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Simulation of Online Learning Interaction Relation Network Based on BA Model

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Abstract: To explore the knowledge dissemination in online learning interaction, the online learning interaction relation network should be constructed firstly. However, the random network, small-world network and scale-free network proposed in the current research can not describe the interactive relationship of online learning interaction. Therefore, how to build the online learning interaction relation network has become a fundamental research problem to be solved. This study updates the BA model algorithm to construct a simulated interaction relation network of online learning. The graphs of degree distribution show that the interaction relation network simulated in this study conforms to the actual rule of online learning interaction of instructors and learners.

Keywords: Online learning, learning interaction, learning relation network, BA model

1. Introduction

Online learning gains more and more attention with its massive resources and instant interactivity (Mikalef, Giannakos, Chorianopoulos, & Jaccheri, 2013; Kuiper, Volman, & Terwel, 2005). In online learning environment, knowledge and information spread by participants' interaction relation path. To explore how knowledge and information disseminate in online learning interaction, the online learning interaction relation network should be built. In online learning interaction relation network, the nodes and edges are significantly different from the social network generated in social media. The online learning interaction relation network can not be described by random network, small-world network and scale-free network (Barabási & Albert, 1999; Erds & Rényi, 1960; Watts & Strogatz, 1998). Therefore, how to generate the online learning interaction relation network to simulate the dissemination of knowledge and information is the fundamental problem in the field of online learning interaction.

As one algorithm for generating the scale-free network, Barabási-Albert (BA) model has great advantages in explaining the formation of social networks because of its two characteristics of growth and priority connection mechanism (Barabási & Albert, 1999). Krawczyk, Kułakowski, and Hołyst (2018) proposed an algorithm to imitate a series of consecutive conflicts between leaders in social groups by using the fragments of scale-free Barabasi-Albert networks. DasGupta, Mobasheri, and Yero (2019) constructed a large number of synthetic networks generated by the Barabasi-Albert preferential attachment model to shed light on privacy violation properties of eight real social networks. In the field of online learning, relation network structure of instructor-learner has not received sufficient attention. This study explored the instructor-learner online learning interaction of one Chinese university, and designed an algorithm for generating an online learning interaction relation network based on the BA model.

Firstly, this paper reviewed the literature of online learning interaction and social network model. Then, we designed an algorithm to generate the online learning interaction relation network based on the BA model. Finally, the degree distribution diagram of generated relation network was presented. The result showed that the interaction relation network simulated in our study conformed to the online learning interaction of instructors and learners in real world.

2. Literature Review

2.1 Online Learning Interaction

Interaction was defined as a dialogue or discourse or event between two or more participants and objects which occurred synchronously and/or asynchronously mediated by response or feedback and interfaced by technology (Muirhead & Juwah, 2004). In the online learning environment, learning interaction was achieved through collaborative behaviors, from learners' sharing the diverse perspectives of the other group members, to being able to seek feedback and clarify ideas through the group's communication, either electronic or through other forms of communication stimulated by the electronic group communication (Wilson & Stacey, 2004).

Online interaction might benefit learning from 3 aspects. (a) Interaction might improve learners' satisfaction. Hong (2002) discovered that interaction may improve learners' satisfaction, and learners who highly perceived the learner-instructor interaction were more satisfied with the course. (b) Interaction might improve learning outcome. Kurucay and Inan (2017) found that learners working collaboratively achieved significantly higher than those working individually. Gunawardena, Linder-VanBerschot, LaPointe, and Rao (2010) reported that interaction between learners was a significant predictor of achievement. Jung, Choi, Lim, and Leem (2002) concluded that learner-to-instructor interaction that included academic and social communications increased achievement. (c) Interaction might enhance learners' sense of community. Nistor, Daxecker, Stanciu, and Diekamp (2015) investigated the correlation between interaction and the sense of community, and found that intensive interactions within the community could lead to stronger emotional connections between members, and a similar conclusion was proved by Luo, Zhang, and Qi (2017). Online learning interaction could promote learning significantly, but how knowledge and information disseminated in online learning environment was still a question to be studied.

2.2 Social Network Model

To explore the knowledge dissemination of online learning interaction, it is necessary to study the network structure of online learning interaction. The existing research explored the network structure by social network theory.

Social network theory pointed out that social network was a social structure made up of a set of social actors (such as individuals or organizations), sets of dyadic ties, and other social interactions between actors (Wasserman & Faust, 1994). In learning contexts, online social networking behavior was related to learning and academic success by creating systems of information, contacts and support (Yu, Tian, Vogel, & Kwok, 2010). Thoms used social network to analyze how social media was chosen in distance learning, they also used social network analysis to build the "read" networks and "reply" networks, and they found that higher network diameters were more characteristic of performing learning networks (Thoms & Eryilmaz, 2014). Hernández-García, González-González, Jiménez-Zarco, and Chaparro-Peláez (2015) explored the relationship between learning analysis parameters and learner outcomes, and showed how the visualization of social learning analysis could help observe the visible and invisible interactions that occur in online distance education.

Common complex network models include: the Erdos-Renyi network, the Watts-Strogatz small-world network and the scale-free network. The Erdos-Renyi network is a complex network that is built through a random process (Erds & Rényi, 1960). It is based on a "natural" construction method: assume that there are n nodes, and assume that the probability of connection between each pair of nodes is constant $0<p<1$. The Watts-Strogatz small-world network is a type of mathematical graph in which most nodes are not neighbors of one another, but the neighbors of any given node are likely to be neighbors of each other and most nodes can be reached from every other node by a small number of hops or steps (Watts & Strogatz, 1998). The scale-free network is a complex network with a degree distribution obeying or close to a power law distribution (Barabási & Albert, 1999). However, these three social networks can not describe the interactive relationship of online learning interaction, so it is necessary to introduce a new relational construction model.

2.3 Relational Construction Model

The Barabási-Albert model was a model proposed by Barabási and Albert (1999) to explain the scale-free characteristics of complex networks. This model was found to be a consequence of two generic mechanisms: (a) networks expand continuously by the addition of new vertices, and (b) new vertices attach preferentially to sites that are already well connected (Song, Havlin, & Makse, 2005). Xie et al. (2012) used a model of Barabasi-Albert scale-free networks to study how the presence of such groups within social networks affects the outcome and the speed of evolution of the overall opinion on the network. Jiang, Chen, and Liu (2014) used the Barabasi-Albert scale-free network to model the dynamic information diffusion process in social networks, which showed that the proposed game theoretic model could well fit and predict the information diffusion over real social networks.

Based on the two characteristics of growth and priority connection mechanism of Barabási-Albert model, this study improves its algorithm and simulates the relation network of online learning interaction.

3. Graph Model of Interaction Network

Social network is usually presented in the form of a graph composed of nodes and edges. In social network, nodes represent individuals or organizations, edges represent their social relationships including friendships, classmate relationships, business partnerships, ethnic beliefs, etc. In online learning interaction relation network, there are two types of nodes, one is the learner node and the other is the instructor node. Edges in online learning interaction relation network represent the interactive relationship of instructors and learners.

In online learning, instructors mainly build knowledge, guide learners, exchange information, and feedback results. Learners access information from network, exchange information from peers, participate in discussions, and reflect on the learning process. There are three types of edges in online learning: instructor-instructor edge, instructor-learner edge, and learner-learner edge. Interaction between instructor-instructor mainly takes place in the online teaching and research community, where instructors can conduct online collaborative learning, share learning resources and research results, and establish knowledge connections. Interaction between instructor-learner can be divided into cognitive interaction and emotional interaction. Instructors and learners conduct cognitive interaction through questions, rebuttals, and assessments, and they conduct emotional interaction by expressing thank-you words, inspiring each other, and emitting emoji. Interaction between learner-learner usually occurs when learners are engaged in group discussions and peer-to-peer evaluations.

For a vertex of social network, the number of heads ends adjacent to a vertex is called the in-degree and the number of tails ends adjacent to a vertex is its out-degree (Bondy & Murty, 1976). Whereas node degrees characterize individual nodes, one can define a degree distribution to quantify the diversity of the whole network (Albert, 2005). The degree distribution $\mathrm{P}(k)$ of a network is defined to be the fraction of nodes in the network with degree k, and the value of k is k=1, 2, 3……There is a power law: $\mathrm{P}(k) = \mathrm{A}k^{-\gamma}$. Where A is a constant that adds up the $\mathrm{P}(k)$ value to 1, and the exponential index of degrees is usually in the range $2<\gamma<3$ (Albert & Barabási, 2002).

Due to the different nature of the two types of nodes in the online learning interaction relation network, the degree distribution of the instructor and the degree distribution of the learner are also different. In order to more accurately analyze the degree distribution of instructors and learners, we separately study the three types of edges of the online learning interaction relation network, which is shown in Figure 1. From the perspective of the instructors alone, the network formed by instructor-instructor interaction is a scale-free network, and its degree distribution is $\mathrm{P}(\mathrm{k_I})_1 = \mathrm{Ak_I}^{-\gamma}$. Similarly, the network formed by learner-learner interaction is also a scale-free network, and its degree distribution is $\mathrm{P}(\mathrm{k_L})_1 = \mathrm{Ak_L}^{-\gamma}$.

From the perspective of the connection between the instructor and the learner, the Tie of L-I is the edge that connects the two networks above. In the network formed only by instructor-learner interaction, the degree distribution of the instructors is $\mathrm{P}(k_I)_2 = Ak_I{}^{-\gamma}$, and the degree distribution of the learners is $\mathrm{P}(k_L)_2 = Ak_L{}^{-\gamma}$. Combining these two situations, the degree distribution of the instructors is $\mathrm{P}(k_I) = P(k_I)_1 + P(k_I)_2$, and the degree distribution of the learners is $\mathrm{P}(k_L) = P(k_L)_1 + P(k_L)_2$.

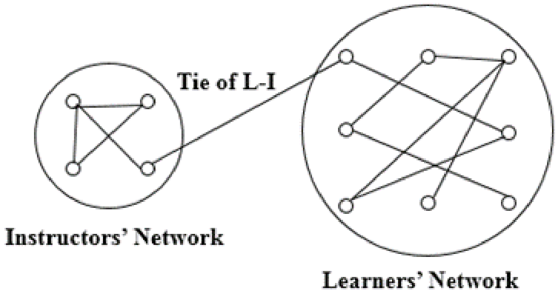

Figure 19 **· The online learning interaction relation network**

4. Algorithm of Interaction Network

In order to generate the online learning interaction relation network to simulate the dissemination of knowledge and information, we improve the algorithm of BA model, which is shown in Figure 2. Firstly, the *mi0* instructor nodes and the *ml0* learner nodes are gathered together to form the initial isolated network. Next, we add new nodes to the initial network to make the network size reach *N* nodes, in which the probability of adding new instructor nodes is *mi*. If the newly added node is an instructor node, it is first connected to *ki* instructor nodes and then to *ni-ki* learner nodes in the existing network by Roulette Method. Similarly, if the newly added node is a learner node, it is first connected to *kl* learner nodes and then to *nl-kl* instructor nodes in the existing network by Roulette Method. Then, the online learning interaction relation network is generated. Finally, the degree distribution of the whole network is shown in the form of degree distribution graph.

Algorithm 1 Starting from the existing network created by m0, BA scale-free network is generated by using growth and priority connection mechanism.

Input: Initial nodes which represents the numbers of instrctors, mi0; initial nodes which represents the numbers of learners, ml0; Number of new edges generated each time an instructor node is introduced, ni; Number of new edges generated each time a learner node is introduced, nl; isolated networks generated by mi0 and ml0, A; network scale after growth, N.

Output: Degree distribution graph.

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0 or 1 randomly generates matix[N-mi0-ml0,1] with probabilities of 1-mi and mi, which
  extends nodes[mi0+ml0,2] to nodes[N,2];
Set the number of interactions between instructors and instructors, k_i and the number of
  interactions between learners and learners, k_l;
for k = mi0 + ml0 + 1 to N do
    Set the total interaction frequency, p and the interaction frequency between instructors
  and instructors, pi and the interaction frequency between learners and learners, pl;
    pp ← cumsum(p); ppi ← cumsum(pi); ppl ← cumsum(pl);
    if New node is an instructor then
        nCount ← ki;
        for i = 1 to nCount do
            Choose an instructor node by Roulette Method, jji;
            A[k, jji] ← 1; A[jji, k] ← 1;
        end for
        nCount ← ni − ki;
        for i = 1 to nCount do
            Choose a learner node by Roulette Method, jjl;
            A[k, jjl] ← 1; A[jjl, k] ← 1;
        end for
    else
        nCount ← kl;
        for i = 1 to nCount do
            Choose a learner node by Roulette Method, jjl;
            A[k, jjl] ← 1; A[jjl, k] ← 1;
        end for
        nCount ← nl − kl;
        for i = 1 to nCount do
            Choose an instructor node by Roulette Method, jji;
            A[k, jji] ← 1; A[jji, k] ← 1;
        end for
    end if
end for
Generate the degree distribution graph of instructors and learners.
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Figure 20. The improved algorithm of BA model

5. Static Properties of Interaction Network

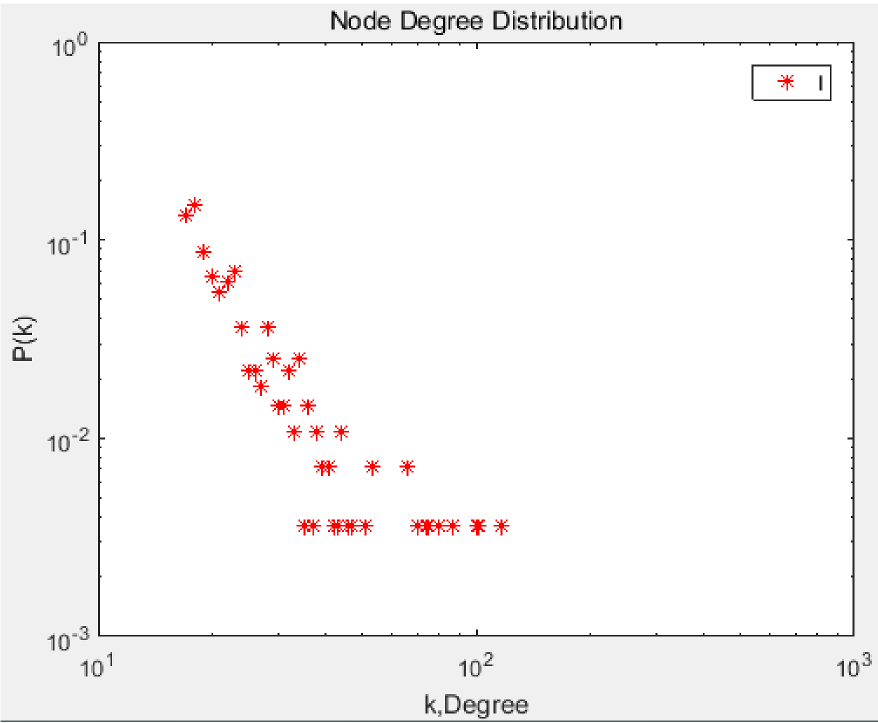
The degree distribution of the online learning interaction relation network generated by our improved algorithm of BA model is shown in Figure 3, and the parameter setting of the algorithm is shown in Table 1.

Table 6

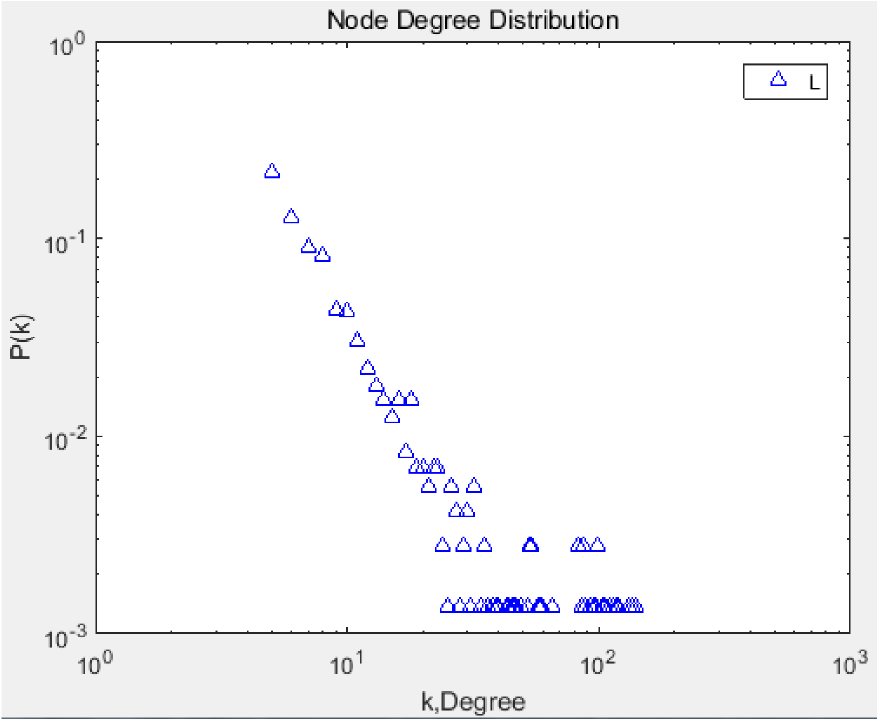
The Parameter Setting

Parameter	Definition	Value
mi0	The initial number of instructor nodes	3
ml0	The initial number of learner nodes	100
mi	The probability of a newly introduced node being an instructor node	0.3
ki	The number of instructor nodes to connect in the existing network when the newly introduced node is an instructor	2
ni	The number of total nodes to connect in the existing network when the newly introduced node is an instructor	17
kl	The number of learner nodes to connect in the existing network when the newly introduced node is a learner	2
nl	The number of total nodes to connect in the existing network when the newly introduced node is a learner	5
N	The scale of the network after the increase	1000

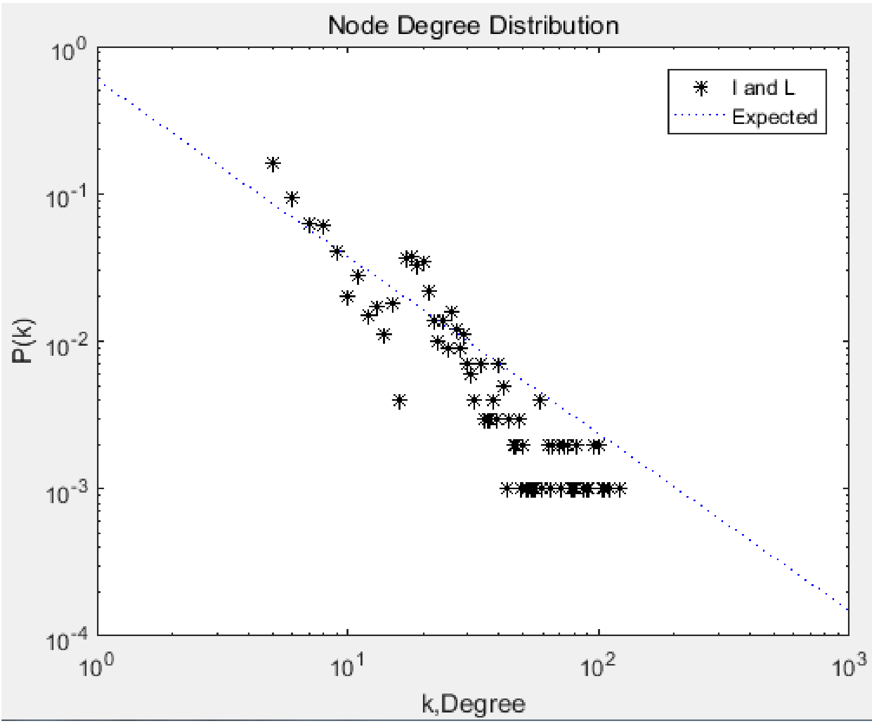
As shown in Figure 3, (a) is the degree distribution of instructors, (b) is the degree distribution of learners, and (c) is the degree distribution of instructors and learners. It can be seen that the degree distribution of the instructors and the learners are both consistent with the characteristics of the scale-free network, and the average degree of the instructors is higher than the average degree of the learners, which is in line with the actual rule of online learning interaction. Although the online learning interaction realtion network consists of two types of nodes and three types of edges, it is still a scale-free network.



(a)



(b)



(c)

Figure 21. The degree distribution of the online learning interaction relation network

6. Conclusion

The purpose of this study is to simulate the interaction relation network in the field of online learning setting. Based on the improved algorithm of BA model, we generate the online learning interaction relation network and show its degree distribution in the form of a degree distribution graph. The result shows that the interaction network generated in our research can greatly simulate the dissemination of knowledge and information during online learning interaction, which has practical significance for further study of the online learning interaction of instructors and learners. In the future, we will try to improve other algorithms to simulate a network that is more in line with the rule of online learning interaction. At the same time, the interactive relationship and interactive content in online learning interaction are also the key content we will explore.

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