, where $q \neq i$ and $iq \notin L_i(G)$
- $U_i\,(G + iq) > U_i\,(G)$

If actor j decides to establish a link with a new actor, and actor i perceives it as a reduction in his utility, actor i may also establish a link with another actor to recover the loss imposed by actor j. Based on the utility function of the co-author model (the lowest number of connections gives the highest utility to actor i), we argue that the creation of a link with an actor at the *distance-K ball* of i, which can be considered as actors *i's* rational behavior to maximize his utility. *Distance-K ball* of node i covers all neighboring nodes of i at a distance K. Therefore, actor i can select any of those possible candidates ($q \in B^K[i]$), with whom its link establishment maximizes its utility. The parameter K points to the bounded rationality and actually relaxes the strong assumption of having access to the entire node set of the network during the utility maximization process. The creation of an additional link leads to a better outcome for actor i and, at the same time, can be considered as a penalty for actor j's action. Contrary to the studies, which are based on structural holes theory or network closure [42, 43], we argue that one can maximize the utility by strategically connecting to the nodes with a low degree of connectivity. This is due to the availability of more resources (e.g., time) of actors with little connectivity and the type of utility function that is used in our interaction model.

3.3. Utility Function

The utility function that is used in our model is the utility function of the co-author model [8]. In the co-author model, the utility function is defined to encourage the cooperation between two individuals. That means, two not directly connected individuals do not receive any payoff. However, as soon as they establish a link with each other, the co-author utility function assigns a positive utility to both individuals. If another individual joins the network and establishes a link with any of the existing two nodes, the receiver of the link gains a credit, while the other one faces a lower utility due to the negative externality caused by the co-author utility function. In this paper, despite the fact that we are using the utility function of the co-author model, we are considering a new scenario, in which individuals are not in competition at the initial stage but organize themselves according to a certain network structure (e.g., scale-free network structure, small-world network, or random network). The competition starts when new members join the network based on strategic growth models. If an actor perceives a utility decrease due to a new link establishment of its direct neighbors, the actor initiates its own new link establishment to another actor of the network.

The co-author utility function of each individual is a function of its own connectivity degree and its neighbors' connectivity degree. The utility function of the co-author model is presented in Equation 1.

$$U_i = \sum_{n \in neig(i)} \left(\frac{1}{l_i(G)} + \frac{1}{l_n(G)} + \frac{1}{l_i(G) l_n(G)} \right) \quad \textbf{(1)}$$

The degree of actor i is denoted as $l_i(G)$. The more direct neighbors of actor i are involved in collaborations with other network members $l_n(G)$, the lower the obtained payoff of actor i is from its collaborations. The term $\sum_{n \in neig(i)} \left(\frac{1}{l_i(G)}\right)$ captures the connectivity degree of node i, while the term $\sum_{n \in neig(i)} \left(\frac{1}{l_n(G)}\right)$ captures the connectivity degree of all its direct neighbors. The term $\sum_{n \in neig(i)} \left(\frac{1}{l_i(G) l_n(G)}\right)$ specifies the joined benefit from their connectivity degrees.

The following example gives an insight on how the utility of a node can be calculated in our interaction model. The graph G depicted in Figure 1 is given and it is supposed that actor j decided to establish a connection with a newly entered actor m during network growth. This imposes a decrease in the utility of actor i from $\frac{5}{3}$ to $\frac{3}{2}$, based on Equation 1. According to the definition of strategic responses, a rational choice of actor i is to establish the link im or the link in (or any other possibility depicted with dashed links) as a best response to the strategy of actor j. It satisfies both conditions and increases the utility of actor i from $\frac{3}{2}$ to $\frac{17}{8}$.

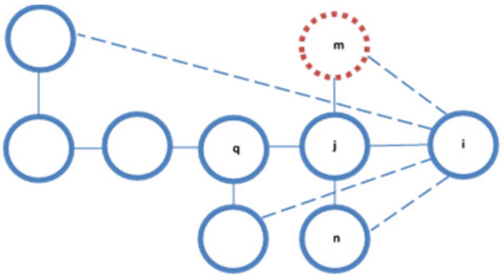

Figure 1. Link creation of node *j* with newly entered node *m* and strategic response of neighbor *i* of node *j* upon it.

3.4 Emerging Network Characteristics

The emerging network characteristics, which we consider in this paper, are the clustering coefficient (CC) and the average shortest path length (AVL). The shortest-path length is defined as the shortest distance between node pairs in a network [5]. Therefore, the average shortest-path length, AVL, is defined according to the following equation:

$$AVL = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \geq j} s_{ij} \qquad (2)$$

where N is the number of nodes, and s_{ij} is the shortest-path length between actor i and actor j.

The clustering coefficient C_i of actor i is given by the ratio of existing links between its neighbors to the maximum number of such connections [5]. Thus, the clustering coefficient C_i is defined according to the following equation:

$$C_i = \frac{2E_i}{k_i(k_i - 1)} \qquad (3)$$

where E_i is the number of links between the neighbors of actor i, and k_i is the degree of actor i. Averaging C_i over all nodes of a network yields the clustering coefficient CC of a network. It provides a measure of how well the node of the network are locally interconnected.

4. Results

4.1. Simulation Environment

We designed an agent-based model in Netlogo [14] to conduct the simulations of the proposed network formation model that is based on our interaction model. The simulation parameters, which have been used in these simulations, and their descriptions are presented in Table 1.

Table 1. Simulation parameters and their descriptions.

Parameter Name	Description	Values
M_{ng}	Methods of network growth	Strategic growth
K	Distance from node *i* to node *j*	$K \in [2\text{-}10]$
$B^k[j]$	Neighbors of node *j* at distance *k*	Subset of N
n_{start}	Population size at start up	25
n_{end}	Total size of the Population	200
U_i	Utility of node *i*	$U_i = 1 + \left(1 + \frac{1}{l_i(G)}\right) \sum_{n \in neig(i)} \left(\frac{1}{l_n(G)}\right)$
I	Type of initial network structure	• Scale-free network • Small-work network • Random network

To demonstrate the significant difference of the initial network topologies that have been used for the simulations, the three initial network structures, are depicted in Figure 2.

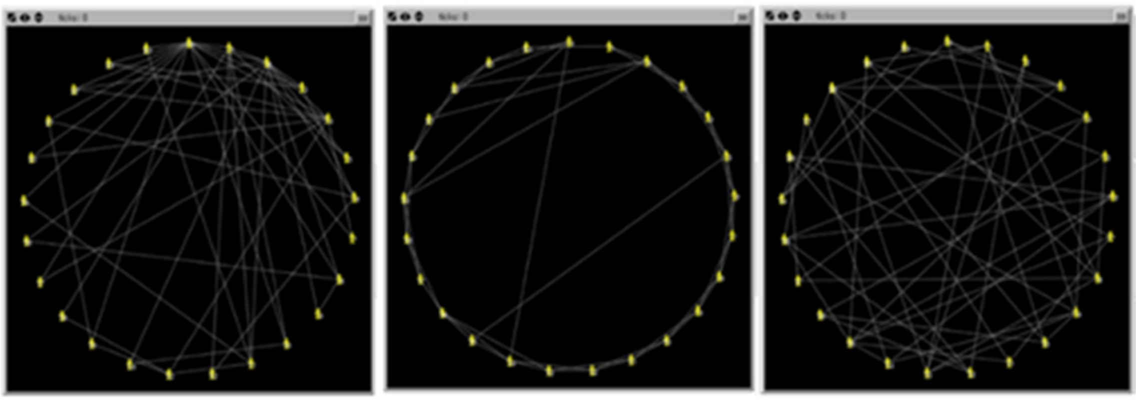

Figure 2. Three different initial network structures with 25 nodes with 50 links at startup (from left to right): scale-free network, small-world network with rewiring probability 0.1, and random network.

4.2 Results

Our simulations comprise two sets of experiments (Figure 3 and Figure 4). Each of them contains three different configurations with respect to the initial network structure. In particular, these figures show the changes in the characteristics of the network (i.e., clustering coefficient and average shortest path length) for the three initial network structures and the different network visibility parameter values.

The process of network growth continues until the size of the network reached 200 ($N = 200$). The x-axes show the simulation periods, while the y-axes show the clustering coefficient (Figure 4) and the average shortest path length (Figure 3), respectively.

Figure 3 depicts the average shortest path length (AVL) of the networked individuals for the three initial network structures and in the presence of one strategic response upon the process of network growth.

Regardless of the initial network structure, if the network visibility is set to a small value (e.g., K = 2) the average shortest path length of the network appears shows only large values. The maximum values of AVL in Figure 3A, 3B, and 3C range from 9 to 13. If k = 2, individuals are only able to search for potential candidates for a link establishment that are two hops away from themselves only. It reduces the chance of finding better candidates from other parts of the network.

Another observation from these series of figures is that, if the visibility of the individuals is set to higher values (e.g., k = 10), a huge reduction in the average shortest path length can be observed. The minimum values of AVL in Figure 3A, 3B, and 3C range from 3 to 5. This shows that visibility of the global topology of the network will provide individuals a better chance to select the best candidate for their utility maximization. Having said that, the smallest AVL value belongs to the network, which had a random network as its initial network structure. The resulting network with the AVL of three is generated, if K = 10.

We also simulated scenarios (though not shown as figures), in which the method of network growth triggers strategic responses from all direct neighbors. An interesting observation is that there is no large gap among the AVL values for different visibility parameter K. If the visibility parameter is set to high values, the AVL values go down but the differences are not significant. This shows that strategic responses of all direct neighbors help the entire population to reach each other in a low number of hops and, consequently, reduces the impact of the visibility parameter K.

Furthermore, the average shortest path length of the network is the highest, if the method of network growth is set to strategic growth. That is to say, new individuals, who enter the network by maximizing their utilities, search for the best candidate among the existing network members to provide them with the highest utility (based on the co-author formulation). This indicates that the utility maximization process of the individuals lead to a network with a high average path length. Consequently, it make the individuals to be far away from each other.

We repeat the same set of experiments by calculating the emerging clustering coefficient (CC) of the network. The results of our experiments are depicted in Figure 4. In particular, Figure 4A, 4B, and 4C show the changes in the clustering coefficient of the network with respect to the three initial network structures and different visibility parameters K. The x-axes show the simulation periods, while the y-axes show the clustering coefficient of the network.

The figures show that, regardless of the initial network structure, if the network visibility is set to a small number (e.g., k = 2), the clustering coefficients appear to be larger. However, if the visibility of the individuals is set to higher values (e.g., k = 10), it leads to a huge drop in the clustering coefficient. This shows that a good visibility of the nodes of the global network topology does not lead to a network with a high clustering coefficient. This indicates the fact that lower visibility towards global topology of the network leads to emergence of network structures with a high clustering coefficient among its members.

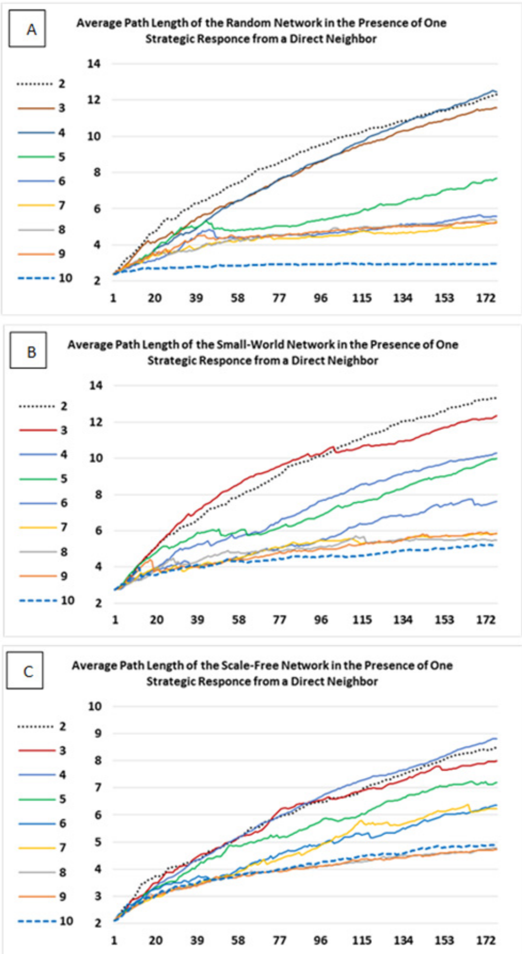

Figure 3. Average shortest path length of the networked individuals with respect to three different initial network structures and in the presence of one strategic response upon the process of network growth. The x-axis shows the simulation periods, while the y-axis shows the networks' average shortest path length). Plot legends show the visibility parameter K.

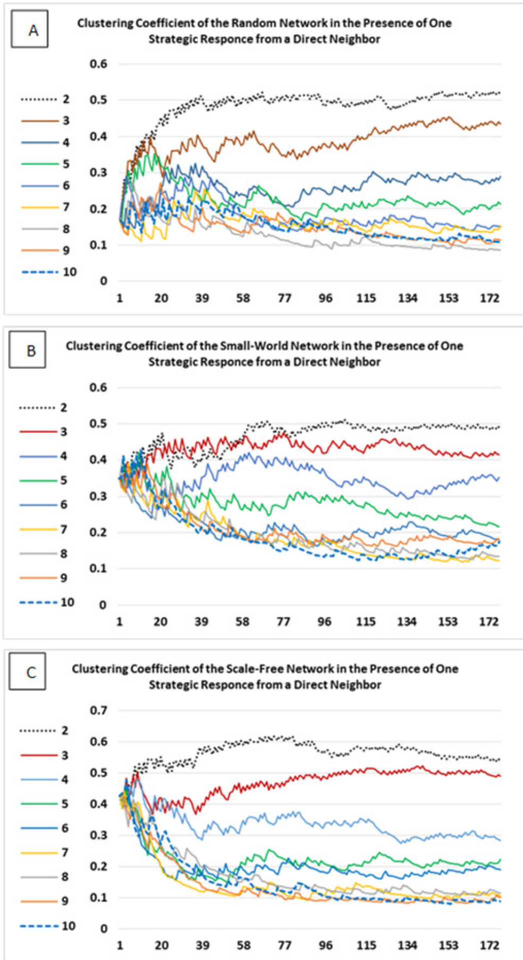

Figure 4. Clustering coefficient of the networked individuals with respect to three different initial network structure and in the presence of one strategic response upon the process of network growth. The x-axis shows the simulation periods, while the y-axis shows networks' clustering coefficients. Plot legends show the visibility parameter K.

5. Discussions and Conclusion

In this study, we argue that the direction of current research must change from "what types of network properties emerges" to "why such network properties emerge". We believe that by looking further and deeper into changes in the structural properties of a network, we can also relate them to the strategic interactions of individuals that are located in it. In the world of networked individuals, usually the main focus of the focal individual is on his or her own networking outcome. Humans are opportunity seeking actors, who behave strategically, in order to maximize their utilities within the network. Consequently, we can explain why the network structure is permanently changing.

Looking at the topological formation of networks (e.g. random graph models, small-world models, and scale-free models) presented in literature, it seems that the interaction between the topology of a network and the strategic choices of the individuals has not been considered. Currently those topologies are only explainable by the type of average behavior of actors in a network [1, 4]. In this study, we tackled this limitation and provide an interaction model to show that the changes of the structural properties of networks are caused through a variety of dynamic processes (e.g., the method of network growth and strategic responses of individuals).

The emergence of certain network characteristics is an important issue, especially from the view point of obtaining an improved performance out of the connectivity of individuals within a network. For example, there have been a few studies in literature, which showed how small-world properties within a network can boost performance of a system [34, 35, 36]. However, a noteworthy aspect of our study is that it examines certain network characteristics from the view point of actors' perception of self-success within the network. That is to say, if individuals within the network care more about their own success, we can expect the emergence of networks, which do not follow small-world properties. Related to these results, it should also be mentioned that the impact of these network properties on the outcome is another interesting aspect to be investigated [37, 38].

The experimental results show that all introduced factors in our interaction model have an influence on the characteristics of a network. If the process of network growth triggers strategic responses of all direct neighbors, we observe a heavy drop in average shortest path length among the networked individuals. In such a scenario, regardless of having a perfect visibility of the global topology of the network, the value of average shortest path length reduces to three. Further reductions in the clustering coefficients are not really significant, if the network visibility for the individuals is set to a value higher than 2. However, in the presence of only a small number of strategic responses and a high value of network visibility, a short average shortest path length and a high clustering coefficient can be observed.

The proposed interaction model is suitable for human-to-human communication environments, in which the process of network growth is not random and triggers a strategic response among the existing network members due to limitations in the amount of available resources (e.g., time). That is to say, if making a link establishment decision, an individual attempts to get the greatest value possible limitation in resources. Therefore, the objective is to maximize the total value derived from the available resources. The hypothesis that utility maximization underlies human behavior is a widely accepted paradigm among economists [7, 8]. However, it has been criticized by sociologists and psychologists [39, 40, 41]. They argue that the assumption of rational choice model, namely having perfect information about all alternatives is not realistic. With the factor network visibility of our interaction model, we address the issue of bounded rationality. With the help of network visibility, some restrictions on having the perfect knowledge about the alternatives during the process of utility maximization can be applied.

However, we should mention that complex networks appear within different social interaction contexts and, for sure, the underlying processes, which determine the emerging characteristics of the social system, are different and are worthy of investigations. In the extension of the current work, we will focus on other strategic responses, which not just will make each individual better off but also will increase the satisfaction level of those actors located at certain distance (i.e., an advanced form of human cooperative behavior). In such a scenario, in addition to checking the self-assessment of each individual, we can consider happiness of individuals at community level. People feel better off if they themselves or their neighbors do well.

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References

[1] Erdős, P. and Rényi, A. 1959. On random graphs. Publicationes Mathematicae, vol. 6, pp. 290-297.

[2] Erdős, P. and Rényi, A. 1960. On the evolution of random graphs. Publications of the Mathematical Institute of the Hungarian Academy of Sciences, vol. 5, pp. 17-61.

[3] Erdős, P. and Rényi, A. 1961. On the strength of connectedness of a random graph. Acta Mathematica Scientia Hungary, vol. 12, pp. 261-267.

[4] Albert, R. and Barabási, A.L. 2002. Statistical mechanics of complex networks. Reviews of Modern Physics, vol. 74, pp. 47-97.

[5] Albert, R. and Barabási, A.L. 1999. Emergence of scaling in random networks. Science, vol. 286, pp. 509-512.

[6] Barabási, A.L., Albert, R. and Jeong, H. 1999. Mean-field theory for scale-free random networks. Physica A, vol. 272, pp. 173-187.

[7] Jackson, M.O. 2008. Social and economic networks (Vol. 3). Princeton: Princeton university press.

[8] Jackson, M.O. and Wolinsky, A. 1996. A strategic model of social and economic networks. Journal of economic theory, 71(1), pp.44-74.

[9] Galeotti, A., Goyal, S., Jackson, M.O., Vega-Redondo, F. and Yariv, L. 2010. Network games. The review of economic studies, 77(1), pp.218-244.

[10] Rittenberg and Tregarthen. Principles of Microeconomics: Chapter 6, Section 4. pp. 2

[11] Lamberson, P.J. 2011. Friendship-based Games. In 37th Annual Conference of the Eastern Economics Association.

[12] Watts, D.J. and Strogatz, S.H. 1998. Collective dynamics of 'small-world'networks. nature, 393(6684), pp.440-442.

[13] Koohborfardhaghighi, S. and Altmann, J. 2015. A Network Formation Model for Social Object Networks. In LISS 2014 (pp. 615-625). Springer Berlin Heidelberg.

[14] Wilensky, U. and Evanston, I. 1999. NetLogo: Center for connected learning and computer-based modeling. Northwestern University, Evanston, IL, pp.49-52.

[15] Bentham, J. (1879). An introduction to the principles of morals and legislation. Clarendon Press.

[16] Koohborfardhaghighi, S. and Altmann, J. 2014. How Variability in Individual Patterns of Behavior Changes the Structural Properties of Networks. In Active Media Technology (pp. 49-60). Springer International Publishing.

[17] Koohborfardhaghighi, S. and Altmann, J. 2014, April. How placing limitations on the size of personal networks changes the structural properties of complex networks. In Proceedings of the companion publication of the 23rd international conference on World Wide Web companion. pp. 1017-1022.

[18] Hamill, L. and Gilbert, N. 2009. Social circles: A simple structure for agent-based social network models. Journal of Artificial Societies and Social Simulation, 12(2), p.3.

[19] Travers, J. and Milgram, S. 1969. An experimental study of the small world problem. Sociometry, pp.425-443.

[20] Dodds, P.S., Muhamad, R. and Watts, D.J. 2003. An experimental study of search in global social networks. science, 301(5634), pp.827-829.

[21] Newman, M., Barabasi, A.L. and Watts, D.J. 2006. The structure and dynamics of networks. Princeton University Press.

[22] König, M., Tessone, C.J. and Zenou, Y. 2009. A dynamic model of network formation with strategic interactions.

[23] Buechel, B. 2009. Advances in strategic network formation: preferences, centrality, and externalities.

[24] Michael, D.K. and Battiston, S. 2009. From graph theory to models of economic networks. a tutorial. In Networks, Topology and Dynamics. pp. 23-63. Springer Berlin Heidelberg.

[25] Buechel, B. 2008. Network formation with closeness incentives. Networks, Topology and Dynamics. Springer Lecture Notes in Economic and Mathematical Systems, 613, pp.95-109.

[26] Bei, X., Chen, W., Teng, S.H., Zhang, J. and Zhu, J. 2009. Bounded budget betweenness centrality game for strategic network formations. In Algorithms-ESA 2009. pp. 227-238. Springer Berlin Heidelberg.

[27] Gallo, E. 2012. Small world networks with segregation patterns and brokers. Review of Network Economics, 11(3).

[28] Borgatti, S.P. 2005. Centrality and network flow. Social networks, 27(1), pp.55-71.

[29] Borgatti, S.P. and Everett, M.G., 2006. A graph-theoretic perspective on centrality. Social networks, 28(4), pp.466-484.

[30] Freeman, L.C. 1978. Centrality in social networks conceptual clarification. Social Networks, 1(3), pp.215-239.

[31] Horn, R. A. and Johnson, C. R. 1990. Matrix Analysis. Cambridge University Press.

[32] Newman, M. E. J. 2007. The New Palgrave Encyclopedia of Economics, Mathematics of networks. Palgrave Macmillan, Basingstoke.

[33] Feld, S. L. 1991. Why your friends have more friends than you do. American Journal of Sociology, pp.1464-1477.

[34] Uzzi, B., Amaral, L.A. and Reed-Tsochas, F. 2007. Small-world networks and management science research: A review. European Management Review, 4(2), pp.77-91.

[35] Smith, R.D. 2006. The network of collaboration among rappers and its community structure. Journal of Statistical Mechanics: Theory and Experiment, 2006(02), p.P02006.

[36] Uzzi, B. and Spiro, J. 2005. Collaboration and creativity: The small world Problem1. American journal of sociology, 111(2), pp.447-504.

[37] Koohborfardhaghighi, S. and Altmann, J. 2014. How structural changes in complex networks impact organizational learning performance. 6th Intl. W. on Emergent Intelligence on Networked Agents.

[38] Koohborfardhaghighi, S. and Altmann, J. 2016. How Strategic Networking Impacts the Networking Outcome: A Complex Adaptive System Approach. In Proceedings of the 18th International Conference on Electronic Commerce.

[39] Thurow, L. 1983. Dangerous currents: The state of economics. OUP Catalogue.

[40] Nell, E. J. 2007. Rational economic man. Cambridge University Press.

[41] Green, D. P., Shapiro, I. and Shapiro, I. 1994. Pathologies of rational choice theory: A critique of applications in political science (p. 3). New Haven: Yale University Press.

[42] Burt, R. S. 2000. The network structure of social capital. Research in organizational behavior, 22, pp. 345-423.

[43] Coleman, J. S. 1988. Social capital in the creation of human capital. American journal of sociology, 94(Suppl.): S95-S120.

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