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Information interaction model for the mobile communication networks

Bin Zhou [a,*], Xiao-Ting Xu [a], Jian-Guo Liu [b], Xiao-Ke Xu [c], Nianxin Wang [a]

[a] School of Economics and Management, Jiangsu University of Science and Technology, ZhenJiang 212003, PR China
[b] Data Science Cloud Service Research Centre, Shanghai University of Finance and Economics, Shanghai 200433, PR China
[c] College of Information and Communication Engineering, Dalian Minzu University, Dalian 116600, PR China

HIGHLIGHTS

- The weight distribution follows the power-law in the mobile communication network.
- An information interaction model based on the node importance is proposed.
- The analysis solution of the weight distribution in the model is presented.
- The model reproduces the topology characteristics of the mobile communication network.

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ABSTRACT

Understanding the information interaction mechanism of the mobile communication networks is great significant for understanding the human communication pattern. In this paper, a mobile communication network is constructed from the mobile phone call records of one specific city in China. We assign one weight on each edge to reflect the strength of social tie, which is the cumulative number of calls placed between the individuals. The experimental results of the weight distribution follows a power-law. In the mobile communication network with strong tie, the degree distribution also follows a power-law. From the perspective of the information interaction between individuals, the evolution mechanism of the mobile communication networks is given to explain the logical relation between the information interaction and the topology structure. Then a novel model based on the evolution mechanism is proposed to reproduce the topology characteristics of the mobile communication network. The analysis solutions of the weight distribution and the degree distribution in the model are presented. The model can help us to understand the law of the human information interaction and has significant implications for dynamic simulation researches of social networks, especially in information diffusion through the social networks.

The development of human society cannot be separated from the information communication among individuals. The information communication technology allows people to keep in touch with each other whenever and wherever [1,2]. In today's society, almost every individual uses mobile phone to communicate with others where their communications generate new knowledge [3,4]. The communication relationships among individuals can form a complex mobile communication network [5–7]. Therefore, the demand for information communication among individuals should play an important role in the evolution process of the mobile communication network [8]. The statistics and dynamics of the information communication on the social communication network are of tremendous importance to researchers who are interested in

* Corresponding author.
E-mail address: bzhou@mail.com (B. Zhou).

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human social behaviors [9,10]. The research of the human information interaction on the social communication network can help us to understand the human communication patterns and build the social network model of the information interaction [11,12]. Many different theories and models were provided to reproduce the characteristics of the social communication network from the perspective of individual [13–18].

In this paper, taking advantage of the society-wide data collection capabilities offered by mobile phone logs, we constructed the mobile communication network from mobile phone call records of one special city in China. Each user is set as the network node and the communication relationship between the users is set as the link. The cumulative number of calls given between the users is set as the link weight. The empirical results of the link weight distribution has the power-law form for the mobile communication network. In the mobile communication network with strong tie, the degree distribution also follows the power-law. The degree of an individual is the number of friends that individual has, and the degree distribution is the fraction of individuals in the network who have exactly the number of friends. Since the social networks following a power-law distribution, a few individuals have an extremely high number of connections to other users, while most individuals only have limited friends [19]. How to understand the structure characteristics and the evolution mechanism of the mobile communication networks is significant for the complex communication systems. We conjecture that the information interaction between individuals may have an important role on the topology structure of the mobile communication networks. The goal of this paper is to analysis the evolutionary mechanism of the mobile communication networks from the perspective of the information interaction and propose a model based on the mechanism to reproduce the structure characteristics of the mobile communication network. This work can help us to understand the communication pattern of the human information interaction and has significant implications for dynamic simulation researches of social networks, especially in field of the information diffusion [20,21].

This paper is structured as follows. Firstly, we empirically analyze the statistical properties of a mobile communication network of one special city in China and show the structure characteristics of the mobile communication network. Secondly, we analyze the inherent features of the mobile communication networks and propose the social mechanism of the information interaction between individuals to explain the structure characteristics. Thirdly, a model is proposed and the analysis solutions of the weight distribution and the degree distribution in the model are presented. Fourthly, the simulation is implemented to regenerate the structure characteristics of the mobile communication network. Finally, we discuss the significance of the work and conclude with a brief summary of our results.

1. Empirical demonstration and analysis

The empirical data represents the mobile phone communication logs of one special city of China. The mobile phone communication logs include 20, 947, 956 mobile phone call records among 232,059 individuals from Feb. 1st, 2012 to Feb. 29th, 2012. For privacy reasons, the telephone number of each individual has been replaced with the individual's ID. Each communication record contains three important information: Who communicates with who and the communication time. Therefore, to translate the phone log data into a mobile communication network, we connected two individuals with an undirected link if there had been at least one phone call between them, i.e. i called j or j called i, resulting in the mobile communication network with 232,059 individuals and 315,403 links. Furthermore, we can quantify the weight of the undirected link (i, j) by the total number of calls made between i and j over the studied period. The weight is denoted by w_{ij} and is also defined as the strength of the social tie between the individuals i and j.

The mobile communication is a kind of the information interaction between people. Fig. 1 empirically shows that the weight distribution of information interaction between two individuals follows the power-law in the mobile communication network. The weight of a link represents the total number of calls made between the two individuals and also represents the strength of the social tie between the two individuals. If these links whose weights are less than a certain threshold are broken, the weak tie are removed and a new mobile communication network with strong tie can be reconstructed from the original mobile communication network. When the threshold takes different values, we want to observe the change in degree distribution of the mobile communication network with strong tie. Fig. 2 empirically shows the degree distribution of the mobile communication network with strong tie under different thresholds. That is interesting that the degree distribution always follows the power-law in the three sub-figures. Therefore, the weight distribution and the degree distribution in the mobile communication network obey the same pattern. The results indicate that human information interaction should play a leading role in the topology structure of the mobile communication network.

What mechanism of human information interaction results in the characteristics of weight distribution and degree distribution in the mobile communication network? We will analyze the mechanisms. On the one hand, the weight distribution of information interaction fallows the power-law in the social communication network. We think that the bigger the weight between two individuals is, the more important the two uses are to the social communication network. A numerical value can be used to quantify the importance of the individual, and the distribution of the numerical value assigned to an individual should follow a power-law [22]. The bigger the numerical value assigned to an individual is, the more important the individual is to the social communication network. On the other hand, the degree distribution in the new mobile communication network with strong tie always follows the power-law distribution under different thresholds. This means that the more important a individual is, the more frequent the individual's communication is in the mobile communication network. we assume that the probability that two individuals are chosen to establish communication relationship depends on the importance of the two individuals. Consequently, the more important two individuals are, the more frequent it is to establish information interaction between the two individuals in the mobile communication network.

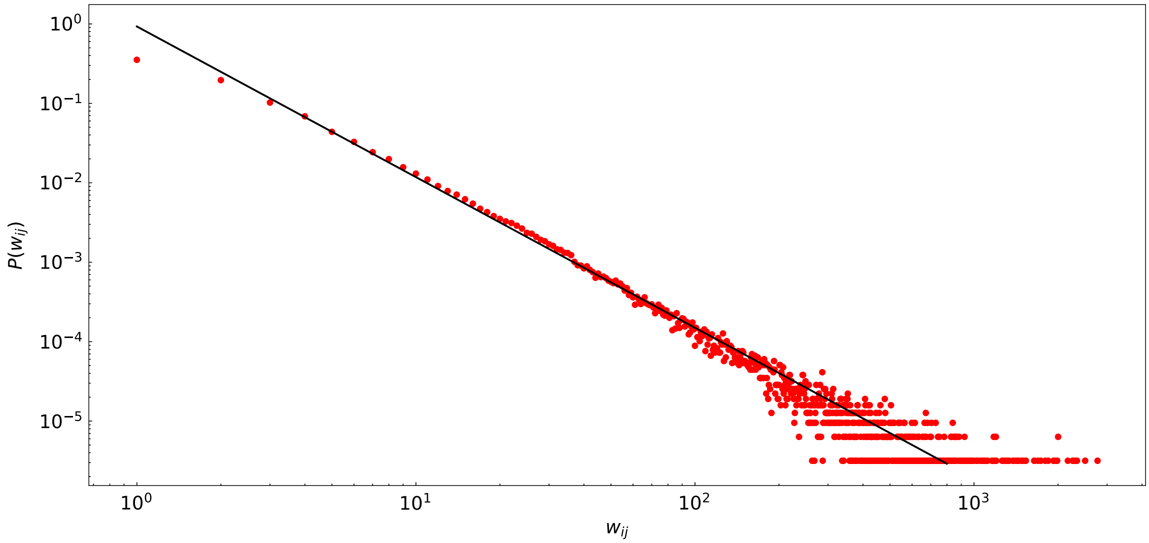

Fig. 1. The weight distribution of information interaction between individuals in the mobile communication network. The red dot represents the empirical result, and the black solid line represents the fitting result of the empirical data, and the slope of the black solid line is −1.90. The parameter w_{ij} is the weight and the parameter $P(w_{ij})$ is the probability of the weight w_{ij}.

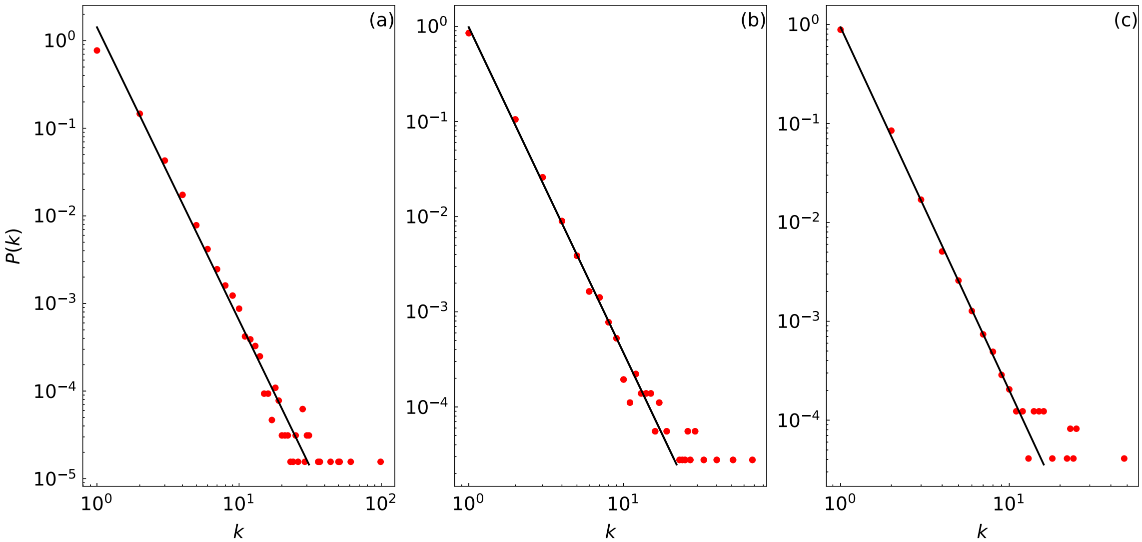

Fig. 2. The degree distribution under different thresholds in the mobile communication network with strong tie. In Fig. 3(a)–(c), the thresholds which are used to draw the new mobile communication network with strong tie are 10, 20, 30, respectively. In the three sub-figures, the red dots represent the empirical results, and the black solid lines represent the fitting results of the empirical data, and the slopes of the black solid lines are $-3.35, -3, 42, -3.67$ respectively.

2. Model, analysis and simulation

We build a model of mobile communication network bashed on the analysis above, which can reproduce the characteristics of weight distribution and degree distribution in the mobile communication network. There are N individuals independently, and i, j are the No. of individuals, and the reasonable ranges of i, j are all from 1 to N. Every individual is assigned a numerical value v according to the power-law distribution $p(v) = c \times v^{-\gamma}$ to quantify the importance of the individual, and c is the normalized constant, and v is the positive integral $v \in [a, b]$, and γ is the power exponent, and a, b are both positive integers. The average value $\overline{v}$ of the importance for an individual is $\overline{v} = \sum_{v=a}^{b} v \times p(v)$. The rules of establishing information interaction between two individuals are as follows:

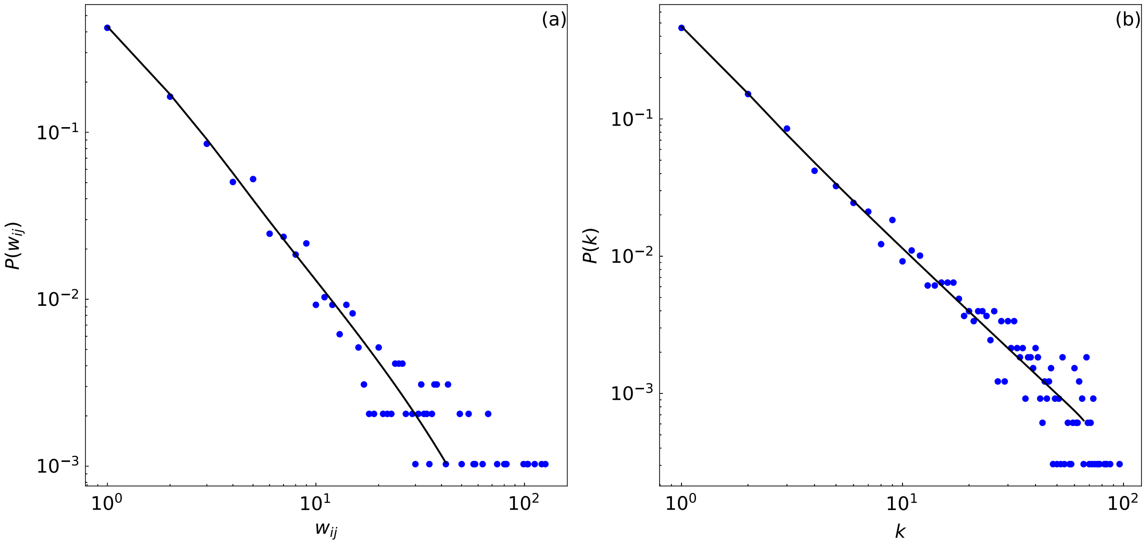

Fig. 3. Comparison between the simulation results and the analysis results. Fig. 2(a) shows the comparison of weight distribution between the simulation results and the analysis results, and the parameters are $N = 1 \times 10^3$, $a = 1$, $b = 1 \times 10^2$, $\gamma = 2$, $t = 1 \times 10^3$, $T = 1 \times 10^5$. Fig. 2(b) shows the comparison of degree distribution between the simulation results and the analysis results, and the parameters are $N = 1 \times 10^4$, $a = 1$, $b = 1 \times 10^3$, $\gamma = 1.5$, $t = 1 \times 10^4$. In the two sub-figures, the blue dot and black solid line represent the simulation results and the analysis results, respectively.

(i) At every time step, two individuals are chosen independently to establish communication relationship and are connected by an undirected link. The probability P that an individual i is chosen depends on the importance v_i of the individual, so that $P(v_i) = v_i/N \times \overline{v}$, and the probability that two individuals i and j are chosen independently and are connected by an undirected link depends on the importance v_i and v_j of the two individuals, so that $P(v_i, v_j) = v_i \times v_j/(N \times \overline{v})^2$. Therefore, there is a higher probability that the communication relationship will be established between two individuals with bigger importance values.

(ii) After t ($t \ll N^2$) time steps of evolution, a simulated network G of the information interaction between individuals is generated with t links. The weight of every link $w_{ij} = 1$ temporarily. With the time continuous evolution, after T ($T > t$) time steps, the weight w_{ij} on a link connecting two individuals i and j in the simulated network G is the cumulative number of times that the two individuals i and j are chosen to establish communication relationship repeatedly over the evolutionary period of T time steps.

The analytical result of the degree distribution $P(k)$ in the simulated social network G will derived as follows. In the model, each individual is assigned an importance value v according to the power-law distribution $p(v) = c \times v^{-\gamma}$, $v \in [a, b]$, and the average importance value $\overline{v}$ of an individual is $\overline{v} = \sum_{v=a}^{b} v \times p(v)$. At every time step, two individuals are chosen independently to establish a communication relationship and are connected by an undirected link, and the probability that two individuals i and j are chosen independently and are connected by an undirected link is $P(v_i, v_j) = v_i \times v_j/(N \times \overline{v})^2$. After t time steps, a simulated network G of information interaction is generated. In most of real social networks, their scale is great large and the average degree of an individual is far smaller than the scale of social network [23–26]. Therefore, most social networks are spare networks. In the model, when N is great large and $t \ll N^2$, the simulated social network G is a spare network. The probability that two different individuals are chosen more than once in t time steps is almost zero and the probability that an individual is chosen twice at one time step is almost zero. Consequently, the duplicate links and self-connected links in the simulated network G can be ignored. After t time steps, there are $2t$ choices and t links are established. In the evolutionary period of t time steps, once an individual is chosen one time, and the degree of the individual is increased by one. After t time steps of evolution, the probability $P(k)$ that the degree of an individual is k in the simulated network G is as follows

$$P(k) = \sum_{v=a}^{b} c \times v^{-\gamma} \times \binom{2t}{k} \times \left(\frac{v}{N \times \overline{v}}\right)^{k} \times \left(1 - \frac{v}{N \times \overline{v}}\right)^{2t-k}, \qquad t \ll N^2. \tag{1}$$

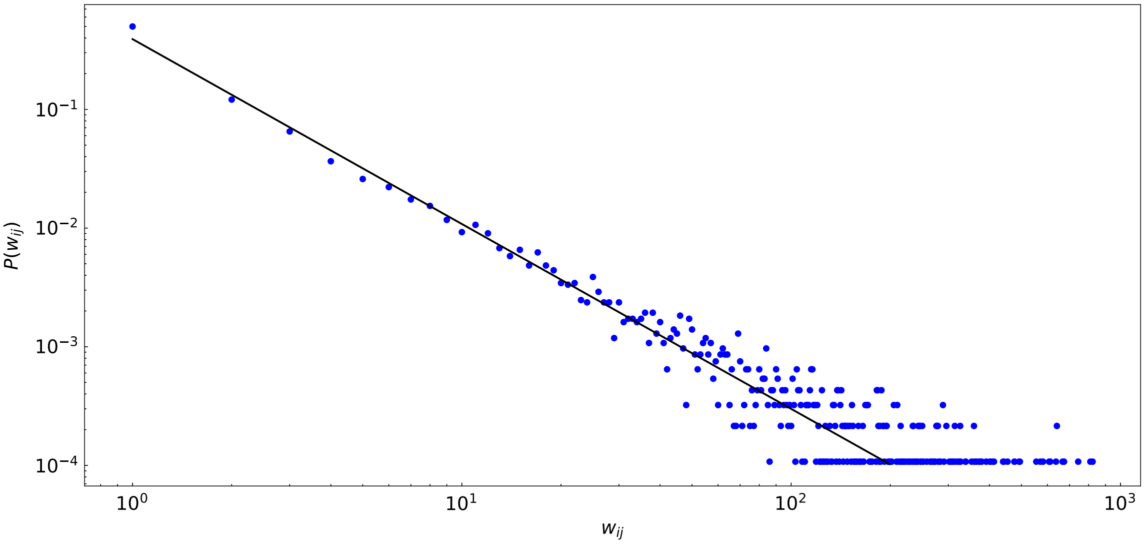

Fig. 4. The weight distribution of information communication between individuals in the model. The parameters of the model are $N = 1 \times 10^4, a = 1, b = 1 \times 10^3, \gamma = 2, t = 1 \times 10^4, T = 1 \times 10^6$. The blue dot represents the simulation result, and the black solid line represents the fitting result of the simulation data, and the slope of the black solid line is -1.56. The parameter w_{ij} is the weight and the parameter $P(w_{ij})$ is the probability of the weight w_{ij}.

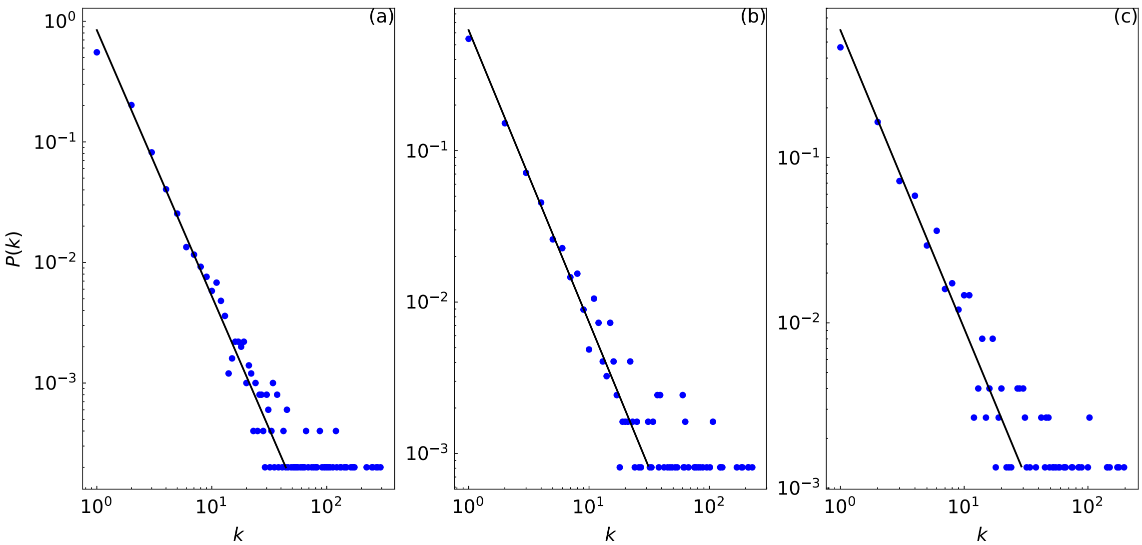

Fig. 5. The degree distribution in the simulation social network with strong tie under different thresholds. The parameters of the model are $N = 1 \times 10^4, a = 1, b = 1 \times 10^3, \gamma = 2, t = 1 \times 10^4, T = 1 \times 10^6$. In Fig. 5(a)–(c), the thresholds which are used to draw the new social communication network with strong tie are 1, 3, 5, respectively. In the three sub-figures, the blue dots represent the simulation results, and the black solid lines represent the fitting results of the simulation data, and the slopes of the black solid lines are -2.21, $-1, 93$, -1.81 respectively.

Then, we will derive the analytical result of the weight distribution $P(w_{ij})$ of information communication between two individuals i and j in the simulated network G. In the model, after t time steps of evolution, the simulated network G of the information communication is generated. With the time continuous evolution, after T $(T > t)$ time steps, the weight w_{ij} on an link connecting two individuals i and j in the simulation network G is the cumulative number of times that the two individuals i and j are chosen to establish communication relationship repeatedly over the evolutionary period of T time steps. At every time step in T time steps, two individuals are chosen independently to establish communication relationship and are connected by undirected link, and the probability that two individuals i and j with the importance v_i and v_j are chosen independently and are connected by undirected link is $P(v_i, v_j) = v_i \times v_j/(N \times \overline{v})^2$. In the evolutionary period from $t + 1$ to T time steps, once two individuals i and j connected by a link in the simulated network G are chosen one time, and the weight of the link is increased by one. After T time steps of evolution, the probability $P(w_{ij})$ that the weight of a link connecting two individuals i and j is w_{ij} in the simulated network G is as follows

$$P(w_{ij}) = \sum_{v_i=a}^{b}\sum_{v_j=a}^{b} c v_i^{-\gamma} \times c v_j^{-\gamma} \times \binom{t}{1} \times \binom{T-t}{w_{ij}-1} \times \left(\frac{2\times v_i \times v_j}{(N\times \overline{v})^2}\right)^{w_{ij}} \times \left(1-\frac{2\times v_i \times v_j}{(N\times \overline{v})^2}\right)^{T-w_{ij}}, \qquad w_{ij} \geq 1. \quad (2)$$

Fig. 3(a) shows the comparison of the weight distribution between the analytical solution and the simulation results, and Fig. 3(b) shows the comparison of the degree distribution between the analytical solution and the simulation results. The predicted results of the analytical solutions are in good agreement with the simulation results. That is to say the analytical solutions are reliable.

Fig. 4 shows the weight distribution of information interaction between individuals in the model. The weight distribution follows the power-law, and the pattern of the weight distribution is consistent with the one in Fig. 1. In the model, if these links whose weights are less than a certain threshold are broken, the weak ties are removed and a new network with strong ties can be reconstructed from the original simulation network. Fig. 5 shows the degree distribution under different thresholds in the simulation social network generated by the model. The degree distribution always follows the power-law in the three sub-figures. The weight distribution and the degree distribution in the model obey the same pattern. By comparing Fig. 5(a)–(c) with Fig. 2(a)–(c) respectively, the pattern of degree distribution in the simulation network is consistent with the one of the mobile communication network. Therefore, the model can reproduce the topology characteristics of the mobile communication network. The information interaction between individuals has an important role on the topology structure of the mobile communication network. The mechanisms of the model can help us to understand the law of the human information interaction in the mobile communication network.

3. Conclusion

We empirically show the characteristics of the weight distribution and degree distribution in a mobile communication network of one specific city in China. The weight distribution follows the power-law. In the new network reconstructed from the original mobile communication network with strong tie, the degree distribution also follows the power-law. The information interaction between individuals should have an important role on the topology structure of the mobile communication network. From the perspective of the information interaction, the evolutionary mechanisms are provided to explain the characteristics of the mobile communication network. A model is proposed and evolutionary analysis solution of the model is provided. The simulation results of the model indicate that the model can reproduce the characteristics of the mobile communication network. Therefore, the mechanisms of the model are helpful for us to understand the human information interaction in the mobile communication network.

The merit of this paper is that a model is proposed to explain the characteristics of the mobile communication network from the perspective of the information interaction. The information interaction between individuals has an important influence on the evolution process of the mobile communication network. The model is closely related to the information communication, so the model has important application for the dynamic simulation researches of information diffusion within social networks. The shortcoming of this paper is that the model is proposed based on the statistical analysis of one mobile communication network. Whether the statistical characteristics of other mobile communication networks are consistent with the ones of the mobile communication network in this paper. Whether the mechanism of the model is still suitable to other mobile communication networks. In the further, we will further research these problems that whether the model is universal to others mobile communication networks and others social networks, such as Email communication network, scientific collaboration network, friendship network and so on. We hope that the universal mechanism can be found to explain the logical relationship between the information interaction and topology evolution of social networks. We also except that the universal mechanism of can be expanded to other fields of complex networks and help to understand the human social behavior, with applicability reaching far beyond the quoted examples.

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