Modeling Study of Knowledge Diffusion in Scientific Collaboration Networks based on Differential Dynamics

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Abstract
Knowledge diffusion based on scientific collaboration is similar to disease propagation through actual contact. Inspired by the disease-spreading model in complex networks, this study classifies the states of research entities during the process of knowledge diffusion in scientific collaboration into four categories. Research entities can transform from one state to another with a certain probability, which results in the evolution rules of knowledge diffusion in scientific collaboration networks. The knowledge diffusion model of differential dynamics in scientific collaboration of non-uniformity networks is formed, and the relationship between the degree distribution and evolution of knowledge diffusion is further discussed, to reveal the dynamic mechanics of knowledge diffusion in scientific collaboration networks. Finally, an empirical analysis is conducted on knowledge diffusion in an institutional scientific collaboration network by taking the graphene field as an example. The results show that the state evolution of research entities in the knowledge diffusion process of scientific collaboration networks is affected not only by the evolution states of adjacent research entities with whom they have certain collaboration relationships, but also by the structural attributes and degree distributions of scientific collaboration networks. The evolution of knowledge diffusion in scientific collaboration entities with different degrees also shows different trends.

Keywords
model of differential dynamics; scientific collaboration networks; knowledge diffusion

Conference Topic
Knowledge discovery and data mining

Introduction
Knowledge plays a vital role in economic growth, which is generally acknowledged by endogenous growth economists (Kline & Rosenberg, 1986; Lucas, 1988; Romer, 1990). The power of knowledge depends on whether the knowledge is diffused and on the diffusion depth and breadth, in addition to the value of the knowledge (Bacon, 1908). When knowledge is diffused, information and experiences gained by both sides would increase linearly; if the knowledge is further diffused with constant feedback and extension of the problems concerned, the information and experience would even increase geometrically (Quinn, Anderson, & Finkelstein, 1908). The knowledge societies are characterized by the proliferation of knowledge-intensive communities, specialized in knowledge production and reproduction, knowledge acquisition and exchange, and the use of information technologies (David & Foray, 2002; Yan, 2016). The production and creation of knowledge are not dependent on a single isolated entity; instead, knowledge is diffused, exchanged, and circulated among various entities (Crane, 1972). The competitiveness and the potential competitiveness of institutions are embodied in the acquisition and mastery of knowledge and innovative capacity (Drucker, 1999). Effective diffusion of knowledge can better promote their competitiveness and research level, and make optimal use of knowledge. Knowledge

diffusion is the link between knowledge acquisition and knowledge application. It has become an important subject of common concern to realize more effective diffusion and management of knowledge (Cronin, 1982; Chen & Hicks, 2004; Lambiotte & Panzarasa, 2009).

Many efforts have been made to improve the understanding of knowledge diffusion in various networks. According to the connection strength of network members, Granovetter (1973) proposed a weak ties theory of social networks, emphasizing the significance of "connection" between network members in knowledge and information diffusion. Cowan and Jonard (2004) and Kim and Park (2009) compared knowledge diffusion in regular, random, and small-world networks, and found that the small-world network is the most efficient structure to diffuse knowledge. Tang, Xi, and Ma (2006), and Lin and Li (2010) argued that the scale-free structure is more effective for knowledge diffusion.

Within the context of the growing complexity of research, collaboration has been considered one of the most crucial and common phenomena in the science community (Persson, Glänzel & Danell, 2004; Wuchty, Jones, & Uzzi, 2007; Adams, 2013; Chung, Kwon, & Lee, 2016). The process of scientific collaboration is also accompanied by the diffusing, sharing, and exchanging of both explicit and tacit knowledge among scientific research entities (Singh, 2005). Collective knowledge production and diffusion processes in science and technology have captured the attention of sociology of knowledge scholars throughout history (Mannheim, 1968; Kuhn, 1970; Scheler, 1980).

A scientific collaboration network, especially the co-authorship network formed by scientists in a deliberate and cautious way, is a structured form of knowledge exchanging and sharing among collaborators. The autonomous and self-organizing nature of scientific practices in knowledge creation and diffusion determines that the scientific collaboration network is the most appropriate mode of knowledge transmission and diffusion (Autant-Bernard, Mairesse & Massard, 2007; Ozel, 2010; Yang, Hu, & Liu, 2015).

Knowledge diffusion based on scientific collaboration is similar to disease propagation. In the process of scientific collaboration, knowledge exchange and diffusion can take place by the social collaboration connection among research entities including individuals, institutions, regions, countries, and so forth, while disease is usually propagated among organisms through air, food, contact, matrix, blood, and so forth (Anderson & May, 1991). From the perspective of information theory, both knowledge diffusion and disease propagation are composed of four elements that are the same in essence: information, information source, information channel, and information sink (Shannon, 1942).

The modeling of knowledge diffusion in scientific collaboration networks can help visualize the knowledge diffusion process through scientific collaboration, reveal the dynamics mechanism of knowledge diffusion in scientific collaboration networks, and realize more effective management and regulation of knowledge diffusion.

Literature Review

Studies on evolution mechanisms and the law of dynamics of knowledge diffusion are conducted from the perspective of model building, the current quantity of which is relatively small, with a majority of the research being qualitative. Usually, well-developed models from such fields as epidemiology, complexity science, and sociology are referenced. The knowledge diffusion process is accompanied by the generation and evolution of the knowledge diffusion network, and the construction of the knowledge diffusion model requires a tangible or intangible carrier network for knowledge diffusion. Currently, most scholars regard co-authorship (Eslami, Ebadi, & Schiffauerova, 2013) and literature citation relationships (Tsay, 2015; Zhu & Yan, 2015) as the paths to knowledge diffusion, and explore abstract representations of the knowledge diffusion process. The present knowledge diffusion models include the citation path model (Lu & Liu, 2013; Yu, Lu, Liu, & Zhou, 2014; Yan, 2014), epidemiological model (Bettencourt, Cinron-Arias, Kaiser, & Castillo-Chávez, 2006; Bettencourt, Kaiser, Kaur, Castillo-Chávez, & Wojick, 2008; Kiss, Broom, Craze, & Rafols, 2009), network structure model (Cowan & Jonard, 2004; Ozel, 2010; Liu, Rousseau, & Guns, 2013; Liu, Jiang, Chen, Larson, & Roco, 2015), individual behavior model (Morone & Taylor, 2004; Klarl, 2014), citation sequential network model (Gao & Guan, 2012), co-citation clustering model (Wang, Zhao, Liu, & Zhang, 2013), etc.

Epidemiological models focus on the transmission of different traits among certain populations; such traits can be transmitted diseases, knowledge, behaviors, or innovative ideas (Yan, 2014). An individual can be classified into one of the basic classes in epidemiological models: the susceptible class (S), the exposed class (E), the infected class (I), the skeptical class (Z), and the recovered class (R) (Hethcote, 2000). In the initial period of the diffusion of a good idea most of the population will be in the susceptible class (S), with a few individuals in the exposed class (E)—having been in contact with the idea while not diffused it—and a small number of infected (I) manifesting it. In addition, there may be competing and mutually exclusive ideas (e.g., where susceptibles are turned off from the idea and become skeptics or idea stiflers, represented by the class Z). Furthermore, individuals may recover or become immune (R), and not manifest the idea again (Bettencourt, Cinron-Arias, Kaiser, & Castillo-Chávez, 2006). Scholars can choose these classes based on their specific research questions.

In consideration of the similarity between knowledge diffusion based on scientific collaboration and disease propagation via actual contact, and inspired by the disease-spreading model in complex networks, the paper classifies research entities in the process of knowledge diffusion in scientific collaboration into potential knowledge recipients, potential knowledge diffusion individuals, knowledge diffusion individuals, and knowledge immunes. The four classifications of research entities can transform from one to another with a certain probability (α, β, ω, and γ, respectively). Then the evolution rules of knowledge diffusion in scientific collaboration networks are made. Furthermore, the knowledge diffusion model of differential dynamics in scientific collaboration of non-uniformity networks is formed, and then the relationship between the degree distributions and evolution of knowledge diffusion is further discussed, to reveal the dynamic mechanics of knowledge diffusion in scientific collaboration networks. Finally, an empirical analysis is conducted on knowledge diffusion in an institutional scientific collaboration network by taking the graphene field as an example.

Theoretical Model

Description of knowledge diffusion process in scientific collaboration networks

States of research entities in the knowledge diffusion process of scientific collaboration networks

For the knowledge exchange and diffusion process among research entities, we define that research entities in different states of knowledge diffusion in scientific collaboration networks fall into four categories: potential knowledge recipients (S), potential knowledge diffusion individuals (E), knowledge diffusion individuals (I), and knowledge immunes (R).

(1) Potential knowledge recipients (S): research entities who have not known the knowledge or have known but not acquired it yet.

(2) Potential knowledge diffusion individuals (E): research entities who have acquired the knowledge but not diffused it yet.

(3) Knowledge diffusion individuals (I): research entities who have mastered the knowledge and are diffusing it to the potential knowledge recipients.

(4) Knowledge immunes (R): research entities who have acquired the knowledge but are immune to it now. They have lost interest in the knowledge and will not continue to diffuse it.

Process of knowledge diffusion in scientific collaboration networks

In the initial phase, there are only small numbers of knowledge diffusion individuals in the network, while others are potential knowledge recipients. The number of potential knowledge diffusion individuals and knowledge immunes is zero. As time goes on, knowledge begins to be diffused in the following ways:

(1) When knowledge diffusion individuals transmit knowledge to potential knowledge recipients, the recipients begin to accept it with a certain probability (α) and become potential knowledge diffusion individuals.

(2) If potential knowledge diffusion individuals are interested in the knowledge, they will continue to diffuse it with a certain probability (β) and become new knowledge diffusion individuals.

(3) Knowledge diffusion individuals lose interest in the knowledge with certain probability (ω) and turn into knowledge immunes.

(4) Knowledge immunes become knowledge recipients again with a certain probability (γ) and take in the knowledge to which they have been immune.

Evolution rules of knowledge diffusion in scientific collaboration networks

At a certain time in the knowledge diffusion process in scientific collaboration networks, which could be marked as *t*, a research entity can only be in one of the four states mentioned above. At the time node t, we can define the proportion of scientific collaboration entities that are in a certain knowledge diffusion state in the whole system as follows.

(1) s(t): the proportion of potential knowledge recipients to all research entities in different states of knowledge diffusion at time t.

(2) e(t): the proportion of potential knowledge diffusion individuals to all research entities in different states of knowledge diffusion at time t.

(3) i(t): the proportion of knowledge diffusion individuals to all research entities in different states of knowledge diffusion at time t.

(4) r(t): the proportion of knowledge immunes to all research entities in different states of knowledge diffusion at time t.

Here, $s(t)+e(t)+i(t)+r(t)=1$.

According to the above description of the knowledge diffusion process in scientific collaboration networks, a schematic paradigm of the dynamic state evolution rules of research entities in knowledge diffusion is presented as follows (Figure 1).

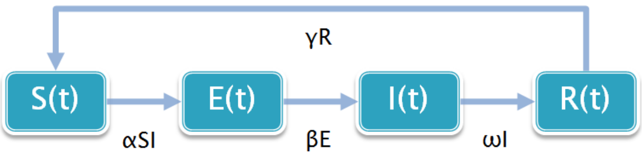

Figure 1. State transformational rules of research entities' knowledge diffusion of scientific collaboration.

When potential knowledge recipients cooperate with knowledge diffusion individuals in the process of scientific collaboration, they could become potential knowledge diffusion individuals with probability α; potential knowledge diffusion individuals become knowledge diffusion individuals with probability β; knowledge diffusion individuals turn into knowledge immunes with probability ω; and knowledge immunes generate feedback with probability γ, and become potential knowledge recipients.

Modeling derivation of knowledge diffusion in scientific collaboration networks

A scientific collaboration network is a kind of complex networks with obvious scale-free features. Its degree distribution accords with the power-law distribution. The connections between nodes are unevenly distributed, which means that only a minority of nodes in the

network have many links, while most nodes have few links (Barabási & Albert, 1999). Research entities of different degrees play different roles in the process of knowledge diffusion. According to the evolution rule of knowledge diffusion mentioned above, the knowledge diffusion model of differential dynamics in scientific collaboration of non-uniformity networks is formed by applying the mean field theory on the basis of the classical disease-spreading equation of SEIRS. The derivation process is deduced as follows.
In accordance with the evolution rule shown in Figure 1, considering the non-uniformity distribution characteristics of nodes, the system dynamics equations for each point (k) can be established from the perspective of mean field theory as follows:

$$\begin{cases} \frac{ds_k(t)}{dt} = -\alpha k N(k) s_k(t) \theta_k(t) + \gamma r_k(t) \\ \frac{de_k(t)}{dt} = \alpha k N(k) s_k(t) \theta_k(t) - \beta e_k(t) \\ \frac{di_k(t)}{dt} = \beta e_k(t) - \omega i_k(t) \\ \frac{dr_k(t)}{dt} = \omega i_k(t) - \gamma r_k(t) \end{cases} \tag{1}$$

In the equation set above, t is the time step; k is the node degree of research entities; N(k) stands for the number of research entities with degree k; $s_k(t)$, $e_k(t)$, $i_k(t)$, and $r_k(t)$ indicate the proportion of research entities with degree k at time t, and their knowledge diffusion states are S, E, I, and R, respectively; and $\theta_k(t)$ represents the probability that a random edge will connect with any knowledge diffusion individual at time t (namely, the infection probability for a research entity through a linked edge with other entities).
For a scientific collaboration network in which node degrees are correlative, $\theta_k(t)$ can be expressed as (Xia, Liu, Chen, & Yuan, 2008):

$$\theta_k(t) = \sum_{k'} P(k' \mid k) i_{k'}(t) \tag{2}$$

where P (k'| k) stands for the probability that an edge will stretch from a node with degree k to a node with degree k'.
If the node degrees are not correlative, then

$$\theta_k(t) = \sum_{k'} P(k' \mid k) i_{k'}(t) = \sum_{k'} \frac{k' P(k') i_{k'}(t)}{<k>} \tag{3}$$

where <k> is the average degree of the scientific collaboration network; P(k') indicates the probability that the research entity with degree k' will collaborate with an entity whose degree is k; and $i_k'(t)$ represents the proportion of research entities with degree k' whose knowledge diffusion state is I at time *t*.
By putting Formula 2 and Formula 3 into Equation Set 1, respectively, the knowledge diffusion models of differential dynamics in scientific collaboration networks with both correlated and uncorrelated node degrees will be formed, eventually, which are represented respectively as follows.
(1) The knowledge diffusion model of differential dynamics in scientific collaboration networks whose node degrees are correlative:

$$\begin{cases} \dfrac{ds_k(t)}{dt} = -\alpha k N(k) s_k(t) \sum_{k'} P(k'|k) i_{k'}(t) + \gamma r_k(t) \\ \dfrac{de_k(t)}{dt} = \alpha k N(k) s_k(t) \sum_{k'} P(k'|k) i_{k'}(t) - \beta e_k(t) \\ \dfrac{di_k(t)}{dt} = \beta e_k(t) - \omega i_k(t) \\ \dfrac{dr_k(t)}{dt} = \omega i_k(t) - \gamma r_k(t) \end{cases} \tag{4}$$

(2) The knowledge diffusion model of differential dynamics in scientific collaboration networks whose node degrees are uncorrelated:

$$\begin{cases} \dfrac{ds_k(t)}{dt} = -\alpha k N(k) s_k(t) \sum_{k'} \dfrac{k' P(k') i_{k'}(t)}{<k>} + \gamma r_k(t) \\ \dfrac{de_k(t)}{dt} = \alpha k N(k) s_k(t) \sum_{k'} \dfrac{k' P(k') i_{k'}(t)}{<k>} - \beta e_k(t) \\ \dfrac{di_k(t)}{dt} = \beta e_k(t) - \omega i_k(t) \\ \dfrac{dr_k(t)}{dt} = \omega i_k(t) - \gamma r_k(t) \end{cases} \tag{5}$$

Empirical Research

Graphene has drawn worldwide research attention because of its unique structure and the excellent characteristics of electricity, mechanics, optics, chemistry, and thermodynamics, becoming one of the hottest research subjects in the fields of physics, chemistry, and material science (Ma, Wan, & Feng, 2012). Scientific collaboration in the field is very common and frequent, and the transmission and communication of knowledge are very active. Carbon nanotubes are allotropes of carbon with a cylindrical nanostructure and one-dimensional quantum materials with a special structure. Graphene and carbon nanotubes are complementary in structure and capability, and there are also marked resemblances between them in research methodology (Baughman, Zakhidov, & De Heer, 2002). Studies of them present an overlapping, mutually permeating, and inseparable trend. Therefore, the knowledge point "carbon nanotubes" in the field of graphene is selected as the research object to form and verify the knowledge diffusion model of differential dynamics that simulates the knowledge diffusing process of carbon nanotubes through the institutional scientific collaboration network of graphene, and the research results are further analyzed and explained. Because the knowledge point "carbon nanotubes" in the field of graphene emerged in 1993, the research period of this model is set from 1993 to 2012.

Data collection

According to the following rules, the data was retrieved from the Web of Science (Table 1).

Table 1. Rules of data retrieval.

Retrieval strategy	TS=(graphen* or "single layer graphit*" or "monolayer graphit*")
Source	SCI-EXPANDED, SSCI, CPCI-S (Conference Proceedings Citation Index – Science)
Document type	Articles, Proceedings Paper
Period	1990-2012

By applying the above retrieval rules, 23,458 primary pieces of literature were obtained. Then the data was imported into the Thomson Data Analyzer (TDA) and data cleaning was conducted. The institutional scientific collaboration network matrixes of graphene and institutional knowledge diffusion network matrixes over the years were ultimately formed. Considering the updating of the network database, the data was collected on June 7, 2014 to maintain data consistency.

Degree correlation of scientific collaboration networks

The Pearson correlation score between the node degree k and the average degree of its adjacent nodes is -0.402. A significant correlation is not observed between them. Therefore, we ultimately select Model 5 as the theoretical model of this study.

State evolution of knowledge diffusion individuals

In this paper, we define research entities in the state of knowledge diffusion individuals at a certain time as the institutions that publish papers containing the knowledge point "carbon nanotubes" in the graphene field at that time. The total number of members in the institutional scientific collaboration network is 2,595. The quantity and proportion of knowledge diffusion individuals from 1993 to 2012 are shown in Table 2.

Table 2. Quantity and proportion of knowledge diffusion individuals during 1993–2012.

Year	Quantity	Proportion
1993	3	0.001156
1994	14	0.005395
1995	8	0.003083
1996	16	0.006166
1997	22	0.008478
1998	45	0.017341
1999	42	0.016185
2000	58	0.022351
2001	67	0.025819
2002	90	0.034682
2003	93	0.035838
2004	113	0.043545
2005	151	0.058189
2006	171	0.065896
2007	230	0.088632
2008	294	0.113295
2009	401	0.154528
2010	577	0.222351
2011	790	0.304432
2012	968	0.373025

It can be seen from the table that the proportion of institutions in the state of knowledge diffusion individuals (in other words, institutions that are diffusing knowledge), is growing continually (from 0.1156% to 37.3025%). The growth rate is slow from 1993 to 2006, and gradually speeds up after 2006. In 1995 and 1999, though, the proportion declines.
The knowledge diffusion of carbon nanotubes is in the embryonic stage from 1993 to 2006, and enters its development stage from 2007 to 2012.

Model construction and validation

In the original state (i.e., in 1993), there were three knowledge diffusion individuals of carbon nanotubes in the network (i.e., Massachusetts Institute of Technology; University of California, Los Angeles; and Drexel University). The others were all potential knowledge recipients. The numbers of both potential knowledge diffusion individuals and knowledge immunes were zero.

Parameter determination

According to the distributing characteristics of the theoretical and practical data values (between zero and one), the Kolmogorov–Smirnov statistic and Likelihood function are employed in this paper for parameter estimation. On the basis of Model 5, we simulate the theoretical model using MATLAB, adjust parameters (α, β, ω, and γ) with a step length of 0.1, and calculate K-S statistic and MLE (L) between the output values of the model with different parameters and actual values from 1993 to 2009, respectively, to determine the optimal parameters of the fitting model.

The set of parameters that result in the minimum values for both K-S and L is the optimal parameter set for the fitting model at the 0.05 significance level (Table 3).

Table 3. Optimal parameter set of fitting model and its K-S and L values.

α	β	ω	γ	K-S	L
0.3	1	0.1	0.1	0.107895	3.670283

Model building

Evolution curves of the theoretical and actual proportions of knowledge diffusion individuals in the optimal fitting model are shown in Figure 2.

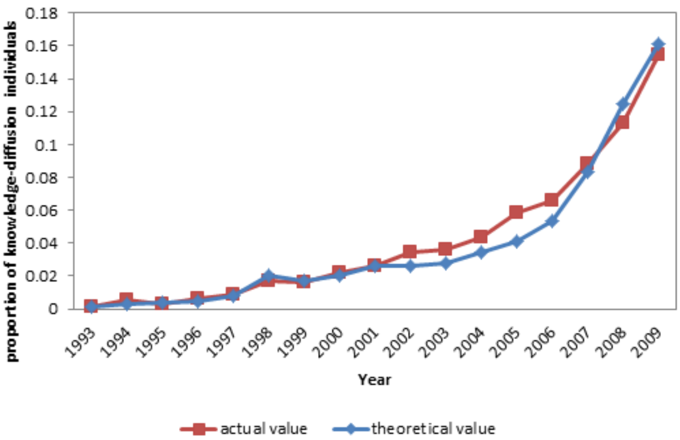

Figure 2. Evolution curves of theoretical and actual proportions of knowledge diffusion individuals with the optimal fitting parameters.

Therefore, the knowledge diffusion model of differential dynamics simulating the knowledge diffusion of carbon nanotubes through the institutional scientific collaboration network of graphene can be described as follows.

$$\begin{cases} \dfrac{ds_k(t)}{dt} = -0.3kN(k)s_k(t)\sum\limits_{k'}\dfrac{k'P(k')i_{k'}(t)}{<k>} + 0.1r_k(t) \\ \dfrac{de_k(t)}{dt} = 0.3kN(k)s_k(t)\sum\limits_{k'}\dfrac{k'P(k')i_{k'}(t)}{<k>} - e_k(t) \\ \dfrac{di_k(t)}{dt} = e_k(t) - 0.1i_k(t) \\ \dfrac{dr_k(t)}{dt} = 0.1i_k(t) - 0.1r_k(t) \end{cases} \qquad (6)$$

The model illustrates that the state evolution of research entities in the knowledge diffusion process of scientific collaboration networks is affected not only by the evolution states of adjacent research entities with whom they have certain collaboration relationships in knowledge diffusion, but also by the structural attributes and degree distributions of scientific collaboration networks. The state change of institutions with different node degrees (k) is influenced by factors such as their own degrees, the number of nodes (N(k)), and the connection probability of states.

Model verification

In accordance with Model 6, the proportions of institutions that are diffusing knowledge from 2010 to 2012 are predicted by the iteration of time steps (Table 4).

Table 4. Predicted value of the proportion of knowledge diffusion individuals from 2010 to 2012 in theory.

Year	Predicted value	Actual value	Deviation
2010	0.217252	0.222351	-2.293%
2011	0.300011	0.304432	-1.452%
2012	0.377568	0.373025	1.218%

The table shows that the deviations between the theoretical value and actual value of the proportion of knowledge diffusion individuals predicted from 2010 to 2012 are -2.293%, -1.452%, and 1.218%, respectively. This is an insignificant discrepancy, and the closeness between the values illustrates the validity of the model.

Results

Evolution analysis of knowledge diffusion in scientific collaboration networks

From 1993 to 2012, the state evolution of research entities diffusing the knowledge of carbon nanotubes in the institutional scientific collaboration network of graphene is shown in Figure 3.

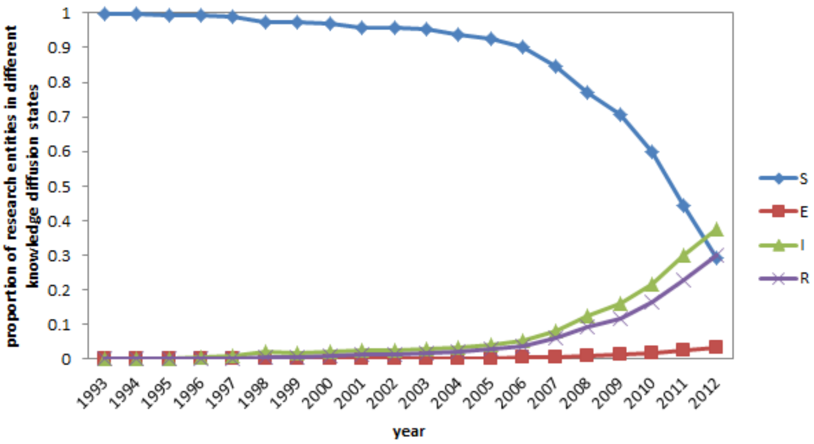

Figure 3. Evolution curves of research entities in different knowledge diffusion states in the scientific collaboration network.

From the perspective of the overall evolution trend of knowledge diffusion, the proportion of potential knowledge recipients in the institutional scientific collaboration network shows an incessant drop with the passage of time. However, the proportion of knowledge diffusion individuals and knowledge immunes rises constantly. Moreover, the proportion of potential knowledge diffusion individuals shows only a slight growth trend. From the perspective of evolution tempo (changing speed of proportion) of knowledge diffusion, the proportion of potential knowledge recipients, knowledge diffusion individuals, and knowledge immunes changes slowly at first and then speeds up rapidly, while the change of proportion of potential knowledge diffusion individuals has shown a slight growth tendency. From the perspective of evolution acceleration (change rate of velocity) of knowledge diffusion, the change rate of potential knowledge recipients ranks first, followed by that of knowledge diffusion individuals and knowledge immunes, and that of potential knowledge diffusion individuals ranks last.

In addition, it can be judged from the evolution trend of state proportion of knowledge diffusion individuals that the knowledge diffusion of carbon nanotubes in the institutional scientific collaboration network of graphene is in its developing stage, having not reached the saturation point. The diffusion scale of the knowledge will continue to expand as time goes on.

Relationship between node degree distribution and knowledge diffusion evolution in scientific collaboration networks

To reveal the impact of node degrees on knowledge diffusion, the relationship between node degree distribution and knowledge diffusion evolution in scientific collaboration networks is further analyzed and explained.

(1) Node degrees and potential knowledge recipients in scientific collaboration networks

The evolution of the proportion of nodes with variable degrees k in the state of potential knowledge recipients is shown in Figure 4.

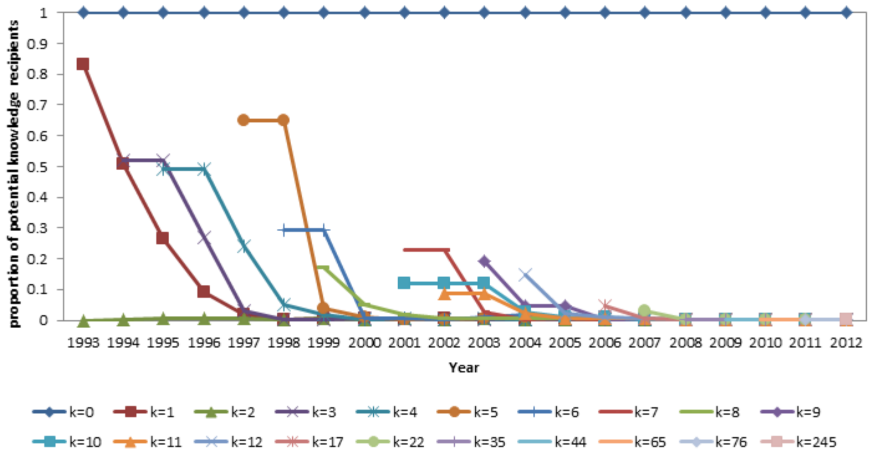

Figure 4. Evolution curves of proportion of nodes with variable degrees k in the state of potential knowledge recipients.

We can see from the above evolution curves that, overall, the proportion of potential knowledge recipients shows a downward trend, with the descending rates slowing down gradually. The proportion of scientific research entities with degree k=2 remains at a low level. Simultaneously, the proportion of potential knowledge recipients at the nodes with larger degrees is higher.

(2) Node degrees and potential knowledge diffusion individuals in scientific collaboration networks

The evolution of the proportion of nodes with variable degrees k in the state of potential knowledge diffusion individuals is shown in Figure 5.

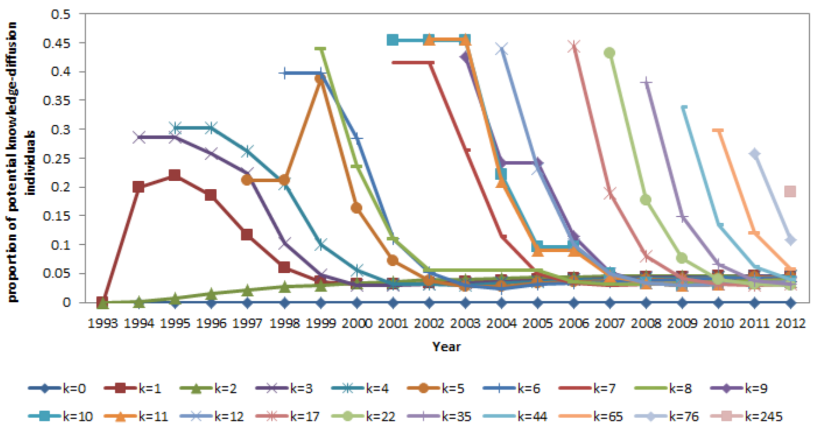

Figure 5. Evolution curves of proportion of nodes with variable degrees k in the state of potential knowledge diffusion individuals.

As shown in Figure 8, generally speaking, the proportion of potential knowledge diffusion individuals is in decline, and the declining rates slow down by degrees. The proportion in research entities with degree k=2, however, is rising slowly, and the proportion with degree k=1 rises rapidly first, followed by a sharp drop, and finally becomes steady.

(3) Node degrees and knowledge diffusion individuals in scientific collaboration networks

The evolution of the proportion of nodes with variable degrees k in the state of knowledge diffusion individuals is illustrated in Figure 6.

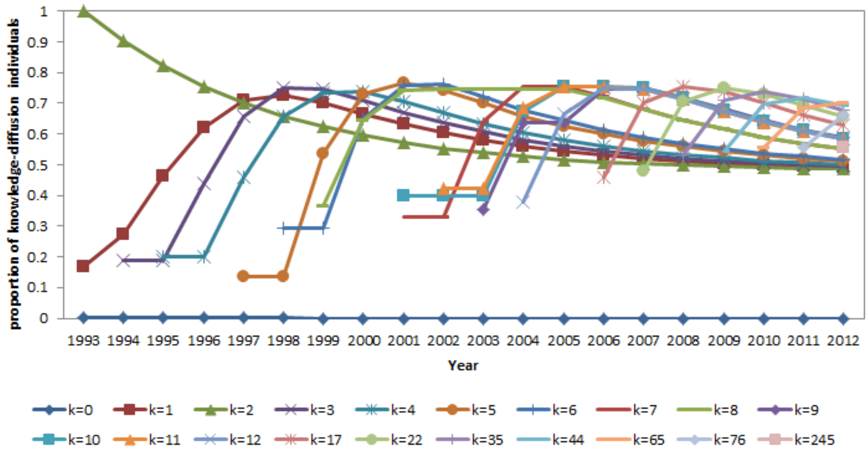

Figure 6. Evolution curves of proportion of nodes with variable degrees k in the state of knowledge diffusion individuals.

As shown in Figure 9, the overall trend of the proportion of knowledge diffusion individuals rises rapidly at first and then descends slowly. The proportion in research entities with degree k=2, however, shows a gradual falling trend. Regarding scientific research entities with node degree k before reaching the highest proportion of the knowledge diffusion individuals, the larger the degree is, the lower the proportion will be; after the highest proportion of the knowledge diffusion individuals, the larger the degree is, the higher the proportion will be.

(4) Node degrees and knowledge immunes in scientific collaboration networks

The evolution of the proportion of nodes with variable degrees k in the state of knowledge immunes is shown in Figure 7.

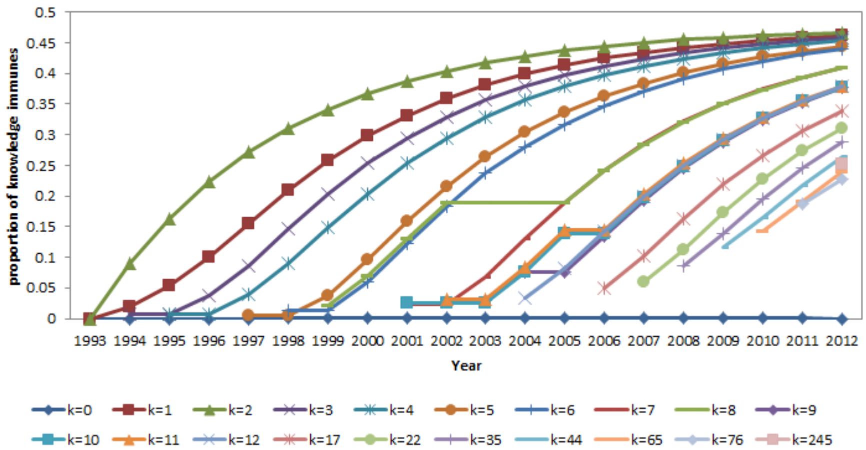

Figure 7. Evolution curves of proportion of nodes with variable degrees k in the state of knowledge immunes.

Generally, the proportion of knowledge immunes with variable degrees rises gradually.

Simultaneously, the larger the degree is, the lower the proportion of knowledge immunes will be.
Additionally, in light of the assumption of the model that knowledge diffuses with the help of scientific collaboration, the node with degree k=0 will not engage in the knowledge diffusion process because it does not participate in scientific collaboration. Therefore, it will remain in the state of potential knowledge diffusion individuals. Once there is scientific collaboration, the node degree will change and be further involved in the recurrent state of knowledge diffusion.

Discussion

Inspired by the disease-spreading model in complex networks, the paper builds the knowledge diffusion model of differential dynamics in scientific collaboration of non-uniformity networks, and conducts an empirical analysis on the model. The research has shown that:
(1) The hypothesis that knowledge can be diffused with the aid of scientific collaboration is justified, and the knowledge diffusion model constructed in this paper is rational and reasonable.
(2) The state evolution of research entities in the knowledge diffusion process of scientific collaboration networks is affected not only by the evolution states of adjacent research entities with whom they have certain collaboration relationships, but also by the structural attributes and degree distributions of scientific collaboration networks. For institutions with different node degrees, the change of states is jointly influenced by their own degrees, the number of nodes, and the connection probability of states.
(3) When the state transition probability meets the conditions that α=0.3, β=1, ω=0.1, and γ=0.1, the knowledge diffusion model of differential dynamics can almost accurately simulate the knowledge diffusion process of carbon nanotubes in the institutional scientific collaboration network of graphene.
(4) In the evolution process of knowledge diffusion in the scientific collaboration network, the proportion of potential knowledge recipients declines constantly, but the proportion of knowledge diffusion individuals and knowledge immunes increases continuously. Meanwhile, the proportion of potential knowledge diffusion individuals shows only a slight growth trend.
(5) The knowledge diffusion evolution of scientific collaboration entities with different degrees also shows different trends.
Based on the previous research results, policy makers can regulate the structure, degree distributions, and transition probability of states in scientific collaboration networks through various means to achieve different evolution effects of knowledge diffusion, and can control the knowledge diffusion process in scientific collaboration by promoting or inhibiting it. For example, they could expand the cooperation breadth of research institutions to further promote the absorption and mastery of knowledge and accelerate diffusion of knowledge with measures such as providing platforms for academic communication, consummating incentive mechanisms for scientific research innovation, etc.

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