Commun. Theor. Phys. (Beijing, China) **50** (2008) pp. 261–266
© Chinese Physical Society Vol. 50, No. 1, July 15, 2008

Weighted Evolving Networks with Self-organized Communities*

XIE Zhou,[1] LI Xiang,[2,†] and WANG Xiao-Fan[1]
[1]Lab of Complex Networks and Control, Department of Automation, Shanghai Jiao Tong University, Shanghai 200240, China
[2]Department of Electronic Engineering, Fudan University, Shanghai 200433, China

(Received September 28, 2006)

Abstract *In order to describe the self-organization of communities in the evolution of weighted networks, we propose a new evolving model for weighted community-structured networks with the preferential mechanisms functioned in different levels according to community sizes and node strengths, respectively. Theoretical analyses and numerical simulations show that our model captures power-law distributions of community sizes, node strengths, and link weights, with tunable exponents of $\nu \geq 1$, $\gamma > 2$, and $\alpha > 2$, respectively, sharing large clustering coefficients and scaling clustering spectra, and covering the range from disassortative networks to assortative networks. Finally, we apply our new model to the scientific co-authorship networks with both their weighted and unweighted datasets to verify its effectiveness.*

PACS numbers: 89.75.Fb, 02.50.-r
Key words: weighted network, community structure, preferential growth, scale-free, hierarchy

1 Introduction

It is widely recognized that many real-world large-scale networking systems exhibit common nontrivial connectivity patterns including the typical small-world phenomenon[1] and scale-free features,[2] which significantly dominate the emergent dynamics over the networks.[3] With the deeper understanding of interplay between the topology and dynamics of complex networks, people find many building blocks or units with a group of closely connected nodes, the so-called communities in social networks or modules in biological networks, play an important role in forming the topological properties and functional dynamics of involved complex networks.[4−7]

With further researches, several important properties are exposed in those community-structured networks. First and the most fundamental one is the connections between nodes are very dense in communities while much sparser between them,[8] which is believed to be caused by the tendency of communication within same community. For example, in world trade web (WTW), it was found that many countries (nodes in WTW) have trading preference inside the same regional economic cooperative organization, such as EU, ASEAN, and NAFTA (communities in WTW), where the local-world preferential attachment mechanism[5] leads to a stronger correlation of economic-cycle synchronization between countries in the same economic organization (Austria and Germany, both in the EU) than that between countries in different economic organizations (Austria and USA).[6]

Another property of communities in categories of complex networks is that the size distribution of communities often follows a power-law,[9,10] which is considered as the scale-invariant feature of complex networks reflected in the community level. And it is also argued that the presence of communities (or modules) is the essential signature of hierarchy in complex networks.[11]

To mimic these topological properties of community structures in complex networks, many evolving models have been proposed in the sense of communities and modules.[12−17] For example, the networked seceder model was proposed to construct community structured networks emerged as an effect of the agents personal rationales.[12] An evolving model by merging building blocks, which are fully connected subgraphs, was proposed with power-law degree distribution of exponent larger than 1, power-law clustering spectra of exponent 1, and high clustering coefficient.[13] Owning to the power-law degree distribution of fixed exponent 3, an evolving network model with inner-community preferential attachment was built.[14] Xuan, Li, and Wu proposed a model for hierarchical and modular networks,[15] in which the power-law distribution of module sizes is derived by a predefined structure. Furthermore, Valverde and Sole presented a simple model of open source communities based on the betweenness centrality.[16]

However, almost all of these models neglected the growing rules of communities, and seldom took into account the preferential mechanism on the community level.[18] Therefore, they failed to explain the phenomenon that many real-world networks show the power-law scaling property of community sizes with exponents between 1 and 2.[9,10] Besides, extended from the Boolean structure of unweighted networks, which are taken into account by most of these models, weighted networks took a step forward to understanding real-world complex networks more realistically, whose links between nodes display heterogeneity in the capacity and intensity.[19−21] Therefore, in the new model proposed in this paper, we develop the preferential mechanism not only on node strengths, but also at the level of community in weighted evolving networks, exhibiting power-law distributed community sizes as well as nodes strengths and link weights with the scale invariant exponents $\nu \geq 1$, $\gamma > 2$, and $\alpha > 2$, respectively. Furthermore, the effectiveness of the model is verified through an example of social networks, the scientific co-authorship networks.

2 The Model

Owing to the community structure in our model, we divide the links of each node into two parts: the inner-community links, which are the links connecting to other nodes within the same community, and the inter-community links, which are the links connecting to the nodes in different communities.

*The project partly supported by National Natural Science Foundation of China under Grant Nos. 60504019 and 70431002
†Correspondence author, E-mail address: lix@fudan.edu.cn

We initialize an undirected weighted network with c_0 ($c_0 > 1$) communities, each of which has n_0 fully connected nodes. There are $c_0(c_0-1)/2$ inter-community links to make the initialized c_0 communities fully connected. Every link connecting node i and node j in the initialized network is assigned the same initial weight $w_{ij} = \omega_0 = 1$. Naturally, as the generalization of degree k_i of node i, the strength of node i is defined as $b_i = \sum\limits_{j\in\Gamma(i)} w_{ij}$, where $\Gamma(i)$ denotes the neighbor set of node i. Therefore, the strength of every node is initialized the same as its degree.

Different from previous community models, we first propose two preferential attachment (PA) rules in the model:

i) Community size preferential attachment (CPA): When a new node chooses an existing community to join (or chooses another community from which to get an inter-community neighbor), we assume the probability of choosing community i, $\Pi(S_i)$, depends on the size of community i, S_i, such that

$$\Pi(S_i) = \frac{S_i}{\sum_k S_k}\,. \tag{1}$$

ii) Strength preferential attachment (SPA): When choosing a new neighbor, a new node firstly chooses a community i according to the CPA, and then connects with one node in it with the SPA. We assume the probability that the new node connects to node j in community i, $\Pi(B_{ij})$, is described by

$$\Pi(B_{ij}) = \frac{B_{ij}}{\sum_k B_{ik}}\,, \tag{2}$$

where B_{ij} stands for the strength of node j in community i.

Apart from the above preferential attachment mechanisms at different levels, another point accounted in our model is that real-world networks usually have large clustering coefficients, indicating that many triangles exist in networks. To show this, we introduce the triad-formation (TF) links[22] in our model. Therefore, during the network growing process, we employ two categories of links driven by different mechanisms in our model: (i) the PA links, which adopt the SPA mechanism to select connected nodes as in many evolving models; (ii) the TF links functioning as the formation of triads in the evolving weighted network, which means if node j is chosen by the new coming node t last time, one of the neighbors of node j will be selected to be the neighbor of node t. The probability of choosing node l is w_{jl}/B_{ij}, where w_{jl} stands for the link weight between node j and node l.

Combined with the PA mechanisms and links categories addressed above, the network growth of our proposed model is schemed as follows, with the illustration in Fig. 1.

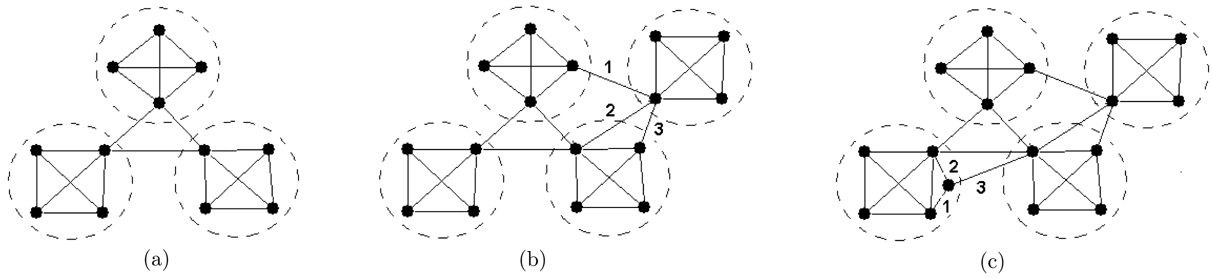

Fig. 1 An illustration of the network growth of our model. (a) A network is intialized with three communities, each of which has four fully connected nodes; (b) With probability p, a new community with four fully connected nodes is created. One node in that community connects to three existing nodes in other communities. The first and second links are PA links with probability $1-\varphi$. For the third link, a TF link is added with probability φ; (c) A new node with three links joins an existing community according to the CPA. The first link is a PA link, and also an inner-community link with probability q. With probability φ, the second link is a TF link. Then with another probability $1-\varphi$, the third link is added as a PA link, which is also an inter-community link with probability $1-\varphi$.

At each time-step, a new community containing n_0 fully connected nodes is added with probability p. In that community, every link is assigned the same initial weight $\omega_0 = 1$, and one node is chosen at random to connect with m existing nodes in other communities. For that node, the first link is a PA link, while the other $m-1$ links are TF links with probability φ or PA links with probability $1-\varphi$.

On the other hand, a new node is added with probability $1-p$. At first, it chooses a community to join according to the CPA rule (i), and then it connects with m existing nodes in the network. Similairly, the first link is a PA link, while the others are TF links with probability φ or PA links with probability $1-\varphi$. For those PA links, they are inner-community links with probability q or inter-community link with probability $1-q$. All these links are assigned the same initial weight $\omega_0 = 1$.

Please note that when a new node chooses an inter-community neighbor, it firstly chooses a community according to the CPA (1), and then chooses one node from that community according to the SPA (ii).

Here, the probabilities satisfy $0 \le p \le 1$, $0 \le q \le 1$, and $0 \le \varphi \le 1$.

To rearrange the weights during the network evolution, similar to the BBV model,[19] the birth of a new link $l(n,j)$ brings in a new information traffic from node n to node j, resulting in a local rearrangement of weights across the network. In particular, the weight of each new edge $l(n,j)$ is initialized as $\omega_0 = 1$, which induces an extra increase of traffic δ to node j in community i. Therefore, the total strength increase of node j is $\delta + \omega_0$, i.e., $B_{ij} \to B_{ij} + \delta + \omega_0$. Furthermore, δ is proportionally distributed among node j's outgoing edges, whose weights are updated as $w_{jl} \to w_{jl} + \Delta w_{jl}$, where $\Delta w_{jl} = \delta w_{jl}/B_{ij}$, $l \in \Gamma(j)$.

3 Property Analysis

3.1 *Scale-Invariant Distributions*

Using the mean-field method,[2] we analytically calculated the scaling exponents of the community sizes, node strengths, node degrees, and link weights in our proposed evolving weighted network model.

In our model, when a new node joins an existing community, it follows the preferential attachment in Eq. (1). Assume the sizes of communities are continuous. Therefore, the size preferential probability can be interpreted as a continuous rate of the change of S_i. Consequently, for community i, we have

$$\frac{\partial S_i}{\partial t} = \frac{S_i}{\sum_k S_k}\,. \tag{3}$$

Since $\sum_k S_k = N$, then

$$\frac{\partial S_i}{\partial t} = \frac{S_i}{\sum_k S_k} = \frac{S_i}{N} = \frac{S_i}{c_0 n_0 + (1-p+p\cdot n_0)t} \approx \frac{S_i}{(1-p+p\cdot n_0)t}\,, \tag{4}$$

whose solution, with initial condition that community i was added to network at time t_i with size $S_i = n_0$, is

$$S_i t) = n_o\bigl(t/t_i\bigr)^{1/(1-p+p\cdot n_0)}\,, \tag{5}$$

Therefore, the probability that a community has a size $S_i(t)$ no less than s, $P(S_i(t)\geq s)$, is

$$P(S_i(t)\geq s) = P\Bigl(t_i \leq \frac{n_0^{1-p+p\cdot n_0}}{s^{1-p+p\cdot n_0}}t\Bigr)\,. \tag{6}$$

For simplicity, we assume that communities are added at equal time intervals to the network. Hence, the probability density of t_i is

$$P(t_i) = \frac{1}{c_0 + pt}\,. \tag{7}$$

Substituting Eq. (7) into Eq. (6), we obtain

$$P(S_i(t)\geq s) = P\Bigl(t_i \leq \frac{n_0^{1-p+p\cdot n_0}}{s^{1-p+p\cdot n_0}}t\Bigr) = \frac{n_0^{1-p+p\cdot n_0}}{s^{1-p+p\cdot n_0}}\frac{1}{c_0 + p\cdot t}\,. \tag{8}$$

It implies that the cumulative distribution of community sizes obeys a power-law, $P(S\geq s)\sim s^{-\nu}$, with the exponent $\nu = 1 + p(n_0 - 1)\geq 1$, which succeeds to mimic the phenomenon of scale-free community size distributions having the scaling exponent $\nu\in[1,2]$ as discovered in many real-world networks.[9,10]

We now move to analyze the distributions of node strengths, node degrees, and link weights. As mentioned before, the links of each node can be divided into two parts: the inner-community links and the inter-community links. The inter-community links are generated from two ways. On one hand, when a community is added with probability p, it brings in m inter-community links. On the other hand, the m links of a new node are introduced as inter-community links with probability $1-q$. Generally, in real networks, links between communities are much sparser than those within communities,[8] thus we suppose the number of links of node j in community i, which is equal to its degree K_{ij}, is approximatively equal to that of its inner-community links marked as $K_{ij(\mathrm{inner})}$. That is, $K_{ij}\approx K_{ij(\mathrm{inner})}$.

First, let us take a look at the distribution of node strengths. When a new node n is created, the strength B_{ij} of the existing node j in community will be affected in four cases. (i) It is selected by node n according to the SPA; (ii) It is connected to node n with the TF links; (iii) One of its neighbor $l\in\Gamma(j)$ is selected by node n according to the SPA; (iv) One of its neighbor $l\in\Gamma(j)$ is connected to node n with the TF links. We suppose the number of TF links is m_{triad}. Thus, the total change rate of strength for node j in community i is

$$\begin{aligned}
\frac{\partial B_{ij}}{\partial t} &= (m - m_{\mathrm{triad}})\frac{S_i}{\sum_k S_k}\frac{B_{ij}}{\sum_k B_{ik}}(1+\delta) + \sum_{l\in\Gamma(j)}\frac{S_v}{\sum_k S_k}\frac{B_{vl}}{\sum_w B_{vw}} m_{triad}\frac{w_{jl}}{B_{vl}}(1+\delta)\\
&\quad + \sum_{l\in\Gamma(j)}(m - m_{\mathrm{triad}})\frac{S_v}{\sum_k S_k}\frac{B_{vl}}{\sum_w B_{vw}}\delta\frac{w_{jl}}{B_{vl}} + \sum_{l\in\Gamma(j)}\biggl[\Bigl[\sum_{u\in\Gamma(l)}\frac{S_v}{\sum_k S_k}\frac{B_{vu}}{\sum_w B_{vw}} m_{\mathrm{triad}}\frac{w_{ul}}{B_{vu}}\Bigr]\delta\frac{w_{jl}}{B_{vl}}\biggr]\\
&= (m - m_{\mathrm{triad}})\frac{S_i}{N}\frac{B_{ij}}{2m(1+\delta)S_i}(1+\delta) + \sum_{l\in\Gamma(j)}\frac{S_v}{N}\frac{B_{vl}}{2m(1+\delta)S_v} m_{\mathrm{triad}}\frac{w_{jl}}{B_{vl}}(1+\delta)\\
&\quad + \sum_{l\in\Gamma(j)}(m - m_{\mathrm{triad}})\frac{S_v}{N}\frac{B_{vl}}{2m(1+\delta)S_v}\delta\frac{w_{jl}}{B_{vl}} + \sum_{l\in\Gamma(j)}\biggl[\Bigl[\sum_{u\in\Gamma(l)}\frac{S_w}{N}\frac{B_{wu}}{2m(1+\delta)S_w} m_{\mathrm{triad}}\frac{w_{ul}}{B_{wu}}\Bigr]\delta\frac{w_{jl}}{B_{vl}}\biggr]\\
&= \frac{m - m_{\mathrm{triad}}}{2mN}B_{ij} + \frac{m_{\mathrm{triad}}}{2mN}B_{ij} + \frac{(m - m_{\mathrm{triad}})\delta}{2m(1+\delta)N}B_{ij} + \frac{\delta m_{\mathrm{triad}}}{2m(1+\delta)N}B_{ij} = \frac{1+2\delta}{2N(1+\delta)}B_{ij}\,.
\end{aligned} \tag{9}$$

On the other hand, the degree of node j will be affected only in the cases of (i) and (ii), thus, we can calculate the change rate of degree for node j in community i as

$$\begin{aligned}
\frac{\partial K_{ij}}{\partial t} &= (m - m_{\mathrm{triad}})\frac{S_i}{\sum_k S_k}\frac{B_{ij}}{\sum_k B_{ik}} + \sum_{l\in\Gamma(j)}\frac{S_v}{\sum_k S_k}\frac{B_{vl}}{\sum_w B_{vw}} m_{\mathrm{triad}}\frac{w_{jl}}{B_{vl}} = \frac{m - m_{triad}}{2m(1+\delta)N}B_{ij} + \frac{m_{\mathrm{triad}}}{2m(1+\delta)N}B_{ij}\\
&= \frac{B_{ij}}{2(1+\delta)N}\,,
\end{aligned} \tag{10}$$

Moreover, since $N = c_0 n_0 + (1-p+pn_0)t \approx (1-p+pn_0)t$, we have

$$\frac{\partial B_{ij}}{\partial t} = \frac{1+2\delta}{2(1+\delta)(1-p+pn_0)t} B_{ij}\,, \tag{11}$$

$$\frac{\partial K_{ij}}{\partial t} = \frac{B_{ij}}{2(1+\delta)(1-p+pn_0)t}\,, \tag{12}$$

respectively, whose solutions with the initial condition that node j was added to community i at time t_j with m links, $K_{ij}(t_j) = B_{ij}(t_j) = m$, are

$$B_{ij}(t) = m\Big(\frac{t}{t_i}\Big)^{(2\delta+1)/2(\delta+1)(1-p+pn_0)}\,, \tag{13}$$

$$K_{ij}(t) = \frac{B_{ij}(t) + 2m\delta}{2\delta+1}\,, \tag{14}$$

respectively. Moreover, there is a linear relationship between them. Therefore, the node degrees and node strengths follow the same form of power-law distributions $P(k) \sim k^{-\gamma}$ and $P(B) \sim B^{-\gamma}$, where $\gamma = 4\delta + 3 + 2p(\delta+1)(n_0-1)/(2\delta+1) > 2$.

Besides, for an existing link (j,s), its weight w_{js} will change if a new node connects to either node j or node s. Hence,

$$\begin{aligned}\frac{\partial w_{js}}{\partial t} &= (m - m_{\rm triad})\frac{S_i}{\sum_k S_k} t \frac{B_{ij}}{\sum_k B_{ik}} t\delta \frac{w_{js}}{B_{ij}} + (m - m_{\rm triad})\frac{S_r}{\sum_k S_k}\frac{B_{rs}}{\sum_v B_{rv}}\delta\frac{w_{js}}{B_{rs}} \\ &\quad + m_{\rm triad}\sum_{u\in\Gamma(j)}\frac{S_v}{\sum_k S_k}\frac{B_{vu}}{\sum_w B_{vw}}\frac{w_{ju}}{B_{vu}}\delta\frac{w_{js}}{B_{ij}} + m_{\rm triad}\sum_{u\in\Gamma(s)}\frac{S_v}{\sum_k S_k}\frac{B_{vu}}{\sum_w B_{vw}}\frac{w_{su}}{B_{vu}}\delta\frac{w_{js}}{B_{rs}} \\ &= (m - m_{\rm triad})\frac{\delta w_{js}}{2mN(1+\delta)} + (m - m_{\rm triad})\frac{\delta w_{js}}{2mN(1+\delta)} + m_{\rm triad}\frac{\delta w_{js}}{2mN(1+\delta)} + m_{\rm triad}\frac{\delta w_{js}}{2mN(1+\delta)} \\ &= \frac{\delta w_{js}}{(1+\delta)N} = \frac{\delta w_{js}}{(1+\delta)(1-p+p\cdot n_0)t}\,.\end{aligned} \tag{15}$$

The solution of Eq. (15) with initial condition link (j,s) added at $t_{js} = \max(t_j, t_s)$ with $w_{ij}(t_{js}) = w_0 = 1$, is

$$w_{js}(t) = \big(t/t_{js}\big)^{\delta/(1+\delta)(1-p+pn_0)}\,, \tag{16}$$

which implies the power-law distribution of link weights as $P(w) \sim w^{-\alpha}$, where

$$\alpha = 2 + p(n_0-1) + [1 + p(n_0-1)]/\delta > 2\,.$$

3.2 *Clustering and Assortative Mixing Patterns*

Having the triad-formation mechanism in our model, we now investigate the clustering property along with the assortative mixing patterns in the evolved networks. As shown in Fig. 2, we come to the conclusion that the average clustering coefficient C increases as the growth of δ and φ. Furthermore, compared with δ, φ plays a more important role in adjusting C since we can get a very wide range of C by changing φ, even for a quite small δ. We suppose it is because that the increase of δ tends to increase the clustering coefficients in a local area, while the increase of φ will cause the increase of clustering coefficients globally for all nodes.

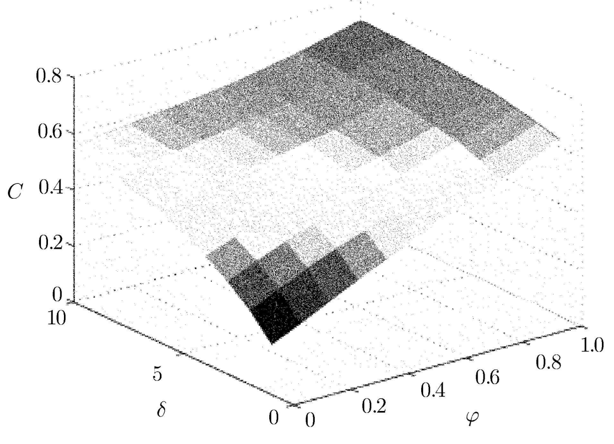

Fig. 2 The comparison of the weighted SCN (2001) and our model.

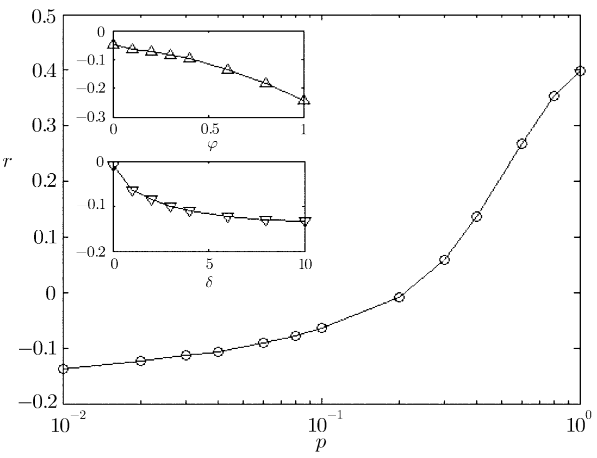

Fig. 3 The variation of r under different p, δ, and φ. The initial condition and other related parameters are $c_0 = 3$, $n_0 = 3$, $q = 0.9$, $m = 4$, and $T = 10\ 000$.

We then observe the influences of different parameters to assortative mixing coefficient r[23] defined as

$$r = \frac{M^{-1}\sum_i j_i k_i - [M^{-1}\sum_i (j_i + k_i)/2]^2}{M^{-1}\sum_i (j_i^2 + k_i^2)/2 - [M^{-1}\sum_i (j_i + k_i)/2]^2}\,, \tag{17}$$

where j_i and k_i are the degrees of the nodes at the ends of the i-th edge, with $i = 1, 2, \ldots, M$, and M is the number of links in the network. In Fig. 3, we shows the relationship between r and p with $\delta = 1.0$ and $\varphi = 0.1$. The top inset shows the relationship between r and φ with $p = 0.1$ and $\delta = 1.0$. The below inset shows the relationship between r and δ with $p = 0.1$ and $\varphi = 0.1$. All curves are averaged from 50 groups of realizations. As shown in Fig. 3, we could see that r grows as p increases, covering the range of both assortative and disassortative networks. Furthermore, as φ and δ increases, r decreases within a relative smaller range; however, they do not change the assortative mixing patterns of the networks. Therefore, we believe that the probability p of adding new community/node significantly determines the degree-degree mixing patterns of the evolving weighted networks in our model. This phenomenon can be easily understood since the community structure of networks is supposed to be related to the hierarchy property in networks.[11]

4 Application to SCN

To verify the effectiveness of our model, in this section, we apply it to real data of a typical social complex network, the scientific co-authorship network (SCN) of the Los Alamos cond-mat e-print archive collected in 2001.[20] In the SCN, nodes are defined as scientists, and two scientists (nodes) are connected if they have coauthored at least one paper in this archive. Furthermore, an article with n authors contributes $(n-1)^{-1}$ to the weight of the links between every pair of its authors. The communities of the largest giant component of the SCN, which is regarded as the SCN for simplicity without loss of generality, are analyzed by the CNM method, yielding 176 communities with the largest modularity Q.[9] We initialized our model with $c_0 = 5$, $n_0 = 5$, $p = 0.015$, $q = 0.9$, $\varphi = 1$, $\omega_0 = 0.5$, $\delta = 0.5$, and $m = 3$. Here p is small since the born of new communities is much rarer than the creation of new nodes, which is very common in real networks. After $T = 13\,162$ steps, we gained a weighted network with the same number of nodes in SCN. As listed in Table 1 and shown in Fig. 4, even having less links, the network generated with our model owns very close clustering coefficient and community number compared to the SCN in 2001, whose distributions of community sizes, weights, and clustering coefficients are almost completely overlapped. Thus, we come to the conclusion that the network generated by our model matches the SCN well. Specially, the communities defined in our model are consistent with those in real networks. One thing we have to state is that we neglect i-th SCN, owing to the fact that the distribution of node strength in the SCN does not follow a power-law, which is beyond our consideration.

Table 1 The comparison of the weighted SCN (2001) and our model.

	Node number	Link number	Average clustering coefficient	Community number
SCN (2001)	13 861	44 619	0.65	176
Our model	13 861	41 229	0.64	174
Relative error	0	7.6%	1.5%	1.1%

Table 2 The comparions of the unweighted SCN (2004) and our model.

	Node number	Link number	Average clustering coefficient	Community number
SCN (2004)	30 561	125 959	0.63	1069
Model	30 561	116 944	0.62	1058
Relative error	0	7.2%	1.6%	1.0%

The comparison of the network generated by our model and the weighted SCN in 2001. (a) Cumulative distribution of community sizes; (b) Distribution of weights; (c) Clustering spectra.

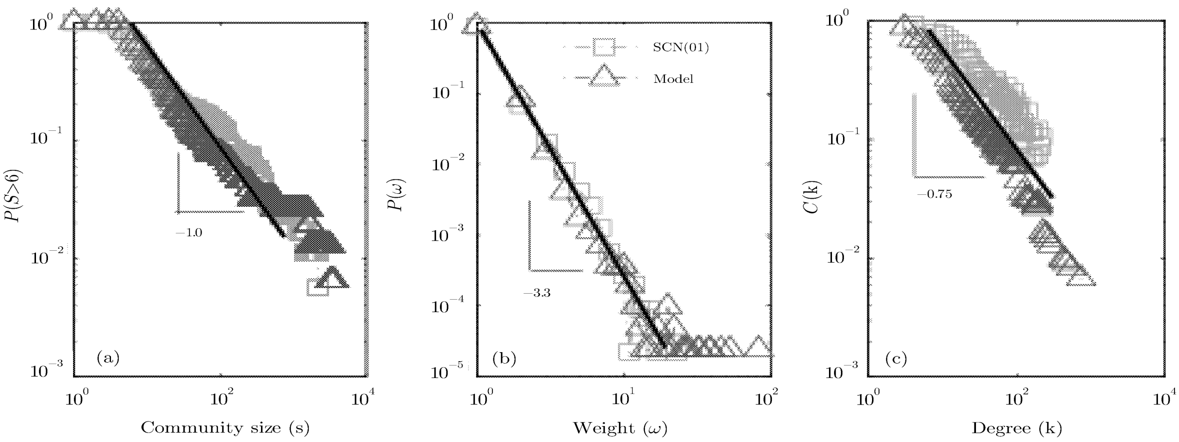

Fig. 4 The comparison of the network generated by our model and the weighted SCN in 2001; (a) Comulative distribution of community sizes; (b) Distribution of weights; (c) Clustering spectra.

Specially, if we set the parameter $\delta = 0$, our model can also be applied to unweighted networks. For example, we compare our model with the unweighted SCN network data collected in February, 2004.[24] After initializing our model with $c_0 = 3$, $n_0 = 3$, $p = 0.04$, $q = 0.9$, $\varphi = 1$, $\delta = 0$, $m = 4$ and after $T = 28\,344$ steps, we gained an unweighted network with the same number of nodes as that of the SCN in 2004. Similarly, our model succeeded in capturing the scale-invariant properties of community sizes, node degrees and clustering spectra of the SCN in 2004, as listed in Table 2 and Fig. 5.

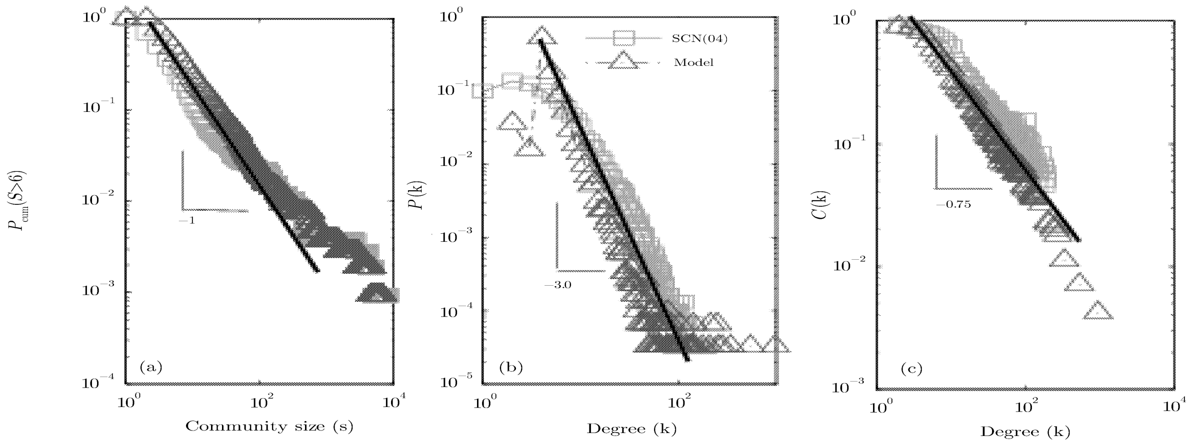

Fig. 5 The comparison of the unweighted network generated by our model and the unweighted SCN in 2004. (a) Cumulative distribution of community size; (b) Distribution of node degrees; (c) Clustering spectra.

5 Conclusions

To summarize, with the preference mechanisms on both the community level and the node level, we have proposed a weighted evolving network model with the self-organized community structure, displaying power-law distributions of community sizes, node strengths, and link weights with arbitrary scaling exponents of $v \geq 1$, $\gamma > 2$, $\alpha > 2$, respectively, which is qualified to model the scientific co-authorship network in both the weighted and the unweighted datasets of 2001 and 2004.

In Ref. [21], a generalized weighted evolving netwrok model was built in the concept of local-world,[5] where the preferential mechanism only functions in the local-world, not globally. However, the size of local-worlds, to which every node belongs, is fixed as the same, and naturally the hierarchy of community structure is neglected. Therefore, as this paper come to the end, we think that the evolving weighted netwrok model with self-organized community structures proposed in this paper is a generalization of the fixed local-worlds in Ref. [21] to self-organized local-worlds in ths sense of community in social complex networks.

Acknowledgments

Authors thank M. Newman for providing the data of scientific co-authorship network of 2001

References

[1] D.J. Watts and S.H. Strogatz, Nature (London) **393** (1998) 440.
[2] A.L. Barabasi and R. Albert, Science **286** (1999) 509.
[3] For the latest survey, please refer to Phys. Rep. **424** (2006) 175 and references therein.
[4] J. Scott, *Social Newwork Analysis: a Handbook*, 2nd ed., Sage, London (2000); E. Ravasz, A.L. Somera, D.A. Mongru, *et al.*, Science **297** (2002) 1551; T. Vicsek, Nature (London) **418** (2002) 131.
[5] X. Li and G. Chen, Physica A **328** (2003) 274.
[6] X. Li, Y.Y. Jin, and G. Chen, Physica A **328** (2003) 287.
[7] E. Oh, K. Rho, H. Hong, and B. Kahng, Phys. Rev. E **72** (2005) 047101; L. Huang, K. Park, and Y.C. Lai, Phys. Rev. E **73** (2006) 035103R; K. Park, Y.C. Lai, S. Gupte, and J.W. Kim, Chaos **16** (2006) 015105.
[8] M.E.J. Mewman, Phys. Rev. E **69** (2004) 066133.
[9] A. Clauset, M.E.J. Newman, and C. Moore, Phys. Rev. E **70** (2004) 066111.
[10] M.E.J. Newman, Phys. Rev. E **69** (2004) 066133; F. Radicchi, C. Castellano, F. Cecconi, *et al.*, Natl. Acad. Sci. USA **101** (2004) 2658; G. Palla, I. Derényi, I. Farkas, and T. Vicsek, Nature (London) **435** (2005) 814.
[11] M. Girvan and M.E.J. Newman, Proc. Natl. Acad. Sci. USA **99** (2002) 7821.
[12] A. Gronlund and F. Holme, Phys. Rev. E **70** (2004 036108.
[13] K. Takemoto and C. Oosawa, Phys. Rev. E **72** (2005) 046116.
[14] C. Li and P.K. Maini, J. Phys. A **38** (2005) 9741.
[15] Q. Xuan, Y.J. Li, and T.J. Wu, Phys. Rev. E **73** (2006) 036105.
[16] S. Valverde and R.V. Sole, eprint/cond-mat: 0602005.
[17] Z. Xie, X. Li, and X.F. Wang, Physica A **384** (2007) 725.
[18] P. Pollner, G. Palla, and T. Vicsek, Europhys. Lett. **73** (2006) 478.
[19] A. Barrat, M. Barthelemy, and A. Vespignani, Phys. Rev. Lett. **92** (2004) 228701.
[20] M.E.J. Newman, Proc. Natl. Acad. Sci. USA **98** (2001) 404.
[21] Z. Pan, X. Li, and X.F. Wang, Phys. Rev. E **73** (2006) 056109.
[22] P. Holme and B.J. Kim, Phys. Rev. E **67** (2002) 026107.
[23] M.E.J. Newman, Phys. Rev. Lett. **89** (2002) 2087011.
[24] http://angele.elte.hu/clustering/.