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An empirical study of Chinese language networks

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Abstract

Chinese is spoken by the largest number of people in the world, and it is regarded as one of the most important languages. In this paper, we explore the statistical properties of Chinese language networks (CLNs) within the framework of complex network theory. Based on one of the largest Chinese corpora, i.e. People's Daily Corpus, we construct two networks (CLN1 and CLN2) from two different respects, with Chinese words as nodes. In CLN1, a link between two nodes exists if they appear next to each other in at least one sentence; in CLN2, a link represents that two nodes appear simultaneously in a sentence. We show that both networks exhibit small-world effect, scale-free structure, hierarchical organization and disassortative mixing. These results indicate that in many topological aspects Chinese language shapes complex networks with organizing principles similar to other previously studied language systems, which shows that different languages may have some common characteristics in their evolution processes. We believe that our research may shed some new light into the Chinese language and find some potentially significant implications.

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Keywords: Complex network; Chinese language; Small-world effect; Scale-free scaling

1. Introduction

Complex network, as a new science [1], has received a tremendous amount of interest [2–6] since the publication of the seminal works of Watts and Strogatz [7] as well as Barabási and Albert [8]. It describes a number of real systems in nature and society, with vertices (nodes) representing the component units and links (edges) standing for the interactions between them. A lot of real-life systems have been examined from the viewpoint of complex networks. Examples include Internet [9], World Wide Web [10], metabolic networks [11], protein networks in the cell [12], co-author networks [13–15], sexual networks [16] and public transport networks [17–21]. These empirical studies have inspired researchers to develop a variety of techniques and models to help us understand or predict the behavior of real-world systems [22–29].

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It is now established that complex network is a powerful tool in the analysis of complex systems by providing intuitive and useful representations for networked systems such as those mentioned above. Recently, human languages as complex systems have been studied from the perspective of complex network theory [30–35]. These works are of fundamental importance for identifying and understanding the topology structure of language networks. Their obtained results are important, not only for the study of languages themselves, but also for cognitive science where one of the most fundamental issues concerns associative memory, which is intimately related to the network topology [30, 34]. However, previous studies discussed only parts of the statistical properties. On the other hand, there were very few works about the topology study on the Chinese language, although it is one of the most widely used languages in the world [36].

In this paper, we do an empirical study on Chinese language networks (CLNs), which are based on a part of PFR People's Daily Corpus, one of the largest Chinese corpora. We present a comprehensive analysis of the network characteristics including degree distribution, clustering coefficient, average path length, betweenness and degree-degree correlations. Our results demonstrate that in addition to the scale-free property and small-world effect, CLNs exhibit a composite power law behavior for both average nearest-neighbor degree and individual vertex's clustering coefficient as a function of vertex degree. Moreover, we find that the vertex betweenness also shows a power-law distribution. Our study makes it possible to investigate the complexity of the Chinese language within the framework of network theory.

The rest of this paper is organized as follows. In Section 2 we introduce the corpus from which CLNs are established and propose the network construction methods. The statistical properties and results are presented in Section 3. Section 4 is devoted to our conclusions and discussions.

2. Construction of Chinese language networks

In order to analyze various topology characteristics of Chinese language networks, we start with proper definitions of the considered networks constructed on the basis of a Chinese corpus.

2.1. The corpus

The corpus we make use of is a part of PFR1.0, one of the largest tagged corpora of Chinese, which is jointly issued by the Institute of Computational Linguistics of Peking University, FUJITSU R&D CENTER CO. LTD, and the Information Center of People's Daily Agency. It consists of news articles published in People's Daily in January 1998, which are well segmented and tagged, covering a wide range of topics, such as economics, politics, society, sports, health, international news and so on.

The chosen corpus is representative, since all its contents are from People's Daily, which is the most authoritative, comprehensive daily in China. Moreover, People's Daily has the biggest circulation in China, and is regarded as one of the top ten newspapers in the world by the United Nations Educational, Scientific, and Cultural Organization (UNESCO).

2.2. Network construction methods

The complexity of the Chinese language offers several possibilities for defining and studying complex networks. Motivated by the public transport networks [17–21], here we construct only two different kinds of Chinese language networks (CLN1 and CLN2), which are treated as undirected and unweighted graphs. The CLN1 and CLN2 correspond to "space L" and "space P" of public transport networks, respectively.

The first network (CLN1) is established as follows: First, every sentence is taken as a subgraph, in which words in the sentence are defined as vertices, and these vertices are connected if they appear next to each other in the sentence; Second, this subgraph will be combined with the one constructed in the last step. Note that If there are two words which are the same in form (characters) but with different parts of speech (POS), they are regarded as two different vertices. Thus, CLN1 may shed some insight into the understanding of syntax in the Chinese language. In Fig. 2, we present an example of the CLN1 construction based on the four sentences shown in Fig. 1. It should be noted that, for convenience, we use English letters to represent the Chinese words, the former are parenthesized behind the latter (see Fig. 1).

Sentence 1 我(A) 爱(B) 北京(C) 天安门(D)
Sentence 2 北京(C) 是(E) 中国(F) 的(G) 首都(H)
Sentence 3 天安门(D) 是(E) 世界(I) 上(J) 最大(K) 的(G) 广场(L)
Sentence 4 中国(F) 的(G) 发展(M) 离(N) 不(O) 开 (P) 世界(I)

Fig. 1. Four sentences used to construct the subgraphs of CLNs.

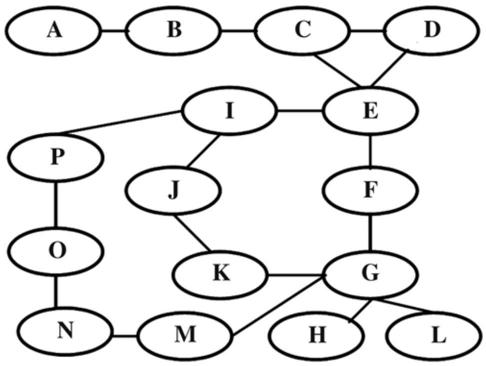

Fig. 2. An example of CLN1 based on the four sentences shown in Fig. 1.

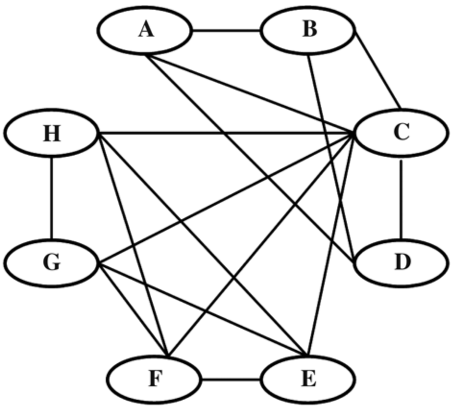

Fig. 3. Illustration of CLN2 based on the first two sentences shown in Fig. 1.

The construction of the second network (CLN2) is different from CLN1 in that every sentence in the corpus is added to the network as a complete subgraph, which is a complete subgraph where all vertices are interconnected with each other. In CLN2, the number of existing cliques passing by a given vertex is just the number of different sentences containing this vertex. An example of part of CLN2 is illustrated in Fig. 3.

Following the construction methods, we get two networks, which are denoted by CLN1 and CLN2 as above. CLN1 consists of 63,803 vertices and 400,897 edges, and contains one giant component of $N_1 = 62{,}281$ vertices and $E_1 = 400{,}717$ edges with a mean degree $\langle k_1 \rangle = 12.8$. CLN2 is composed of 60,482 vertices and 2136,164 edges, and includes a giant component of $N_2 = 59{,}013$ vertices and $E_2 = 2136{,}097$ edges with a mean degree $\langle k_2 \rangle = 72.3$. In what follows, we will only consider the topologies of the giant connected components of the two graphs, which will be still denoted as CLN1 and CLN2 for brevity.

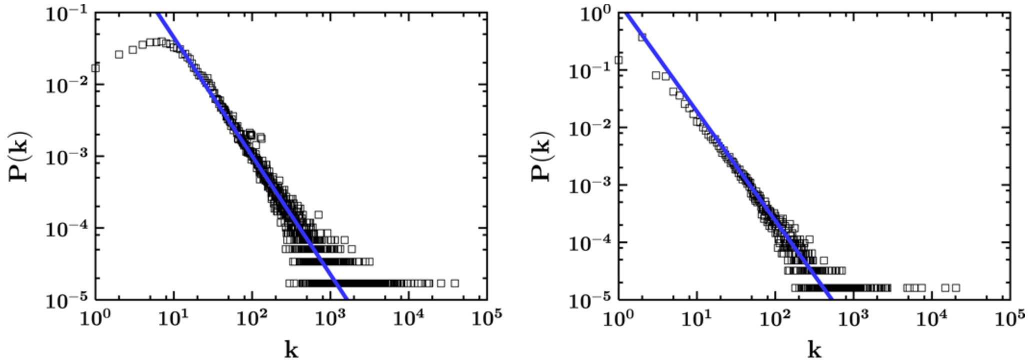

Fig. 4. Log–log graph of the degree distribution, with the left and right panels corresponding to CLN1 having a slope of −1.9 and CLN2 having a slope of −1.65, respectively.

3. Relevant network properties

Although the construction approaches generating CLN1 and CLN2 differ in important ways, we will see that both the networks are similar in the statistics of their large-scale organization.

3.1. Scale-free behavior

Degree distribution $P(k)$ is one of the most important statistical characteristics of a network, which is defined as the probability that a randomly selected node has exactly k edges. For many real complex networks, $P(k)$ follows a power-law distribution:

$$P(k) \sim k^{-\gamma}. \tag{1}$$

Such networks are called scale free.

The considered CLN1 and CLN2 obviously exhibit a scale-free behavior. Fig. 4 shows typical plots of degree distributions for CLN1 and CLN2. The slopes of the fitting lines are about −1.9 and −1.65, respectively. From Fig. 4, one observes a power-law scaling, which means that the majority of vertices in the networks have only a few connections to other nodes, whereas some vertices (hubs) are connected to many other nodes. These hubs with highest degree correspond to some functional words, such as conjunction words, or adverbial words related with time and location. They are important for the whole CLNs. In fact, people can communicate conveniently by connecting hubs with some meaningful words according to syntax rules.

As a matter of fact, such scale-free behavior is related to frequency of occurrence of a word. If we define the weight of a link between two given nodes as the times (frequency) that the two nodes appear next to each other in CLN1 or simultaneously in a sentence in CLN2, then the total weight of a node, defined as its strength s [37,38], corresponds to its total frequency. In Fig. 5, we report the relationship between a node's strength and degree. It is found that there is a nontrivial power-law scaling relation between the average strength s of vertices and degree k, which is also observed in some other real-life systems [37]. The nontrivial correlation $s \sim k^{\beta}$ ($\beta = 1.20$ for CLN1, and $\beta = 1.12$ for CLN2) demonstrates the phenomenon of "the rich get richer", which may account for the power-law degree distribution of the networks.

From Fig. 4, we also observe that there is a plateau region in $P(k)$ for small values of k. Indeed, it is not exclusive; many other real-life networks such as the World Wide Web [10] and the actor collaboration graph [39] exhibit the phenomenon of deviation from power-law to some degree for small k values. Several network models have been proposed to interpret this behavior [40–42].

3.2. Small-world effect

Small-world effect is measured by clustering coefficient and average path length (APL). By definition, clustering coefficient C_i of a node i is the ratio of the total number e_i of edges that actually exist between all its k_i nearest

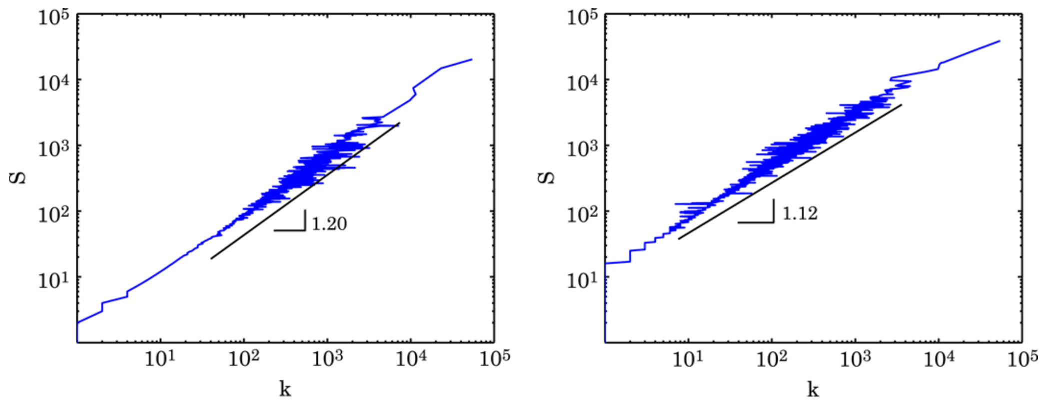

Fig. 5. Log–log graph showing node strength as a function of its degree distribution.

Table 1
Results for CLN1 and CLN2, and comparisons with corresponding random networks (denoted as R1 and R2, respectively) with the same parameters

Graph	N	E	$\langle k\rangle$	C	L
CLN1	62,281	400,717	12.8	0.5091	3.04
R1	–	–	–	0.0002	4.35
CLN2	59,013	2136,097	72.3	0.7530	2.40
R2	–	–	–	0.0012	2.57

N is the total number of vertices, $\langle k\rangle$ is the average vertex degree, C is the average clustering coefficient over all vertices, and L is the average path length.

neighbors and the number $k_i(k_i-1)/2$ of all possible edges between them, i.e. $C_i = 2e_i/k_i(k_i-1)$. The clustering coefficient C of the whole network is the average of all individual C_i's.

Average path length L means the minimum number of edges connecting a pair of vertices, averaged over all pairs of vertices, which plays an important role in both transportation and communication within a network. The longest shortest path among all pairs of vertices is called the diameter of the network. Recent empirical researches show many real systems exhibit small-word effect which is characterized by two key factors: on the one hand, the APL and diameter grow at most logarithmically with the number of vertices; on the other hand, the clustering coefficient C of the whole network is large compared with that of random graph C_{rand} [43].

We find that both CLN1 and CLN2 possess small-world effect. First, the networks are highly clustered. The numerical calculation of C yields 0.5091 and 0.7530 for CLN1 and CLN2, respectively, which is compared in Table 1 with the corresponding values for the random networks [43] with the same parameters. Second, the average path length L is small. The calculations of L yield 3.04 and 2.40 for CLN1 and CLN2, respectively, which are even smaller than those of the corresponding random networks estimated from the relation $L \approx \ln N/\ln\langle k\rangle$, as shown in Table 1.

The reason why the average path length is so small may be related to the existence of hubs, which are bridges between different nodes of the network that would otherwise be separated by many links. To show the small-world behavior, we also analyze the shortest path distribution. As shown in Fig. 6, most of the shortest paths fall in the scope of 2, 3, and 4, while the diameter for CLN1 and CLN2 is 12 and 7, respectively.

3.3. Hierarchical organization

Let $C(k)$ denote the average clustering coefficient of the vertices with the same degree k. In a network, if $C(k)$ follows a power-law distribution:

$$C(k) \sim k^{-\beta}, \tag{2}$$

then it is said to show the presence of hierarchical organization. Such a behavior has been observed in many real systems [44,45].

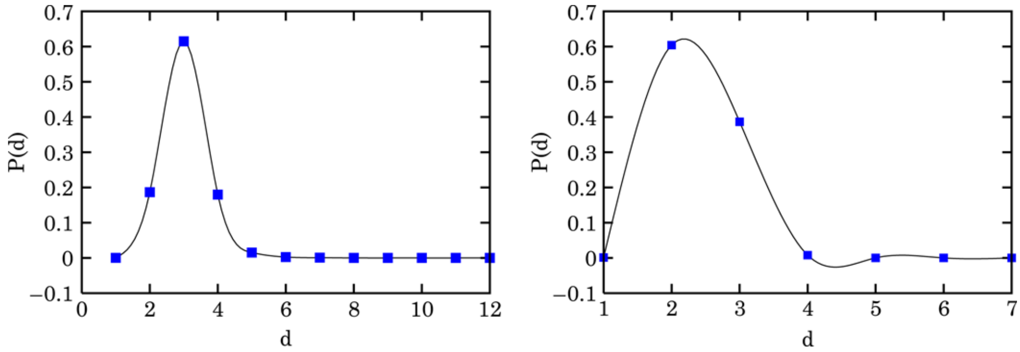

Fig. 6. Shortest path length distribution, with the left and right plots represent CLN1 and CLN2, respectively.

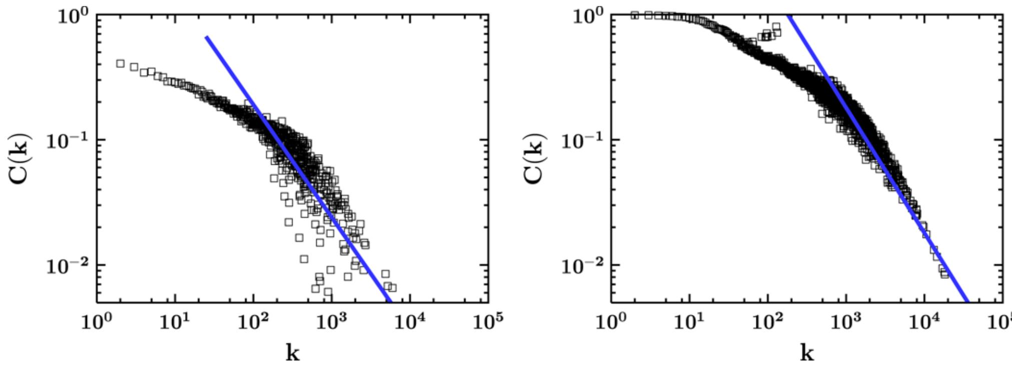

Fig. 7. Clustering coefficient $C(k)$ as a function of the node degree k. The left and right panels correspond to CLN1 having a slope of -0.9 and CLN2 with a slope of -1.0, respectively.

In Fig. 7, we plot the clustering coefficient $C(k)$ as a function of degree k for CLN1 and CLN2. As it can be seen, in both cases $C(k)$ follows an asymptotical power-law scaling, with the exponent about -0.95 ± 0.05, which implies that CLNs take on a hierarchical organization. The same behavior has been found in some other real systems such as the World Wide Web, Internet, and actor collaboration network [45].

According to complex network theory, the more close to power law the distribution of $C(k)$ approaches, the more obvious the hierarchical organization looks. Compared with the previously reported result [35], one can see that the hierarchical organization of the Chinese language is more obvious than Czech, German and Romanian, which may reflect the differences in syntactic rules for these languages. We believe that this kind of hierarchical organization might shed some new light on the research of the Chinese language.

3.4. Power-law betweenness distribution

As is known to us all, the communication of a pair of vertices depends on other vertices belonging to the paths connecting the two ones. A measure of the relevance of a given node can be obtained by counting the number of shortest path between all pairs of vertices, which is called betweenness. More precisely, the betweenness of a vertex i, $b(i)$, is defined as

$$b(i) = \sum_{j \neq k} \frac{b_{jk}(i)}{b_{jk}}, \tag{3}$$

where b_{jk} is the number of shortest paths between vertex j and k, while $b_{jk}(i)$ the number of shortest paths running through vertex i.

We investigate the betweeness distribution $P(b)$ of CLN1 and CLN2, and find that they follow a power-law behavior. Utilizing the algorithm introduced in Ref. [46], we calculate the betweenness of all vertices. In Fig. 8, we present the cumulative betweenness distribution $P_{\mathrm{cum}}(b)$ of vertices defined as $P_{\mathrm{cum}}(b) = \sum_{b'=b}^{\infty} P(b)$. Notice that for

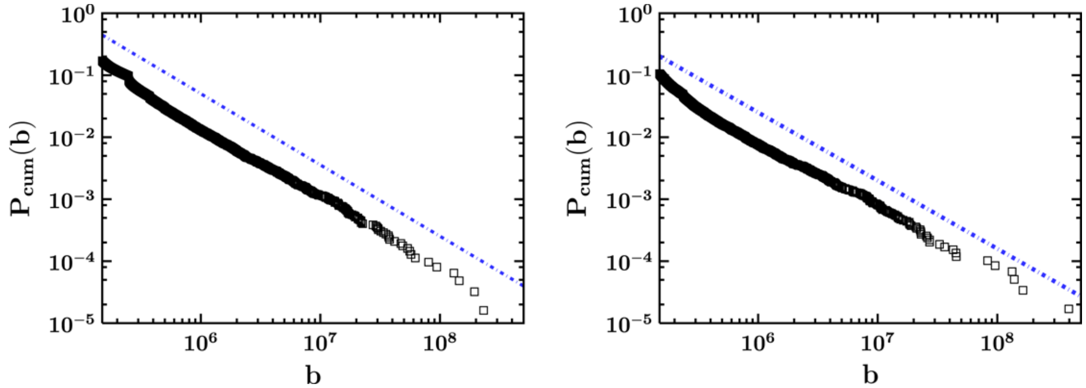

Fig. 8. Cumulative betweenness distribution as a function of betweenness, with the left and right corresponding to CLN1 and CLN2, respectively. The slope of both lines is −1.1.

a network with a cumulative betweenness distribution $P_{\mathrm{cum}}(b) \sim b^{-(\omega-1)}$, its betweenness distribution corresponds to $P(b) \sim b^{-\omega}$. From Fig. 8, we can see that $P(b)$ follows a power-law distribution, with the exponent $\omega = 2.1$.

It has been reported that although many real networks exhibit scale-free behavior, the value of the exponent is not universal. However, the betweenness distribution is less varying, the exponent of many real systems falls into 2.0 or 2.2, which has been used as a powerful characterization of complex networks in terms of universality class [47]. According to a previous report [35], in many language (such as Czech, German and Romanian) networks, the exponent of the betweenness distribution is 2.1, which is the same as that of CLNs. So a rational hypothesis can be made that human language networks may belong to a different kind of universality class.

3.5. Negative correlations

The above properties do not provide sufficient characterizations of the real-world systems. In fact, it has been observed that real networks exhibit ubiquitous degree correlations among their vertices. This translates into the observation that the degrees of nearest-neighbor nodes are not statistically independent but mutually correlated. Correlations in a network can be conveniently measured by means of the quantity, called average nearest-neighbor degree (ANND), which is a function of vertex degree, and is more convenient and practical in characterizing degree-degree correlations. The ANND is defined as [48,49]

$$k_{nn}(k) = \sum_{k'} k' P(k'|k). \tag{4}$$

If there are no two degree correlations, $k_{nn}(k)$ is independent of k. When $k_{\mathrm{nn}}(k)$ increases with k, it means that vertices have a tendency to connect to vertices with a similar or larger degree. In this case the network is defined as *assortative*. In contrast, if $k_{\mathrm{nn}}(k)$ is decreasing with k, which implies that vertices of large degrees are likely to have the nearest neighbors with small degrees, then the network is said to be *disassortative*.

According to Ref. [50], the amount of assortative mixing can be quantified by the normalized correlation function:

$$r = \frac{1}{\sigma_q^2} \sum_{jk} jk(e_{jk} - q_j q_k) \tag{5}$$

where e_{jk} is the joint probability distribution of the remaining degrees of the two vertices at either end of a randomly chosen edge, q_k is the remaining degree distribution, $\sigma_q^2 = \sum_k k^2 q_k - [\sum_k k q_k]^2$. For practical evaluation, r can also be computed as [50]:

$$r = \frac{M^{-1} \sum_i j_i k_i - \left[M^{-1} \sum_i \frac{1}{2}(j_i + k_i) \right]^2}{M^{-1} \sum_i \frac{1}{2}(j_i^2 + k_i^2) - \left[M^{-1} \sum_i \frac{1}{2}(j_i + k_i) \right]^2}, \tag{6}$$

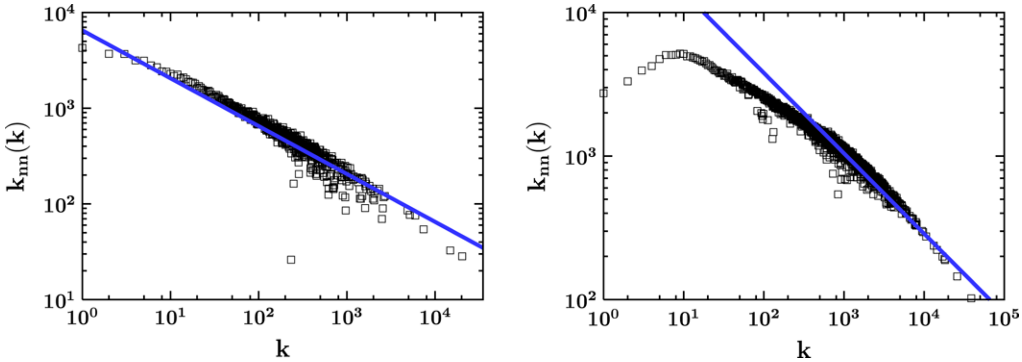

Fig. 9. The average nearest-neighbor degree as a function of the vertex degree, with the left and right panels corresponding to CLN1 with slope −0.5 and CLN2 with slope −0.56, respectively.

where j_i, k_i are the degrees of the vertices at the ends of the ith edge, with $i = 1, 2, \ldots, M$, where M denotes the number of edges in the network. The coefficient is in the range $-1 \leq r \leq 1$. If the network is uncorrelated, the correlation coefficient equals zero. Disassortative networks have $r < 0$, while assortative graphs have a value of $r > 0$.

We find that both CLN1 and CLN2 exhibit negative correlations. In Fig. 9, we show that the Chinese language networks strikingly exhibit a clear power-law dependence on the degree $k_{nn}(k) \sim k^{-\mu}$, with $\mu \sim 0.5$ and 0.56 for CLN1 and CLN2, respectively. This result clearly implies the existence of a nontrivial correlation property for CLNs.

A series of recent measurements indicate that most biological, technological and information networks are disassortative [50]. Here we show that CLNs also exhibit negative correlations, which further confirms the validity of the disassortativeness of information networks, although the origin is not yet understood.

In order to further confirm this disassortativeness of CLNs, we also compute r according to both Eqs. (5) and (6). According to Eq. (5), the calculations of r yield −0.0971 and −0.1120 for CLN1 and CLN2, respectively. Based on Eq. (6), the values of r are −0.0759 and −0.0707 for CLN1 and CLN2, respectively. So it again indicates that both CLN1 and CLN2 are disassortative mixing. This disassortativeness can be intuitively explained by the fact that highly-connected nodes are some functional words which are not often related together.

4. Conclusions and discussions

We have presented a comprehensive investigation on the statistical properties of Chinese language networks within the framework of complex network theory. We have found that both networks constructed in quite different ways show similar statistical features: scale-free behavior, small-world effect, hierarchical organization and disassortative mixing. Although the results reported in this paper represent only the starting point towards understanding Chinese language networks, they could be relevant for a more realistic modeling of the Chinese language networks, and could find other implications.

Indeed, there exist other methods for the construction of Chinese language networks. For instance, by taking into account the effect of weights and direction of edges one can construct weighted [51–54] and directed Chinese language networks in future. For example, the CLN2 may be expanded to a weighted network, where the strength of a node denotes the word frequency. We believe that the potential for new and important discoveries is high.

Acknowledgments

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