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Developing Students' Awareness of Network Dynamics by Spreadsheet Environment

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Abstract: This paper deals with the problem of learning in a new digital or networked society. Specifically, the study is focused on the development of students' network awareness by constructing and investigating the network learning environment. An environment comprising the spreadsheet EXCEL and the visualization tool NodeXL is introduced. Students construct their own models of the network and are able to observe the behavior of the constructed network in the form of a dynamically evolving graph. Models are defined by simple algorithms. The algorithms correspond to different rules of network evolution. Specifically, rules for attaching the next vertex to the existing network are presented. A number of network examples, constructed and studied by using the proposed approach, are presented and discussed.

Key words: networked learning, network awareness, leaning environment, constructionism, spreadsheets, network simulation, scale-free networks

1. Introduction

21st century society is, first of all, the so-called networked society, the functioning of which is tightly bound to human resources and various services connected to global networks. Self-recognition of an individual, who is an element in worldwide network space, is a new phenomenon that was never studied. It is obvious that such self-recognition becomes an important component of everyday life in today's technology-based society and in particular — an important component of the education system.

The remarkable contemporary philosopher and thinker, Luciano Floridi, when asked about education being transformed to a new network era said:"… the question becomes: what sort of abilities should we privilege and teach to tomorrow's consumers, curators, producers, and designers of information? The answer seems to me quite obvious: the very languages through which information is created, manipulated, accessed, and consumed." (Floridi, 2013). This means that the main issue today is the new learner, the "networked learner".

To understand the principles of learning underlying the new, networked student, special research is required.

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Today's students, being connected with one another, with teachers, with sources of information they need for study, with media comprising various content, become so-called "network personalities" or "digital personalities" and acquire new, previously unknown characteristics (Levin, 2012; Levin, Kojukhov, 2013). The network itself becomes an important (if not the main) element of a modern educational environment. It is not just by chance that changes in a network with time, i.e., the network's evolution, are thoroughly watched and intensively studied. The changing network, as in any dynamic system, requires a mathematical model for its description. A description of the network as a dynamic system should be clear and understandable, similar to traditional types of dynamic systems, such as electro-mechanic systems or systems of digital control that were successfully studied in school using various learning environments. These learning environments were suitable for reflecting, implementing, or modeling different dynamic systems, ranging from primitive mechanical assemblies working according to Newton's laws, to automata and microprocessors.

Today, networks and their components are at the center of scientific interest, both as mathematical objects, and as a new social reality known as a social network. The dynamics of social networks' topology is of great interest, since it allows detecting and explaining some unexpected phenomena and laws connected with the networks' functionality. The problem of explaining such laws is a scientific problem similar to the problem of analyzing dynamic systems. Of course, there is a difference between these problems, stemming from the different nature of various types of dynamic systems. Whereas traditional dynamic systems have a natural character and are described by natural physical processes, the social networks constitute artificial worlds. In these artificial worlds, the present laws governing communication networks not only do not depend much on the network designer, who has developed specific communication means and protocols, but also do not depend on the behavior of the participants of the social network. The fact that the behavior of the network users affects the topology of the network is of principal importance. In social networks, the topology depends on and can be explained by the rules of the so-called "network behavior" of the network participants.

Furthermore, research on the network behavior of users is connected with the scientific field of collective cognition or "social learning", which actively grows today. Indeed, if today's "network students" constantly and intensively interact and cooperate with their classmates and teachers while learning, the students' self-recognition and network awareness are very interesting for a researcher to investigate both theoretically and in practice. Network awareness is something that can be learned, for example, in the framework of a concept for obtaining skills in network awareness, conducted by Social Learning Analytics (Schreurs, Teplovs, Ferguson, De Laat, & Buckingham Shum, 2013). This relatively new field of research and development is expected to provide, to the network participants, tools for analyzing the network behavior as a whole, depending on the behavior of the network elements. In Pardo (2013), so-called Social Learning Graphs were studied as a framework to represent the interactions among multiple entities in a learning environment. The approach provides a graph notation for representation of relations among students and for study of such network procedures as: link-prediction, recommendation and abstractions.

The importance and actuality of research and development of network learning environments seems to be clear. The most widely known tool today is the program environment Node XL. (Smith et al., 2009), which is a tool that allows one to visualize various networks in the form of graphs. For this purpose, it uses the widely known spreadsheet software, Excel. In the Node XL environment, students can easily present the status of social networks known to them through their personal experience. This allows the students to observe the network dynamics by analyzing their own behavior in the network, on the one hand, and changes in network topology, on the other hand.

The present paper is interesting, not only in that it describes how NodeXL can be used for analyzing a network — it also demonstrates how NodeXL can be used for modeling a network. Thus, the environment acquires features of a micro-world, and in this micro-world students may not only observe the dynamics of the networks in which they are active — they also may construct their own models of functioning networks and may analyze the dynamics of these models. Such a learning environment allows one to reach a number of pedagogical objectives corresponding to the principles of constructionism (Papert, 1991) as well as constructivist theory suitable for educational micro-worlds. Among the principles of constructionism are the following:

(1) Reflectivity — i.e., ensuring that students understand the connection between their own behavior and the laws governing the functioning of the network..

(2) Visualization — i.e., ensuring that the network may be represented as a graph reflecting the ways/results of the network's functioning according to the rules set by the students.

(3) Discovery — i.e., the possibility to construct various new networks corresponding to various laws governing network functioning.

(4) Experimentation — i.e., the ability to check a scenario "What if?" — the possibility to formulate, model, and verify various rules (algorithms) for forming networks, followed by analysis of the modeling results and formulation of conclusions.

This paper presents a network modeling method performed within a spreadsheet-based constructionist learning environment, which helps to develop the students' network awareness. This paper is organized as follows. It consists of two different parts. In the first, to some extent the "humanitarian" part, concepts of network pedagogy and Social Learning Analytics are discussed; the newly introduced method of network simulation is presented. The second, to some extent, the "mathematical" part of the paper, deals with studying a number of specific networks by using the proposed simulation approach and applying mathematical analysis to the simulation results.

2. Learning within Networks

2.1 Network Pedagogy

Network pedagogy is one of the fastest growing trends of education. Research in the field of network pedagogy focuses on studying cognitive processes and methods of development and support for networks of social relations, in a framework where learning takes place. Network learning is a type of non-formal learning that attracts people who highly rank social contacts as a tool for self-development (Jones, Asensio, & Goodyear, 2000). Recent studies show that network learning positively affects both the scholastic activity of the students, and the school's functioning (Coburn & Russel, 2008; Penuel et al., 2010). The network learning includes using information technologies as a platform for fostering cooperation between students, their teachers, and the teaching resources.

The network pedagogy focuses on differences in social relations, on which people base their strategies, which they use to support these relations, and regarding the positive effect that can be obtained from these relations for that type of teaching. The theory of network teaching is closely connected to, and utilizes the methodology of social networks theory, including network analysis (Ferguson & Buckingham Shum, 2012).

Analysis of social networks is based on the assumption that networks comprise nodes and the connections between them. Nodes are individual actors in the network, and the connections between these nodes function as the relations between the actors. The influence of the network structure can be studied at three levels: the level of the actors' position (the individual level), the level of relations in the network (the level of connections), and the level of the general network structure (the network level).

The network pedagogy is based on a number of principles (Patarakin, 2007):

- Study takes place in a learning environment in which new knowledge is being learned; the environment should provide activity that is supposed to achieve specific results by using specific instruments, tools, and technologies.
- Study takes place in cooperation, where the newcomers gradually become experts through practical participation in solving some problems in a specific field of knowledge. Cognition is related to the specific situation in which it takes place.
- Study takes place through building a network. This is the so-called connectivism principle (Siemens, 2004). Study is a process that takes place in a changing environment, in which its basic nodes are constantly reorganized. During the transformation, the network nodes form connections, which are more convenient for transferring information, data, and knowledge. All participantsin the network have specific autonomy regarding their individual behavior, and the network has a very limited influence on that individual behavior.

Each participant of a network community may perform its simple operations, thus forming topology and dynamics of the network as a whole. Such a model of network interaction can be used in pedagogical practice for teaching the principles of decentralization. Experience in working under decentralized conditions is quite important for a networked student, and it may be obtained inside today's network communities. To obtain such experience, students only have to join any network community and to feel that there are an element thereof. It is therefore very important to organize the learning process as a practical activity in which the students actually participate.

Complex and sometimes unexplainable relations between the behavior of an individual and collective behavior have been acknowledged by scientists, and have been intensively studied for a long time. We wish to just mention some remarkable works in this field, which seem to appear earlier than the problem appeared in the social networks (Zetlin, 1963; Varshavsky, 1973; Resnick, 1997). The pedagogic depth of these works was not sufficiently recognized before the appearance of network reality, which characterizes the new digital society.

2.2 Social Learning Analytics

Social Learning Analytics (SLA) is being developed to assist both the students in their learning with the aid of social networks, and professional teachers — by involving all of them in an informal studying process via participation in new and existing virtual communities (Schreurs, Teplovs, Ferguson, De Laat, & Buckingham Shum, 2013).

The students and the teachers, who participate in a functioning real network in formal or informal pedagogic contexts, should be considered as objects that form the network of social relations, which reflects the flow of social informational resources there-between (Lave-Wenger, 1991). There are various examples. One example is a virtual group, which gains experience in using a specific technology by exchange of knowledge and information there-between. Another example is a virtual community collectively building a system of knowledge about their own history and which collects the corresponding informational resources (Wenger, Trayner & De Laat, 2011).

SLA enables members of such virtual communities (students, teachers, and researchers) to establish and answer a number of questions, which lead them to network awareness. Examples of such questions are as follows:

Who teaches and who learns in the network?

What is the direction of information flow?

Is the interaction of the network members effective? How do they affect changes in the network topology?

The above list could be extended; however, the proposed research focuses on the specific questions outlined above, since they could be effectively studied based on the method of network modeling proposed in the present paper.

In SLA environments, students answer the proposed questions by constructing computer models of networks in a suitable software environment, followed by analyzing the resulting computer simulation. In our paper, we develop a constructionist approach for the above activity. According to this approach, students have to pass through the classical way of modeling, which comprises the following sequentially performed activities: Construction, Explanation, Prediction, Experimentation, Discovery, and Justification. Note that students' discoveries about the network's functioning are not necessarily correct. Network dynamics is a complex phenomenon and cannot be described by simple algorithms. Accuracy of the student's discoveries is secondary for tasks of such a class. There is something more important: the process of setting a task in the form of a model, on the one hand, and experimental study of the model, on the other hand.

2.3 Simulating Network Dynamics by Using the NodeXL Environment

In our study, we developed a new SLA environment comprising NodeXL and Excel. The NodeXL software is utilized for visualizing and analyzing a network, whereas the standard Excel software is used for synthesizing models for various networks and for further experiments with the models (Smith et al., 2009).

Basically, NodeXL deals with importing a list of network edges/links (which is built by any specialized program) into a specific space in Microsoft Excel, and with processing the list to visualize the network as a graph and to further analyze the graph. As a result of processing the list of network links, the user gains access to various characteristics of the network and to various forms of its graphical representation. That is all the NodeXL can give a user. Analytic activity of the user, though being always welcome, cannot by itself be considered the object of SLA. It is quite obvious that the analytical component of NodeXL should be fulfilled by a synthetic component, thereby providing students with options to model/synthesize and to analyze different networks. These options together mean providing students with the possibility of research, which is the main advantage of work in computer-based educational environments.

In our paper, we propose a method for modeling networks within the Microsoft Excel environment, followed by importing a list of the network edges into NodeXL and by further visualizing the networks. The dynamics of a network is a process that occurs in discrete time. Each step of the process occurs in one time unit. A new vertex can be added to the current network at each step. The main issue in constructing the network is developing and implementing the algorithm of adding a new vertex to the current network. The list of edges for the network to be modeled is formed as a result of applying the algorithm. The adding of a vertex at each predetermined time period is defined by the algorithm that forms a new edge of the network. Comparing parameters of all possible vertices-candidates creates a complete list of edges. A decision regarding attaching a new edge is made in accordance with the algorithm (the set of rules) specified in advance. The algorithm defines the topology of the network as well as its dynamics.

Note that the network's topology and its dynamics as well as the corresponding algorithms for forming the network are quite complex. The essence of the proposed modeling approach lies in its orientation to non-professionals. It allows modeling a network by formulating simple rules and avoids manipulating sophisticated mathematical constructions.

The proposed method of network modeling can be described as follows.

Let, in time unit *n*, a new vertex *Vn* be added to the list of vertices. Furthermore, parameters of the new vertex are compared with parameters of the existing network vertices V_0,…*Vn-1*, and, according to a predetermined rule, a decision about creating a new edge is made. Each new edge is added to the existing list of edges.

The algorithm for constructing network models is implemented in Visual Basic for Applications (VBA) and comprises two nested loops (external and internal). The external loop forms the list of vertices, whereas the internal loop forms the list of edges. Both of the lists are located at a specific position in Microsoft Excel, which is intended for analysis by means of NodeXL.

For example, let us consider modeling an arbitrary network, in which decisions about creating an edge are taken randomly. Let us call such a rule "a rule of random connection". An edge V_iV_j will be created if, when checking the pair of vertices V_i and V_j, probability p of their connection (and the creation of the edge) will be greater than some predetermined value. In other words, in Excel, the statement "*RAND( )< p*, where $0 < p < 1$" should be true for creating a new edge. By changing the value of p, we can change the probability of creating new edges. Figure 1 illustrates a graph of such a network for two different values of p.

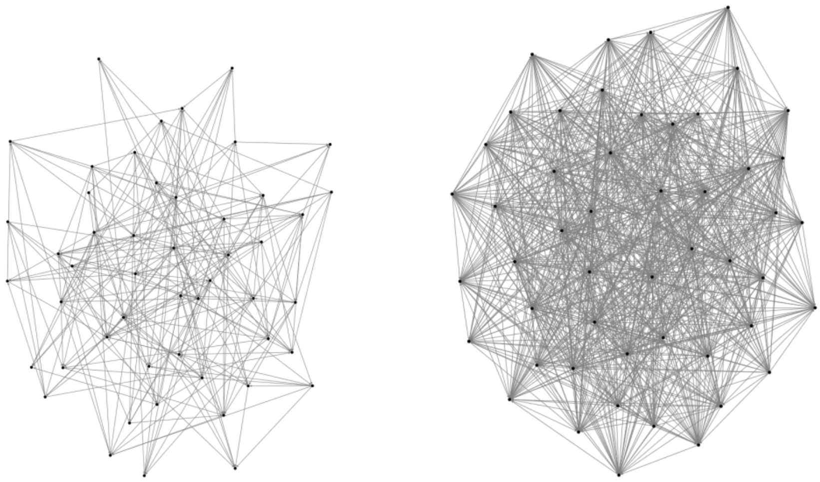


Figure 1 Graphs of Networks, Formed According to the Rule of Random Connection, when p = 0.2 (Left) and p = 0.7 (Right)

The proposed method enables a user to build models of networks by defining various sets of rules for forming connecting edges, and for further studying the obtained models by changing the rules. Moreover, the user is able to study the dynamics of the network's evolution by gradually adding to it a number of vertices and observing changes in the network graph, which is provided by NodeXL.

The next section presents the results of a number of examples from Social Learning Analytics studies, performed by using the proposed simulation method.

3. Analysis of Network Simulation

We start our study by considering the widely known model of so-called scale-free networks proposed by Barabási and Albertin (1999). According to the Barabási-Albertmodel, scale-free networks are based on two key mechanisms: continuous growth and preferential attachment (Barabási, Albert, & Jeong, 2000). That is, (a) the networks expand continuously adding new vertices, and (b) there is a higher probability that a new vertex will be linked to a vertex already having many connections, i.e., characterized by a large degree.

In their works, Barabási and Albert did not specify which model of preferential attachment they propose to consider, whereas these models may be very heterogeneous (Raigorodski, 2010). In our first example, we try to clarify the above issue. We study a number of network models built in the NodeXL environment based on the proposed method. These models are characterized by the following features: (i) each new vertex may be connected to at most one old vertex, i.e., at every time step at most one new edge appears in the network; (ii) any connection event is realized with the same probability p due to external factors; (iii) the probability Π that a new vertex will be connected to vertex i depends not directly on its degree d_i but on the place of d_i in the sorted list of vertex degrees. We call these models *one-max constant-probability models*.

3.1 Constant-Probability Search Network Model

The first model (we call it the *Constant-Probability Search Model* or *CPSM*) is based on a regular linear search of a vertex with a maximum degree by consecutive comparisons of a current maximum degree with the degree's value of a currently checked vertex. If this value is greater than the current maximum, the maximum is updated. For vertices with equal degrees, an earlier arrived vertex is preferable. However, in contrast to the standard search, every comparison is not always performed but instead, it is performed with probability p. A new vertex is connected to a vertex v with a found maximum degree, which, correspondingly, is equal to a true maximum degree with probability p. The degree of vertex v is incremented by 1 and the new vertex's degree is assigned to 1 if it has been connected to any vertex.

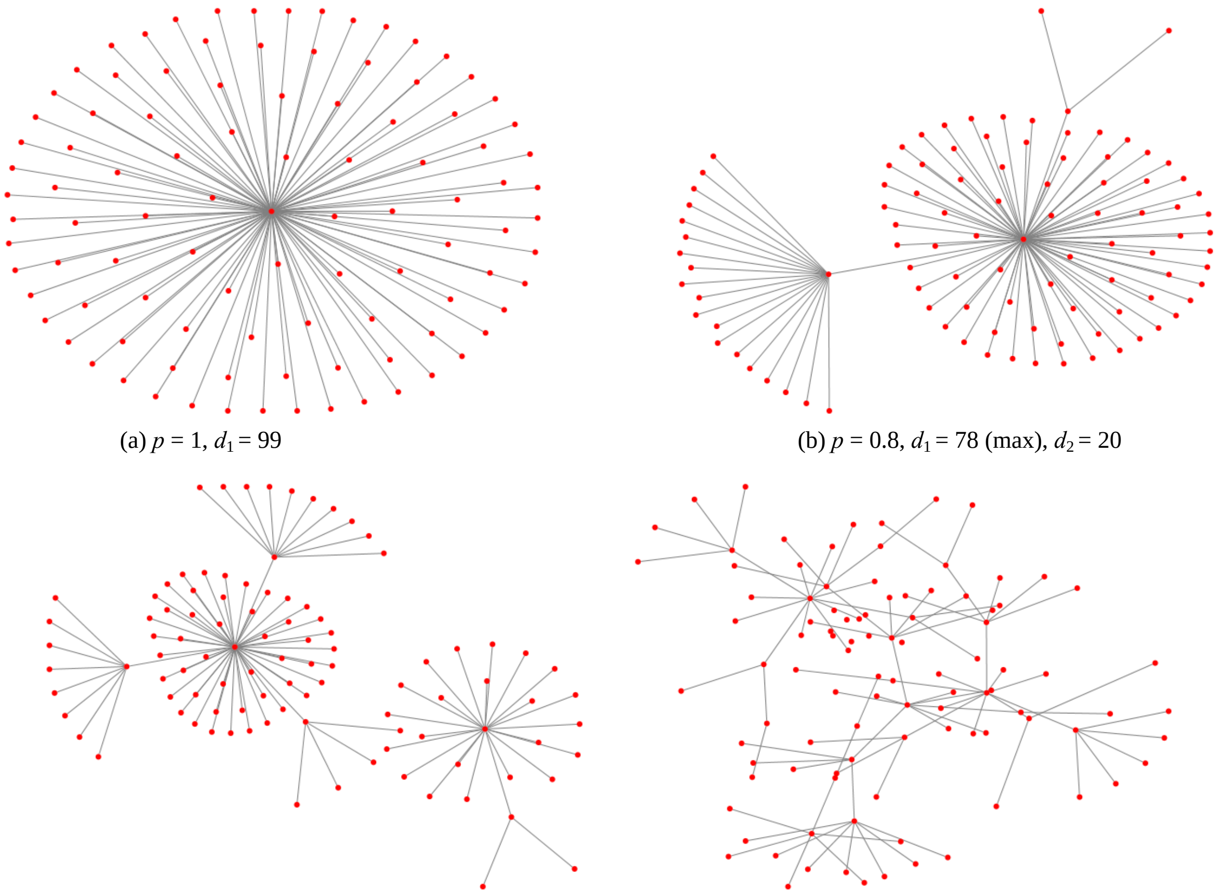
Therefore, the vertex with the 1st largest degree will be "chosen for connection" by a new vertex with probability p, the vertex with the 2nd largest degree — with probability $(1-p)p$, …, and the vertex with the *ith* largest degree — with probability $(1-p)^{i-1}p$ (for equal degrees, the degree of a vertex checked earlier is quasi larger). For n existing vertices, the probability that the new vertex will connect to no vertex is equal to $(1-p)^n$. Given an n-vertex network based on CPSM or any other one-max constant-probability model, the lower bound of the expected maximum degree in the network is equal to $p\,(n-1)$.

It is clear that the higher p is, the larger is the degree of the first vertex in the network and the rather this degree is the maximum. That is, the older vertices increase their connectivity at the expense of the younger ones and a "rich-get-richer" phenomenon (Barabási & Albert, 1999) is detected for high p values.

Diagrams of some 100-vertex networks simulated in the NodeXL environment for different values of p are presented in Figure 2 (the degree of a vertex that arrived at time step t is denoted by d_t).

3.2 Constant-Probability Ordered Network Model

The second network model that we consider, the so-called *Constant-Probability Ordered Model* (*CPOM*), is similar to CPSM but the algorithm used for connecting a current vertex is more subtle and efficient. In accordance with the model's rules, the list of existing vertices is kept sorted in decreasing order of their degrees so that the vertex with a maximum degree is on top of the list. The list is scanned from the top and a new vertex is connected to the first vertex v which "is allowed to be connected by the probability p". The degree of vertex v is incremented by 1, and this vertex is moved toward the top of the list in order to find a proper new place for it. The new vertex's degree is assigned to 1 and this vertex is inserted into the list above vertices with degrees 0 (*isolated vertices*) if it has been connected to any vertex.



(a) $p = 1$, $d_1 = 99$ (b) $p = 0.8$, $d_1 = 78$ (max), $d_2 = 20$

(c) $p = 0.5$, $d_1 = 23$, $d_2 = 51$ (max), $d_3 = 9$, $d_4 = 11$ (d) $p = 0.1$, $d_1 = 6$, $d_2 = 9$, $d_9 = 12$ (max), $d_{17} = 10$

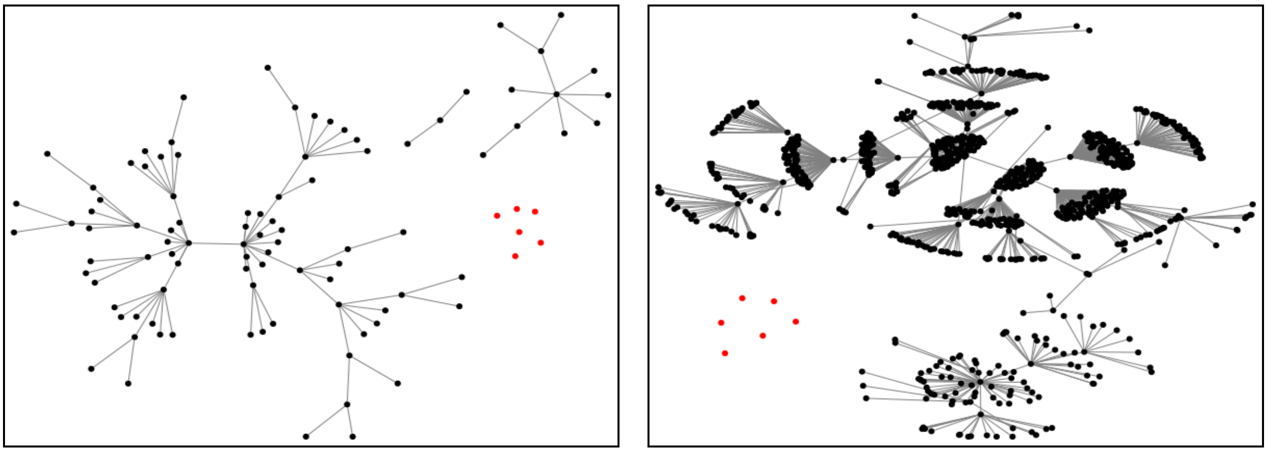
Figure 2 100-Vertex Networks Based on CPSM

This model exhibits a real network whose mechanism keeps most referred sites at the top of the list and makes them, correspondingly, more reachable than others.

Despite the different algorithms used by CPSM and CPOM, both models provide identical network topologies and diagrams (illustrated in Figure 2), which are appropriate for CPOM as well.

CPOM (like CPSM) is characterized by the following phenomenon that becomes apparent for low p values. Some vertices that come first may remain isolated, i.e., with zero degree. The reason is that while a network is not large, a new vertex may rather connect to neither of the existing vertices, and thus find itself at the bottom of the list. Next later vertices will find more vertices in the network and the probability of their connecting to one of the existing vertices will be higher. At that, they will be linked with a higher probability to vertices with larger degrees, and their degrees after connection will be 1. Therefore, as the size of the network increases, the probability of vertices with zero degrees "to be found" by new vertices decreases.

Figure 3 illustrates this phenomenon for $p = 0.1$. A network after 100 time steps (Figure 3 (a)) and the same network after 1000 time steps (Figure 3 (b)) have the same 6 isolated vertices with order numbers 1, 5, 11, 15, 23, and 27.



(a) A network after 100 time steps　　(b) The same network after 1000 time steps

Figure 3　A Phenomenon of First Isolated Vertices for CPOM (p = 0.1)

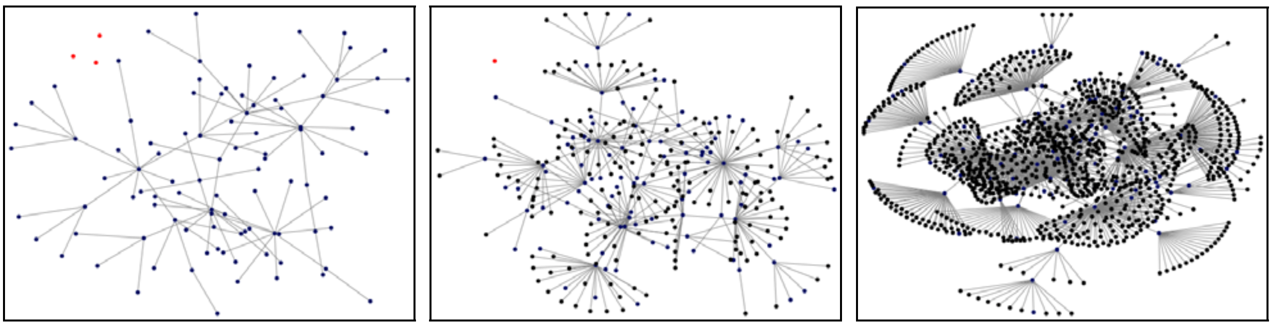
An important feature of the proposed modeling method is the fact that NodeXL, in combination with VBA, allows one to simulate the network's growth in a continuous mode to any predetermined size, to analyze the intermediate result, and to continue the modeling in the continuous mode until the next specified size. This allows one to see the development of the network in dynamics.

Computer experiments implemented in the NodeXL environment show that for $p < 0.5$, the higher that p is, the smaller is the network size for which the expected number of isolated vertices achieves saturation, and the smaller is the number itself in saturation. For $p > 0.5$, the expected number of isolated vertices is less than 1.

3.3 Constant-Probability Ordered Non-0 Model

In order to neutralize the negative effect described in the previous subsection, when some vertices, which come first may remain isolated, we slightly modified CPOM. A new vertex connected to one of the existing vertices is not inserted above the isolated vertices and remains at the bottom of the list. Thus old vertices with zero degrees will not be at the bottom and the list will be sorted only concerning degrees exceeding 1. Such a model is appropriately called *Constant-Probability Ordered Non-0 Model* (*CPOM-N0*).

An example of this model's behavior for p = 0.1 is shown in Figure 4. In Figure 4(a) one can see a network after 100 time steps. This network has 3 isolated vertices: 5, 12, and 17. The same network after 300 time steps is presented in Figure 4(b). It has the only isolated vertex 5. Finally, after 1200 time steps, there are no isolated vertices in this network (Figure 4(c)).



(a) The network after 100 time steps　　(b) The network after 300 time steps　　(c) The network after 1200 time

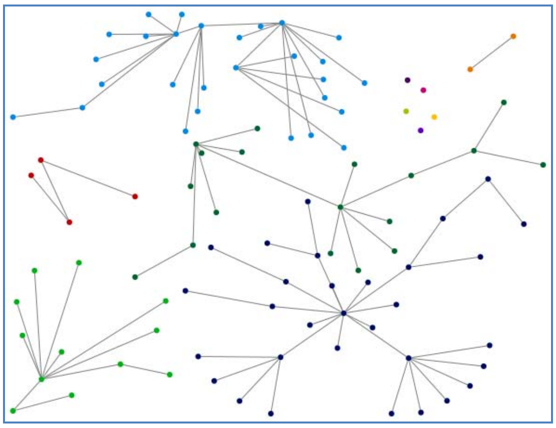
Figure 4　A Network Based on CPOM-N0 (p = 0.1)

CPOM-N0 is evidence that the additional advantage of CPOM, in contrast with CPSM, lies in its flexibility. The list of existing vertices in CPOM is actually the priority list. While in CPSM a vertex's degree directly determines the vertex' priority, in CPOM the vertex's place in the list determines this criterion. One can define this place not only as a function of a degree but as a function of additional parameters as well.

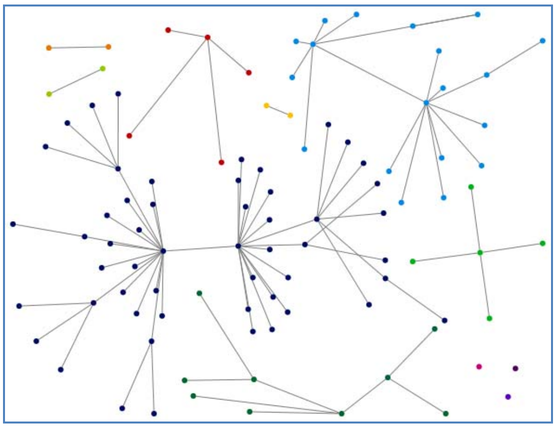
There are also other differences regarding the behavior of CPOM and CPOM-N0. Isolated vertices not only disappear in networks based on CPOM-N0 as they grow. For small networks, the expected number of vertices with zero degree in a CPOM-N0 network is less than in a CPOM network of the same size. On the other hand, the expected number of connected components consisting of more than one vertex in a CPOM-N0 network is greater than in a CPOM network of the same size. This phenomenon can be explained by the following. An isolated vertex of a CPOM network may rather remain isolated in the ensuing time steps than in a CPOM-N0 network in which this vertex has a higher probability of becoming a starting vertex of a new autonomous part of the network. In any case, networks based on constant-probability models are characterized by the same expected number of connected components including isolated vertices. This number is equal to the number of vertices that were isolated at some time, i.e., to the number of appearances of isolated vertices.

Two corresponding examples are illustrated in Figure 5. In Figure 5(a) one can see the CPOM network after 100 time steps. This network has 11 connected components, 5 of which (5, 12, 14, 30, and 57) are isolated vertices. The CPOM-N0 network after 100 time steps (presented in Figure 5(b)) has also 11 connected components but only 3 of them are isolated vertices (25, 33, and 40). With increase of the network in Figure 5(b), new vertices will connect to these 3 vertices sooner or later, while the probability of connecting new vertices to 5 isolated vertices in Figure 5(a) will decrease at every time step. Herewith, both networks will consist of 11 connected components, and the probability of new connected components appearing will decrease with an increase of the networks.

It is appropriate to recall that all these network effects have been seen in the course of modeling. The above arguments, while interpreting the behavior of the network, were carried out based on analyzing the simulation results.



(a) A CPOM network (p = 0.1)



(b) A CPOM-N0 network (p = 0.1)

Figure 5 100-Vertex Networks

3.4 Constant-Probability Ordered Directed Model

In previous models, it was assumed that connecting a new vertex to an old one leads to an increase in the number of connections, both in the old and the new vertices. However, not always a subject that initiates a connection is considered as one that acquires this connection. At the same time, a referred object is regarded as a possessor of this connection in any case. Thus there are systems that should be simulated by directed networks (e.g., web pages are connected by directed links (Barabási, Albert, & Jeong, 2000)).

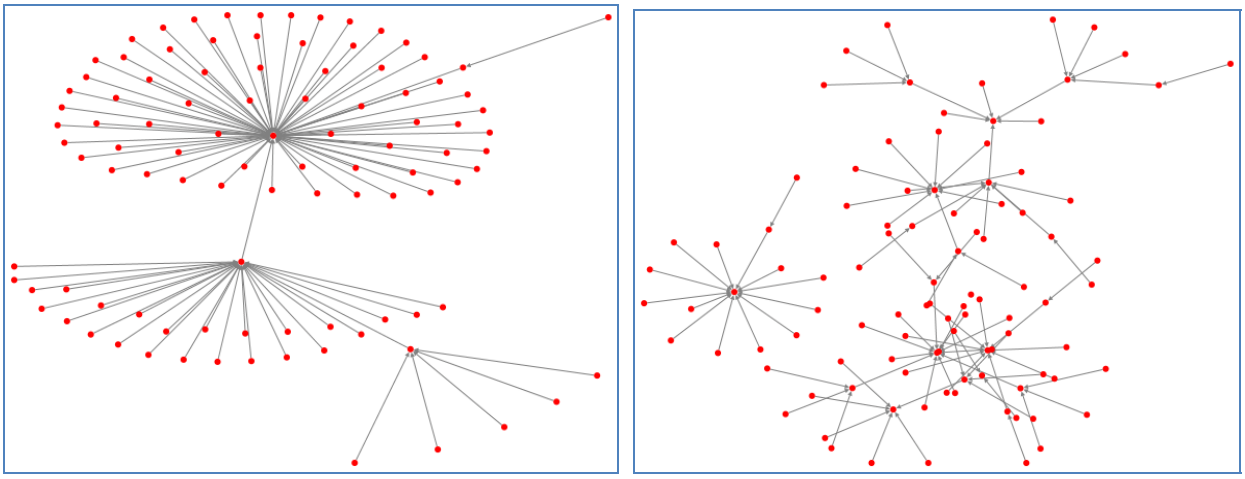
We slightly modify CPOM (the new model will be called *Constant-Probability Ordered Directed Model* or *CPODM*) and transform our network to the directed one. An edge corresponding to a new connection leaves the new vertex and enters the old one. The list of vertices is sorted by their in-degrees. It is clear that the in-degree of a new vertex is 0 even if it has been connected to any existing vertex and, therefore, a new vertex is always at the bottom of the list.

The out-degree of any vertex in a network based on CPODM is 1 (if the vertex has been connected to any vertex when arriving) or 0 (if the vertex has not been connected to any vertex upon arriving). As follows from the model's description, the list of vertices does not distinguish between vertices with zero and non-zero out-degrees. For two vertices with zero in-degrees, the older vertex will be closer to the top. Thus old *isolated vertices* (with zero in-degrees and out-degrees) will not be at the bottom of the list.

Note that the NodeXL software distinguishes between directed and undirected networks and, accordingly, may determine in-degrees and out-degrees for vertices of directed networks.Diagrams of two 100-vertex networks simulated for different values of p are presented in Figure 6 (in- degree of a vertex arrived at time step t is denoted by d_t).

One can see that CPODM is similar to CPOM-N0. Although CPOM-N0 describes an undirected network, it distinguishes in special cases between a vertex that is connected to another one and a vertex to which another vertex is connected. In fact, both CPOM-N0 and CPODM identically process new vertices. For this reason, the same characteristic features are inherent in both models. Like in CPOM-N0 networks, isolated vertices disappear in large networks based on CPODM. For small networks, expected numbers of isolated vertices and of connected components consisting of more than one vertex for CPODM are the same as for CPOM-N0.

In this section, we described a number of artificial network models developed by using a spreadsheet-based learning environment and visualized by using NodeXL software. The models are visualized and studied by applying different experiments and allow one to detect a number of network phenomena that could not be detected before.



(a) $p = 0.7$, $d_1 = 67$, $d_2 = 26$, $d_4 = 5$, $d_3 = 1$ (b) $p = 0.1$, $d_8 = 13$, $d_{10} = 11$, $d_2 = 9$, $d_4 = 9$

Figure 6 100-Vertex Networks Based on CPODM

4. Conclusions

As citizens of a digital or networked society, we must have knowledge of networks in terms of our global environment. Studying the regularities inherent in a network becomes one of the central issues today.

To the best of our knowledge, previous researches in the field of networked learning never studied the problem of developing the network awareness of students. We tried to fill this vacuum by proposing an approach based on constructing a learning environment appropriate for modeling networks by students, and, as the result, improving their network awareness. The environment uses the spreadsheet Excel as the simulation platform and NodeXL software as a visualization tool. Such an environment provides all components of learning by modeling: construction, explanation, prediction, experimentation, discovery, and justification.

Importantly, this paper describes models restricted by using the proposed environment. These artificial models, constructed by applying simple algorithms, allow one to study the significant regularities of different types of networks. A number of unexpected properties of the networks can be detected by students and studied.

Our study demonstrates the perspective of using a spreadsheet-based environment as a learning environment for a contemporary networked learner.

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