SEOUL NATIONAL UNIVERSITY
College of Engineering
Technology Management, Economics, and Policy Program

Technology Management, Economics, and Policy Discussion Paper Series

How Variability in Individual Patterns of Behavior Changes the Structural Properties of Networks

Somayeh Koohborfardhaghighi, Jörn Altmann

TEMEP Discussion Paper No. 2014:114

서 울 대 학 교
공 과 대 학, 기술경영경제정책 대학원과정
151-742 서울시 관악구 관악로 599

Technology Management, Economics, and Policy Program
College of Engineering, Seoul National University
599 Gwanak-Ro, Gwanak-Gu, Seoul 151-742, South-Korea
Phone: ++82-2-880-9140, Fax: ++82-2-880-8389

The *Technology Management, Economics, and Policy Program (TEMEP)* is a graduate program at Seoul National University. It includes both M.Sc. and Ph.D. programs, which are integrated into the graduate programs at the College of Engineering.

The *TEMEP Discussion Paper Series* is intended to serve as an outlet for publishing research about theoretical, methodological, and applied aspects of industrial economics, especially those related to the institute's areas of specialization, namely management of technology, information and communication technology, telecommunication, services, health industries, energy industries, as well as infrastructures for development. In particular, paper submissions are welcome, which analyze current technology and industry related issues, discuss their implications, and suggest possible alternative policies. The objective is to gain insights into important policy issues and to acquire a balanced viewpoint of policy making, technology management, and economics. It will enable us to identify the problems in industries accurately and to come up with optimal and effective guidelines. In addition, another important aim of this series is to facilitate communication with external research institutes, individual researchers, and policy makers worldwide.

Research results disseminated by TEMEP may include views on policies for information and communication technologies, technology management, telecommunication, energy, health, and development economics, but the institute itself takes no institutional policy position. If appropriate, the policy views of the institute are disseminated in separate policy briefs. Thus, any opinion expressed in the TEMEP Discussion Paper Series is those of the author(s) and not necessarily the opinion of the institute.

Finally, the current editor of this series would like to thank Prof. Dr. Almas Heshmati for establishing this working paper series in January 2009 and for guiding its development during the course of the first 55 issues. In particular, Prof. Heshmati provided invaluable contributions for setting up the local IT infrastructure, registering the series with RePEc, disseminating the working papers, and setting the quality requirements.

Jörn Altmann, Editor

Office: 37-305
Technology Management, Economics, and Policy Program
College of Engineering
Seoul National University
599 Gwanak-Ro, Gwanak-Gu
Seoul 151-742
South-Korea

Phone: +82-70-7678-6676
Fax: +1-501-641-5384
E-mail: jorn.altmann@acm.org

How Variability in Individual Patterns of Behavior Changes the Structural Properties of Networks

Somayeh Koohborfardhaghighi, Jörn Altmann

Department of Industrial Engineering
College of Engineering
Seoul National University
Seoul, South-Korea
skhaghighi@snu.ac.kr, jorn.altmann@acm.org,

June 2014

Abstract: Dynamic processes in complex networks have received much attention. This attention reflects the fact that dynamic processes are the main source of changes in the structural properties of complex networks (e.g., clustering coefficient and average shortest-path length). In this paper, we develop an agent-based model to capture, compare, and explain the structural changes within a growing social network with respect to individuals' social characteristics (e.g., their activities for expanding social relations beyond their social circles). According to our simulation results, the probability increases that the network's average shortest-path length is between 3 and 4, if most of the dynamic processes are based on random link formations. That means, in Facebook, the existing average shortest path length of 4.7 can even shrink to smaller values. Another result is that, if the node increase is larger than the link increase when the network is formed, the probability increases that the average shortest-path length is between 4 and 8.

Keywords: Network Properties, Network Growth Models, Small World Theory, Network Science, Simulation, Clustering Coefficient, Complex Networks.

JEL Classification Numbers: C02, C6, C15, D85.

1. Introduction

Small world theory comprises the idea of being connected to any other person by a chain of only five people in average [2, 3]. It has created a resurgence of interest in the field and motivated researchers to experimentally evaluate this theory. Despite controversies and empirical evidences on the existence of such pattern of connections [1], the variety in the obtained experimental results somehow should also be explainable. While the observed average shortest-path lengths in the range of 4 to 8 support the small world theory, it is still hard to draw solid conclusions on why the values differ.

In his famous experiments, Stanley Milgram was interested in computing the distance distribution of the acquaintance graph [2, 3]. The main conclusion outlined in Milgram’s paper is that the average path length of individuals within the network is smaller than expected. The average path length was set to 6. Despite further empirical studies on this topic [4, 5, 6], the results obtained in various environments differ widely from an average path length of six.

In social networks, the nodes and links represent the users and the social relations among the users, respectively. Assuming that a social network is a product of its constituents’ interactions, the first question that comes to mind is what kinds of interactions take place within it and how these interactions can be categorized. The social distance between a source individual and a destination individual within the network can be utilized for categorization of their relations. This means that different degrees of friendships can be observed within the social circle belonging to each person. For instance, only degree-1 persons, who have either familial bonds or share a similar social character and personality with the respective person, are observed in the social distance equal to 1. These relationships can be established almost anytime (i.e., spare time, working time). In larger social distances such as friend-of-a-friend (FOAF) relation, the persons become more socially distant, but it is not necessarily concluded that individuals with similar characteristics cannot be found among them. The user is merely unaware of their presence. It is interesting to note that the social networking platforms including Facebook attempt to reduce these social distances as daily social activities take place online. Once a user specifies its social circle after registering on a social networking web site, the feature “Recommendation of a friend of a friend” enables the users to extend their social circles, and to change their social distance from 2 to 1. Although this is by itself very desirable, it is to be noted that such processes certainly have significant impact on the properties of a social network. According to this discussion, our hypothesis is: “*The interactions among constituents of a network can be regarded as dynamic processes which lead to changes in the structural properties of the network.*”

There are different social networks in the real world. Regardless of the relationships among the various constituents of a network, a network property such as degree distribution can be used to find similarities or differences among networks. Moreover, formation mechanism, based on these degree distributions, can result in different growth models. For example, the preferential attachment growth model, introduced by Barabási and Albert [9], is capable of generating power law degree distributions. In this model, new nodes are more willing to link to high-degree nodes during the growth of a network. The high-degree nodes can be imagined as nodes with better social skills compared to others [17]. The individuals having more activities in a social networking platform would find more friends or are even more likely to establish relationships with other people, whereas a huge number of users lack such capabilities. However, some other types of network formation mechanisms choose the attachment point for new nodes with the same probability for all nodes. Based on this random linking, a number of models have been offered in literature since the mid-19th century [10, 11, 12]. These models are able to create networks with bell shape or Poisson degree distributions.

As the process of network growth does not only depend on the method of new nodes entrances but also on the establishment of new links between existing nodes within the network, these interactions could definitely play a substantial role in the formation of networks as well. Based on this, our hypothesis can be extended to: "*Dynamic processes can be categorized into two groups: (1) The process that occurs during the growth of a network and represents the tendency of new users to establish links to other members upon entry into a network; (2) The process that occurs among users of a network in order to establish potential links.*"

Undoubtedly, adoption of a random network formation model for a growing social network is not an obvious practice. However, the significance of such random patterns can easily be justified. Although, as a member of a social network, we attempt to establish relationships with individuals of similar social character, we also realize that our social circle can easily be made more valuable through getting familiar with strangers. For example, an academic professional might meet a broad range of new people, with whom s/he shares similar characteristics, when attending conferences, presenting papers, and giving seminars. These random acquaintances have a positive influence on the performance of academics. If it is agreed here upon the existence of such random patterns, the question raises about the level of influence on the structural properties of a network. Our hypothesis can be extended to: "*The process which occur among existing users of a network in order to establish links is also divided into two categories: (a) The first category includes the establishment of potential links of FOAF type; (b) The second category includes the establishment of random potential links with other users, who are present in a network.*"

As this article engages with the idea that the human behavior (i.e., dynamic processes) is the key to formulate a network growth model, our major research question in this paper is how the level of influence of these dynamic processes impacts the structural properties of a network. With respect to our contribution, we propose a generative network growth model for analyzing the influence of the dynamic processes (i.e., the establishment of FOAF links and random links for existing nodes, as well as the establishment of random links for new nodes) on the structural properties of a network.

Based on our simulation analysis, these dynamic processes play a significant role in the formation of networks. The structural network properties of a network change. In particular, we analyzed the evolution of two structural properties of a network, namely the clustering coefficient and the average shortest-path length. The clustering coefficient is a fundamental measure in social network analysis, assessing the degree, to which nodes tend to cluster together, while the average shortest-path length provides a measure of how close individuals within the network are.

One of the main essential implications of the result derived from our simulations is the explanation for the different values of the average shortest path lengths that have been reported in empirical studies [4, 5, 6].

The remainder of this paper is organized as follows. In section 2, we discuss the theoretical background on the topic. In section 3, we detail our network formation model and its parameters. Simulation results and a discussion are presented in section 4. Finally, we present our conclusion and discuss the future work in section 5.

2. Theoretical Background

Our research work is based on literature on small world network topologies and network formation models.

2.1. Small World Network Topology

In the literature on network topology, we find different networks with their specific patterns of connections. Examples of these network topologies are random, regular, preferential attachment, and small-world networks. Despite the empirical studies of small world networks, the results obtained in various environments differ [4, 5, 6]. The following paragraphs are a summary of studies that tried to replicate Milgram's results with respect to small world networks.

Dodds et al. performed a global social search experiment to replicate the small-world experiment of Milgram and showed that social searches could reach their targets in a median of five to seven steps [5]. They classified different types of relationships and observed their frequencies and strength. The result of their analysis showed that senders preferred to take advantage of friendships rather than family or business ties. It was also indicated that the origin of relationships mainly appear to be family, work, and school affiliation. The strengths of the relationships were fairly high. Therefore, we can say that the most useful category of social ties were medium-strength friendships that originated in social environments.

Backstrom et al. repeated Milgram’s experiment by using the entire Facebook network and reported the observed average shortest path length of 4.74, corresponding to 3.74 intermediaries or “degrees of separation” [4]. The study indicates the fact that various externalities such as geography have the potential to change the degree of locality among the individuals and, finally, increase or decrease the average shortest-path length.

Ugander et al. studied the anatomy of the Facebook social graph and computed several features [6]. Their main observations are that the degrees of separation between any two Facebook users are smaller than the commonly cited six degrees, and, even more, it has been shrinking over time. They also found that the graph of the neighborhood of users has a dense structure. Furthermore, they identified a globally modular community structure that is driven by nationality.

With our network formation model, we aim at providing an explanation for the differences found in the empirical studies. Our network formation model is capable to highlight the different processes that contribute to changes in the overall outcome.

2.2. Network Formation Models

There are two branches of literature that are related to network formation models. The first branch focuses on strategic network formation models, which are beyond the scope of this paper [13, 14, 15, 16]. The second one represents growth models of networks and is presented in this section.

From the view point of network growth, which is also our primary focus, several models have been proposed to produce predetermined structural properties. Proposals on network formation models have mainly been based on social networking service (SNS) networks with power law degree distributions. Examples of such SNS networks are Cyworld, Myspace, LiveJournal, and Facebook. In fact, based on observed features of the structures of these networks, different network formation models have been presented, accounting for those features.

Ishida et al. focused on modeling social network service networks, which can be characterized by three features, namely, preferential attachment, friends-of-a-friend (FOAF), and influence of special interest groups [17]. They borrowed the idea of preferential attachment from the fitness model [18]. That is to say, nodes have various capabilities to make links and communicate with others. The resulting network follows a power law degree distribution. The idea of friends of a friend is captured from the connecting-nearest-neighbor (CNN) model [20, 21]. In that model, a network grows based on the establishment of new links with friends of friends. In the same way, a random link formation strategy was adopted to model the establishment of links beyond the range of individuals' neighborhoods. It can be imagined to be equal to receiving benefits due to positive externalities from communication with individuals in other groups.

Consequently, it is reasonable to assume that the variability in individual patterns of behavior in social environments is the base for a model of network formation. However, the extent, to which such behaviors affect the network‘s structural properties, is still unclear and has not been discussed in literature. This is the significant difference to our research.

3. Simulation Model

3.1. Simulation Environment and Parameters

The experimental setting for our model is as follows: We conduct a multi-agent-based simulation in Netlogo [22], in order to verify our hypotheses. In our model, an agent represents an individual or a decision maker who is capable of joining the network and establishing links with others. The simulated network formation model is a generative model that is based on the ideas laid out in the introduction section. This model represents a growing network, in which new members follow the classical preferential attachment or the random growth model (uniform probability of attachment for all nodes) for connecting to other users. The probability of a new node joining the network is denoted as P_{GM}. Furthermore, existing users in this model have the ability to create new links. For this purpose, two parameters (i.e., P_{FOAF} and P_{RAN}) are used, representing the rate of establishment of links of FOAF type, and the rate of establishment of links of random type, respectively.

The value of P_{RAN} is assumed to be equal to 1- P_{FOAF}. Thus, if the value of the P_{FOAF} parameter equals 1, no random link formation process exists in the generative model. These parameters have values in the range from 0 to 1 and represent the probability for formation of potential links. If $P_{FOAF} = 0.5$, it signifies that the probability of random link formation or conversion of a link with social distance of 2 to a link with social distance of 1 is 50%. Such network modeling enables us to simulate and profoundly comprehend the dynamic transformations of a network and its effects on its structural properties.

The values of P_{GM}, which are set for the analysis, are 25%, 50%, or 75%. They are used either for representing the preferential attachment growth model or the uniform probability attachment growth model.

3.2. Structural Properties

In this paper, the structural properties used are the clustering coefficient (CC) and the average shortest path length (AVL) of a network.

The shortest path length is defined as the shortest distance between a node pair in a network [19]. Therefore, the average shortest-path length (AVL) is defined according to the following equation:

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

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

The clustering coefficient of a node i, C_i, is given by the ratio of existing links between its neighbors to the maximum number of such connections [19]. Thus, the clustering coefficient, C_i, is defined according to the following equation:

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

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

3.3. Simulation Environment

The graphical user interface of our simulation environment consists of a two-dimensional field that allows to set parameter values (e.g., simulation time, P_{GM}, P_{FOAF}, network growth model), visualize the formation of the network, and to calculate the structural properties of the network (i.e., AVL and CC) formed over the simulation time.

4. Simulation Results

4.1. Scenarios

The properties of the networks derived from our network growth model are computed over 10 suits of experiments and the average results are plotted on the diagrams shown in Figure 1 and Figure 2. The model was tested with thirty configurations and the results of the model were compared with each other. Figure 1 A-F show the results based on the preferential attachment growth model (P_{GM} = 25%, 50%, and 75%). Figure 2 A-F illustrate the results based on the uniform probability growth model (P_{GM} = 25%, 50%, and 75%).

The x-axes of Figure 1 and Figure 2 show the simulation periods, while the y-axes represent the CC values and the AVL values obtained with both network formation strategies, respectively.

By comparing the successive series of results shown in Figure 1 A-F, the CC values decrease and the AVL values increase with an increase in P_{GM} values. Furthermore, in the early stage of the simulation, the networks' clustering coefficients and average shortest path lengths have a significantly large variability in their values. However, as time goes by, the curves get much steadier.

Figure 2 A-F demonstrate a trend that is analogous to the one shown in Figure 1, though the CC values and AVL values are different from those in Figure 1. The difference in the results reflects the influence of the different network growth models (i.e., the preferential attachment strategy (Figure 1) and the uniform distribution attachment strategy (Figure 2)) on the structural properties. It can clearly be observed that the networks derived from the preferential attachment growth model always have smaller AVL and larger CC values than the networks derived from the uniform distribution attachment strategy. The ranges of the CC values and the AVL values of the preferential attachment growth model are [0.41, 0.58] and [3.1, 6], respectively. The ranges of the CC values and the AVL values derived from the uniform distribution attachment strategy are [0.28, 0.55] and [3.8, 7.9], respectively.

Furthermore, as our objective is also to investigate the influence of the social circle through the establishment of FOAF-type links and random-type links in addition to the influence of the preferential attachment and uniform distribution network growth models, we also assign the values 0.25, 0.5, 0.75 and 1 to the parameter P_{FOAF} (As mentioned, the parameter P_{RAN} is the complement of P_{FOAF} ($P_{RAN} = 1 - P_{FOAF}$)).

Figure 1 A-C and Figure 2 A-C show that the CC values consistently decline with a decrease of the value of FOAF-type links (i.e., with an increase of the value of random-type links) regardless of the P_{GM} value. Furthermore, the analysis of the simultaneous impact of the network growth model and the FOAF-type links suggest that the CC value reaches its minimum with a maximum value of the growth model and a minimum in the influence of FOAF-type links (Figure 1 C and Figure 2 C). Additionally, the CC values increase with the reduction in the influence of the growth model (Figure 1 A-B and Figure 2 A-B). It must also be noted that CC values reach their maximum in early simulation stages due to a small number of nodes in the network (i.e., small network size).

Although the trend of the influence of the network growth model and the parameter P_{FOAF} on AVL is similar, it seems that the influence is more intricate than in the case of

CC. Although the AVL values decreases as a result of reducing the influence of FOAF-type links at constant influence rate of the network growth model in Figure 2 D and Figure 2 F, the remaining figures show some derivations from that behavior.

4.2. Discussion

Nowadays, no matter where we are in the world, social networking platforms are able to shrink our world. They make the world a smaller place by bringing people together. They form an important part of online activities and networking. The processes that are at work here are the bases for our research question in this paper. In particular, we ask how the rate of influence of these dynamic processes impacts the structural properties of a network (i.e., the clustering coefficient and the average shortest path length).

Despite the existence of some empirical studies on the topic, the variety of results of these studies led us to investigate how human behavior contributes to the formation of a social network. We utilized theories of sociology on human relations in a society to maneuver over the problem at hand. We base our work on the assumption that the extent of value change of the clustering coefficient and the average shortest-path length is the result of the variability in individual patterns of behavior in social environments.

Those patterns of behavior are related to situation-specific differences. For example, some people are particularly sociable. They can easily handle interpersonal relationships that come from random contacts (random-type links) and are able to extend their relationship boundaries. Other people need to be introduced via their friends (FOAF-type links). The extent, to which such behaviors affect the structural properties of networks, is still unclear and has not been discussed in literature until now.

Reported results of our simulation model are in line with the result of empirical studies and show the fact that the variety in the obtained results can be caused by different types and different levels of dynamic processes among the constituents of a network.

Our obtained results also indicate that, in social networking platforms such as Facebook, the average shortest path length (which is 4.7) can even be shrunk to smaller values if users show more patterns of random link formations. Therefore, we can expect that our world is getting smaller and smaller. Our results may also justify the result of the “communication project” mentioned in Stanley Milgram’s papers, which was discussed in [1] and showed an average shortest path length of eight. If the individuals recruited for the project were not well-connected through random links to other people, the average number of individuals between source users and target users could increase.

Finally, our results confirm two points with respect to the effect of network growth models on AVL: First, networks derived from a preferential attachment growth model always have a smaller AVL than networks based on a uniform distribution growth model. Second, if the rate of network growth increases to larger values, the probability increases that the network’s average shortest-path length lies between 4 and 8. That scenario could happen when the rate of network growth is more than the rate of establishment of potential links among the existing users of the network. These results also contribute to explaining the differences found in empirical studies. Experiments performed at different times, depending on the ongoing dynamic processes with different rates, will have different network properties.

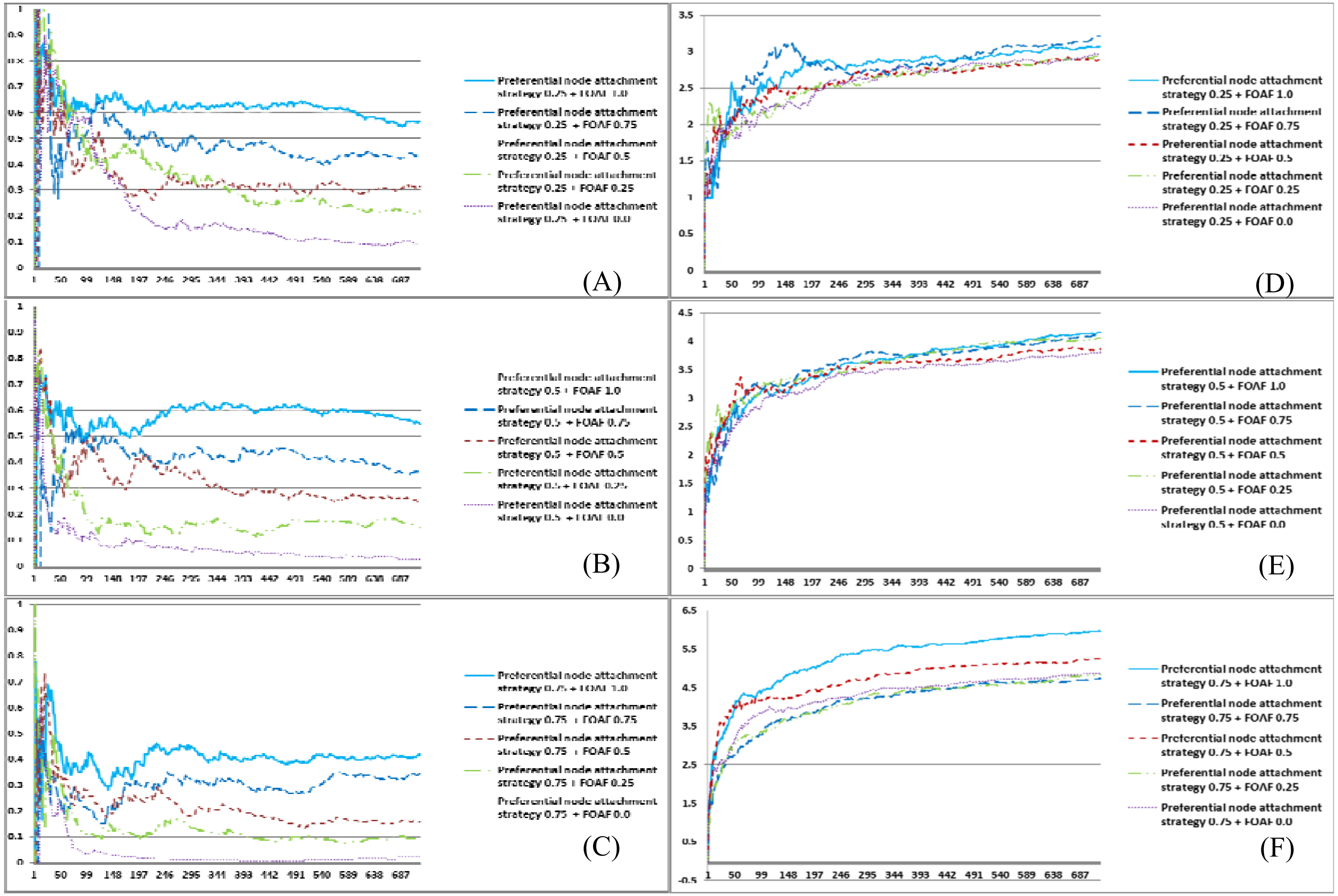

Figure 1. Changes in the clustering coefficient, CC, with respect to the preferential node attachment strategy are shown in (A), (B), and (C). Changes in the average shortest path length, AVL, with respect to the preferential node attachment strategy are shown in (D), (E), and (F).

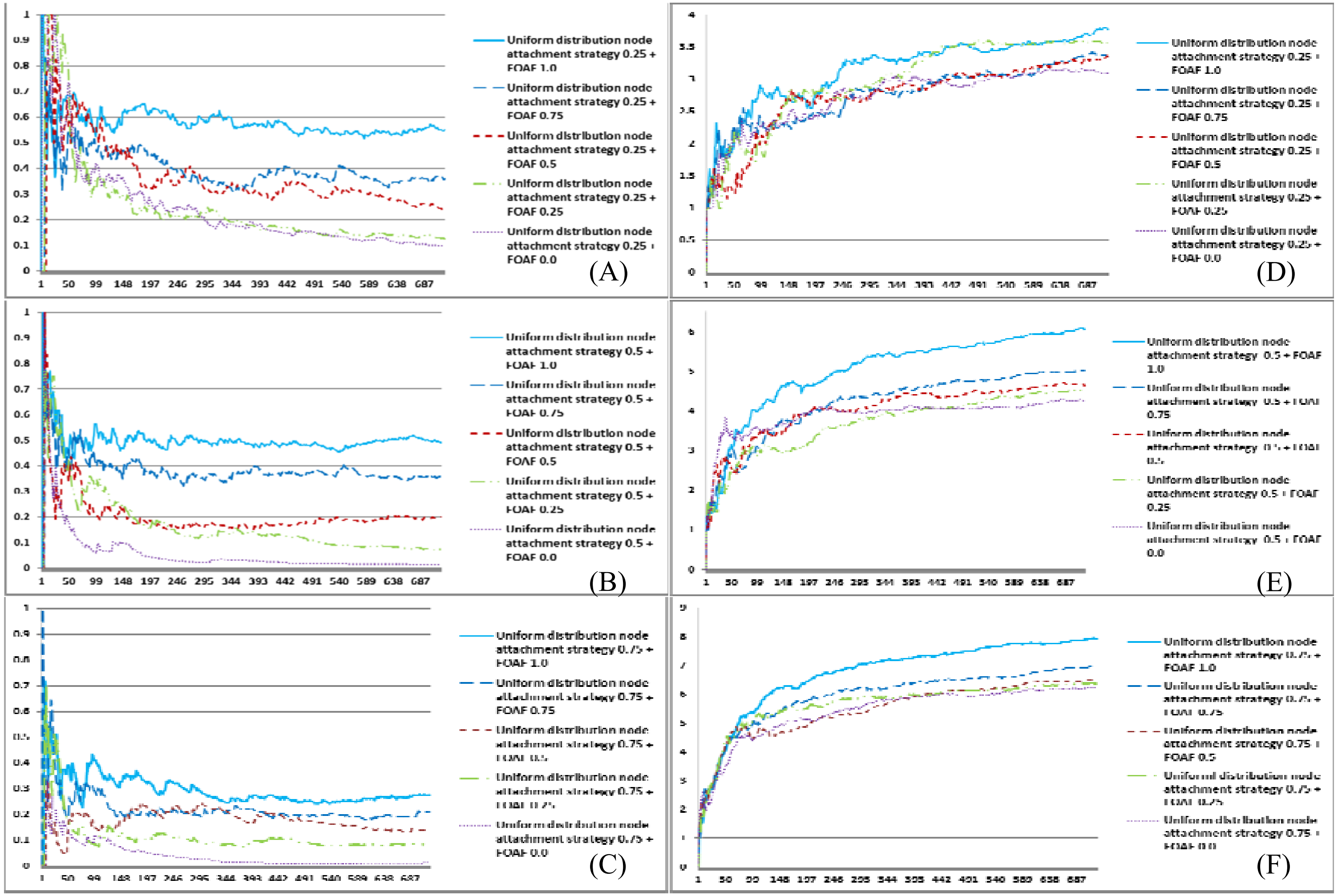

Figure 2. Changes in the clustering coefficient, CC, with respect to the uniform distribution node attachment strategy are shown in (A), (B), and (C). Changes in the average shortest path length, AVL, with respect to the uniform distribution node attachment strategy are shown in (D), (E), and (F).

5. Conclusions

This paper presents a comprehensive network formation model for analyzing the influence of the establishment of FOAF-type links and random-type links on structural properties (i.e., clustering coefficient and average shortest-path link) of networks. Our network formation model works based on the idea that human behavior is the key to formulate a network formation model.

Since social phenomena are complex, we followed an agent-based simulation approach, in order to depict a complex structure emerging from the interaction of many simple parts over time. Our model is able to capture and explain the structural network changes within a growing social network due to certain social characteristics of individuals.

We conducted numerical simulations to calculate and compare networks' clustering coefficient values and average shortest-path length values. Our network formation model was tested with thirty different parameter configurations and the results were compared with one another. The result of the comparison showed that different rates of variability in individual patterns of behavior in social environments lead to changes in the structural properties of networks.

As clearly observed, the comparisons confirm that networks derived from preferential attachment growth models always have smaller average shortest-path length values and larger clustering coefficient values compared to those of uniform distribution growth models. The comparisons also showed that there is an increase in the probability that a network's average shortest-path length lies between 3 and 4, if most of the dynamic processes within the network are the result of a random-type link formation. This result indicates that, in social networking platforms such as Facebook, the average shortest path length (4.7) can even shrunk to smaller values if users show behavior patterns of random-type link formation. However, bringing people closer together can only be achieved through the development of more innovative ideas and techniques in social networking platforms. Finally, another observation is that, if the rate of network growth increases to values of more than 50%, the probability increases that the network's average shortest-path length value is between 4 and 8. It means that, if most of the dynamic processes during the formation of a network are related to its growth, we can expect larger average shortest-path length among the population.

These results of our research provide an explanation for the differences in the average shortest-path lengths found in earlier empirical studies. These studies did not take into consideration the individual pattern of behavior, when they conducted their research. We also tested the effect of placing limitations on the size of personal networks on the structural properties of complex networks in one of our previous works [7]. Therefore, new empirical studies can now be conducted that consider these new results of our research.

As an extension to the current work, similar to [8], we are interested to investigate how network's characteristics positively or negatively affect individuals (e.g., how certain network features make contribution to user utility) that are located in the network. As another future extension of this study, we are also interested to investigate the effect of node's removal or deactivation on the obtained results.

Acknowledgements

This work was supported by Korea Institute for Advancement of Technology of the Ministry of Knowledge Economy within the ITEA 2 Project 10014, EASI-CLOUDS.

References

[1] Kleinfeld, J. (2002) Could it be a big world after all? The six degrees of separation myth. Society, vol. 36, pp. 61–66.

[2] Milgram, S. (1967) The small world problem. Psychology Today, vol. 2, pp. 60–67.

[3] Travers, J., Milgram, S. (1969) An experimental study of the small world problem. Sociometry, vol. 32(4), pp. 425–443.

[4] Backstrom, L., Boldi, P., Rosa, M., Ugander, J., Vigna, S. (2012) Four degrees of separation. In: Proc. 4th ACM Int'l Conf. on Web Science (WebSci).

[5] Dodds, P. S., Muhamad, R., Watts, D. J. (2003) An experimental study of search in global social networks. Science, vol. 301, pp. 827–829.

[6] Ugander, J., Karrer, B., Backstrom, L., Marlow, C. (2011) The anatomy of the Facebook social graph. [Accessed at http://arxiv.org/abs/1111.4503].

[7] Koohborfardhaghighi, S., Altmann, J. (2014) How placing limitations on the size of personal networks changes the structural properties of complex networks. In: 6th Intl. Workshop on Web Intelligence & Communities.

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

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

[10] Erdős, P., Rényi, A. (1959) On random graphs. Publicationes Mathematicae, vol. 6, pp. 290–297.

[11] Erdős, P., 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.

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

[13] Jackson, M. O., Wolinsky, A. (1996) A strategic model of social and economic networks. Journal of Economic Theory, vol. 71, pp. 44–74.

[14] Galeotti, A., Goyal, S., Jackson, M. O., Vega-Redondo, F., Yariv, L. (2010) Network games. The Review of Economic Studies, Vol. 77(1), pp. 218–244.

[15] Rittenberg, L., Tregarthen, T.: Principles of Microeconomics. (2009).

[16] Jackson, M. O. (2008) Social and economic networks. Princeton University Press, Princeton, NJ.

[17] Ishida, K., Toriumi, F., Ishii, K. (2008) Proposal for a growth model of social network service. Web Intelligence and Intelligent Agent Technology.

[18] Bianconi, G., Barabási, A.-L. (2001) Competition and multi-scaling in evolving networks. Europhysics Letters, vol. 54(4), pp. 436–442.

[19] Albert, R., Barabási, A.-L. (2002) Statistical mechanics of complex networks. Reviews of Modern Physics, vol. 74(1), pp. 47–97.

[20] Davidsen, J., Ebel, H., Bornholdt, S. (2002): Emergence of a small world from local interactions: Modeling acquaintance networks. Physical Review Letters, vol. 88(12).

[21] Vazquez, A. (2003) Growing network with local rules: preferential attachment, clustering hierarchy, and degree correlations. Physical Review E, vol. 67(5).

[22] Wilensky U.: NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. [Accessed at http://ccl.northwestern.edu/netlogo], (1999).

TEMEP Discussion Papers

2010-64: Juthasit Rohitratana and Jörn Altmann, "Agent-Based Simulations of the Software Market under Different Pricing Schemes for Software-as-a-Service and Perpetual Software"

2010-65: Radoslaw R. Okulski and Almas Heshmati, "Time Series Analysis of Global Airline Passengers Transportation Industry"

2010-66: Alireza Abbasi and Jörn Altmann, "On the Correlation between Research Performance and Social Network Analysis Measures Applied to Research Collaboration Networks"

2010-67: Kibae Kim, Jörn Altmann and Junseok Hwang, "An Analysis of the Openness of the Web2.0 Service Network Based on Two Sets of Indices for Measuring the Impact of Service Ownership"

2010-68: Bory Seng, "The Driving Forces Underlying the Growth of Total Factor Productivity in Cambodia, Quantitative and Qualitative Studies"

2010-69: Michael Maurer, Vincent C. Emeakaroha, Ivona Brandic and Jörn Altmann, "Cost and Benefit of the SLA Mapping Approach for Defining Standardized Goods in Cloud Computing Markets"

2010-70: Khin Swe Latt and Jörn Altmann, "A Cost-Benefit-Based Analytical Model for Finding the Optimal Offering of Software Services"

2010-71: Jung Eun Lee, Younghoon Kim, Yeonbae Kim and Donghyuk Choi, "The Impact of Technology Licensing Payment Mechanisms on Firms' Innovative Performance"

2010-72: Dongook Choi and Yeonbae Kim, "Effects of Piracy and Digital Rights Management on the Online Music Market in Korea"

2011-73: Tai-Yoo Kim, Jihyoun Park, Eungdo Kim and Junseok Hwang, "The Faster-Accelerating Digital Economy"

2011-74: Ivan Breskovic, Michael Maurer, Vincent C. Emeakaroha, Ivona Brandic and Jörn Altmann, "Towards Autonomic Market Management in Cloud Computing Infrastructures"

2011-75: Kiran Rupakhetee and Almas Heshmati, "Rhetorics vs. Realities in Implementation of e-Government Master Plan in Nepal"

2011-76: Alireza Abbasi, Jörn Altmann and Liaquat Hossain, "Identifying the Effects of Co-Authorship Networks on the Performance of Scholars: A Correlation and Regression Analysis of Performance Measures and Social Network Analysis Measures"

2011-77: Ivona Brandic, Michael Maurer, Vincent C. Emeakaroha and Jörn Altmann, "Cost-Benefit Analysis of the SLA Mapping Approach for Defining Standardized Cloud Computing Goods"

2011-78: Kibae Kim and Jörn Altmann, "A Complex Network Analysis of the Weighted Graph of the Web2.0 Service Network"

2011-79: Jörn Altmann, Matthias Hovestadt and Odej Kao, “Business Support Service Platform for Providers in Open Cloud Computing Markets”

2011-80: Ivan Breskovic, Michael Maurer, Vincent C. Emeakaroha, Ivona Brandic and Jörn Altmann, “Achieving Market Liquidity through Autonomic Cloud Market Management”

2011-81: Tai-Yoo Kim, Mi-Ae Jung, Eungdo Kim and Eunnyeong Heo, “The Faster-Accelerating Growth of the Knowledge-Based Society”

2011-82: Mohammad Mahdi Kashef and Jörn Altmann, “A Cost Model for Hybrid Clouds”

2011-83: Daeho Lee, Jungwoo Shin and Junseok Hwang, “Application-Based Quality Assessment of Internet Access Service”

2011-84: Daeho Lee and Junseok Hwang, “The Effect of Network Neutrality on the Incentive to Discriminate, Invest and Innovate: A Literature Review”

2011-85: Romain Lestage and David Flacher, “Access Regulation and Welfare”

2012-86: Juthasit Rohitratana and Jörn Altmann, “Impact of Pricing Schemes on a Market for Software-as-a-Service and Perpetual Software”

2012-87: Bory Seng, “The Introduction of ICT for Sustainable Development of the Tourism Industry in Cambodia”

2012-88: Jörn Altmann, Martina Meschke and Ashraf Bany Mohammed, “A Classification Scheme for Characterizing Service Networks”

2012-89: Nabaz T. Khayyat and Almas Heshmati, “Determinants of Mobile Telecommunication Adoption in the Kurdistan Region of Iraq”

2012-90: Nabaz T. Khayyat and Almas Heshmati, “Determinants of Mobile Phone Customer Satisfaction in the Kurdistan Region of Iraq”

2012-91: Nabaz T. Khayyat and Jeong-Dong Lee, “A New Index Measure of Technological Capabilities for Developing Countries”

2012-92: Juseuk Kim, Jörn Altmann and Lynn Ilon, “Using Smartphone Apps for Learning in a Major Korean University”

2012-93: Lynn Ilon and Jörn Altmann, “Using Collective Adaptive Networks to Solve Education Problems in Poor Countries”

2012-94: Ahmad Mohammad Hassan, Jörn Altmann and Victor Lopez, “Control Plane Framework Emergence and its Deployment Cost Estimation”

2012-95: Selam Abrham Gebregiorgis and Jörn Altmann, “IT Service Platforms: Their Value Creation Model and the Impact of their Level of Openness on their Adoption”

2012-96: Ivan Breskovic, Jörn Altmann and Ivona Brandic, “Creating Standardized Products for Electronic Markets”

2012-97: Netsanet Haile and Jörn Altmann, “Value Creation in IT Service Platforms through Two-Sided Network Effects”

2012-98: Soyoung Kim, Junseok Hwang and Jörn Altmann, "Dynamic Scenarios of Trust Establishment in the Public Cloud Service Market"

2012-99: Lynn Ilon, "How Collective Intelligence Redefines Education"

2013-100: Ivan Breskovic, Ivona Brandic and Jörn Altmann, "Maximizing Liquidity in Cloud Markets through Standardization of Computational Resources"

2013-101: Juseuk Kim, Lynn Ilon and Jörn Altmann, "Adapting Smartphones as Learning Technology in a Korean University"

2013-102: Baseem Al-Athwari, Jörn Altmann and Almas Heshmati, "A Conceptual Model and Methodology for Evaluating E-Infrastructure Deployment and Its Application to OECD and MENA Countries"

2013-103: Mohammad Mahdi Kashef, Azamat Uzbekov, Jörn Altmann and Matthias Hovestadt, "Comparison of Two Yield Management Strategies for Cloud Service Providers"

2013-104: Kibae Kim, Wool-Rim Lee and Jörn Altmann, "Patterns of Innovation in SaaS Networks: Trend Analysis of Node Centralities"

2013-105: Netsanet Haile and Jörn Altmann, "Estimating the Value Obtained from Using a Software Service Platform"

2013-106: A. Mohammad Hassan and Jörn Altmann, "Business Impact Analysis of a Mediator between the Network Management Systems of the IP/MPLS Network and the Transport Network"

2013-107: A. Mohammad Hassan and Jörn Altmann, "Disjoint Paths Pair Computation Procedure for SDH/SONET Networks"

2013-108: Kibae Kim and Jörn Altmann, "Evolution of the Software-as-a-Service Innovation System through Collective Intelligence"

2014-109: Shahrouz Abolhosseini, Almas Heshmati and Jörn Altmann, "The Effect of Renewable Energy Development on Carbon Emission Reduction: An Empirical Analysis for the EU-15 Countries"

2014-110: Somayeh Koohborfardhaghighi and Jörn Altmann, "How Placing Limitations on the Size of Personal Networks Changes the Structural Properties of Complex Networks"

2014-111: Somayeh Koohborfardhaghighi and Jörn Altmann, "How Structural Changes in Complex Networks Impact Organizatioanl Learning Performance"

2014-112: Sodam Baek, Kibae Kim and Jörn Altmann, "Role of Platform Providers in Service Networks: The Case of Salesforce.com App Exchange"

2014-113: Somayeh Koohborfardhaghighi and Jörn Altmann, "A Network Formation Model for Social Object Networks"

2014-114: Somayeh Koohborfardhaghighi and Jörn Altmann, "How Variability in Individual Patterns of Behavior Changes the Structural Properties of Networks"