Pairwise Interaction Pattern in The Weighted Communication Network

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***Abstract*—Although recent studies show that both topological structures and human dynamics can strongly affect information spreading on social networks, the complicated interplay of the two significant factors has not yet been clearly described. In this work, we find a strong pairwise interaction based on analyzing the weighted network generated by the short message communication dataset within a Chinese tele-communication provider. The pairwise interaction bridges the network topological structure and human interaction dynamics, which can promote local information spreading between pairs of communication partners and in contrast can also suppress global information (e.g., rumor) cascade and spreading. In addition, the pairwise interaction is the basic pattern of group conversations and it can greatly reduce the waiting time of communication events between a pair of intimate friends. Our findings are also helpful for communication operators to design novel tariff strategies and optimize their communication services.**

***Keywords*-information spreading; human dynamics; weighted network;**

I. Introduction

Connections based on both information transmission and human relationships coexist in different types of electronic person-to-person communications, like in e-mail networks [1]–[3], instant message services [4], mobile phone calls [5]–[7], and mobile phone short messages [8]–[10]. Basically, there are two significant factors affecting spreading processes on social contact networks: topological structures [11], [12] and human dynamics [2], [3], [13]. Previous studies have uncovered how different topological structures (such as degree distribution [11], [14], assortativity [15], [16], modularity [17], [18]) affect spreading dynamics. At the same time, it has been proved that the non-Poissonian pattern of human dynamics can slow down information propagation [2], [3], [7], [19].

Although the above studies give us valuable insights into how information spreads on human communication networks, they do not provide a unified framework to combine the effects of topological structures and human dynamics on information diffusion. To uncover the complicated interplay between network structures and human dynamics, recently the concept of temporal networks has been proposed [20] and related statistics have been utilized to analyze human communication networks [21]. For example, Miritello and collaborators show that group conversations are significant to understand the dynamic coupling of individuals and the mechanism of information spreading [7]. Furthermore, some basic statistics for local group conversations, such as temporal motif [22], [23] and weighted reciprocity [24]–[26], have been utilized to measure how individuals interact with their direct neighbors. However, up to now, what the accurate interaction pattern among individuals in electronic person-to-person communications is and how the interaction pattern affects spreading behaviors has not been satisfactorily uncovered.

In recent years, the mobile short message service has emerged as one of the most popular tools for personal communication in China because of the relatively low telecommunication tariff [8]–[10]. Basically, people can send and receive short messages anytime, anywhere, and to and from any mobile phone in their daily life. In contrast, e-mails and instant message services (e.g., MSN) are not as popular as short messages in China for they need people to have a personal computer or a mobile smart phone. Furthermore, handling a short message is easier than writing an e-mail, and is more flexible than dialing a phone call. The flexibility of short messages means that you can send or respond a short message promptly, or put some particular short messages to a waiting list as a lower priority task [9]. These features thus provide a very attractive proxy for studying the dynamic behaviors of single individuals and the nontrivial interaction pattern of human communication activities.

In this study, we build a weighted communication network based on a short message dataset of a telecommunication provider in China. By analyzing the network topology and interaction strength, we find that most users have only one major active communication partner. Furthermore, the results of multiple statistics indicate that the weighted communication network has specific structural features compared with its randomized counterpart: densely mutual (reciprocal) links, highly weighted reciprocal coefficients [26], and fragmented pairwise rich nodes. All these topology properties can prove the existence of the pairwise interaction pattern in the weighted network, which has not been reported in

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previous studies.

The pairwise pattern shows that most information in the short message service is local, especially tends to happen between a pair of users. Therefore, the pairwise interaction is the basic pattern of group conversations in the self-organizing artificial communication system (e.g., mobile phone short message service). This finding is significant for our understanding of local and global information spreading in electronic person-to-person communications. We also find the pairwise conversation can strongly affect human dynamics in the short message service. Moreover, our study provides an integrated framework for analyzing the collective communication behaviors in the self-organizing communication system based on weighted network theory. Therefore, communication operators can use our findings to design novel service plans, provide new tariff strategies, and optimize the communication services.

II. Short message network

A. Degree and weight distributions

The short message dataset investigated in this work was obtained from a mobile phone operator in China. The original data includes all the charging accountant bills over one month period for three corporate users who use the same mobile phone operator service. In this study, we only calculate the result for the company that has the most number of users. In this dataset, the total number of the short message communication records is $643,502$, and the number of the users is $72,146$. Each record comprises a sender mobile phone number, a recipient mobile phone number and a time stamp with a precision of 1 s. All the phone numbers were hashed and no other information is available for identifying or locating users. More detailed information about this dataset can be found in [9].

To show the interaction pattern among the communication network neighbors, we build a weighted complex network representing the communication relationships among the members of the company. To eliminate spurious relationships, we only retain the links with bidirectional short message communication within the largest connected component (as has been done for mobile phone call data in [6]), thus the out-degree always equals the in-degree. The link weights are the number of short message events. We list the number of friends (degree) distribution and the number of short messages (weight) distribution in Fig. 1. The degree and weight distributions are both like a power-law distribution [14], which suggests that a very large percentage of users have small values of degree/weight, and few users possess very high degrees/weights. However, the values of natural cutoff for the degree and weight are very different: $k_c \approx 30$ and $w_c \approx 400$ [27], [28]. The result of $w_c \gg k_c$ indicates that the weight distribution is more heterogeneous than the degree distribution.

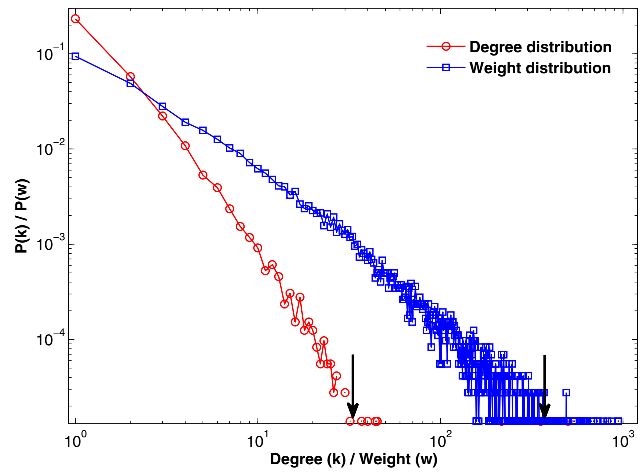

Figure 1. (Color online) Degree and weight distributions for the short message communication network. The dataset includes all the charging accountant bills over one month period for the users who use the same mobile phone operator service in a company. The total number of the short message communication records is $643,502$, and the number of the users is $72,146$. The two arrows are the natural cutoff degree k_c and the natural cutoff weight w_c respectively [27], [28].

B. Uncorrelation of degree and weight

We extend the vertex degree k_i to be a new definition of the vertex out-strength as $s_i = \sum_{j \in N} w_{ij}$ [29]. To shed more light on the relationship between the vertices' strength and degree, we investigate the dependence of the average strength $s(k)$ with the degree k increasing. If there is no correlation between the weight and the degree, we can obtain $s(k) = \langle w \rangle \sum_j a_{ij} = \langle w \rangle k$, where a_{ij} is the adjacency matrix of the unweighted graph and $\langle w \rangle$ is the average out-weight in the network [29]. We show the results of $s(k)$ for both the real weighted network and its randomized version in Fig. 2. To get the randomized network, we maintain the topology of the original network and shuffle the weights globally to remove possible correlation of the weight and degree [30]. The two curves are very similar and both closely fitting the relationship: $s(k) = \langle w \rangle k$. The strength of a vertex is simply proportional to its degree, which means that link weights are independent upon node degrees.

Another method of measuring the correlation between the degree and weight is to calculate the dependence of the weight w_{ij} on the degrees of the end-point node degrees k_i and k_j [29]. As we can see in Fig. 3, the average weight $\langle w_{ij} \rangle$ is almost constant for about three decades of $k_i k_j$, confirming a general lack of correlations between the weight and the end-point node degrees. All the above results imply that the weight and degree have fundamentally different coupling rules, so we need to consider not only the network topology, but also interaction strengths among nodes in the following sections.

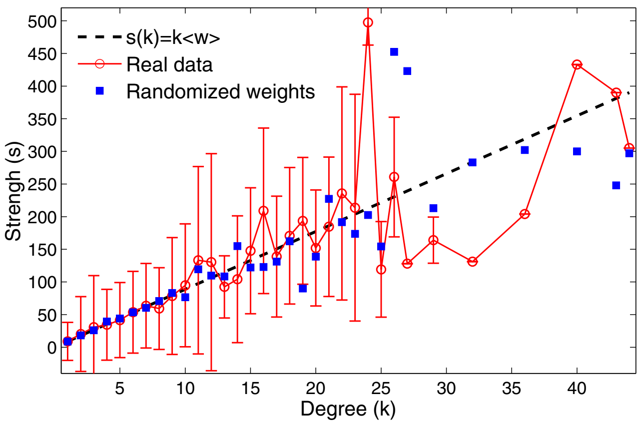

Figure 2. (Color online) The out-strength $s(k)$ is an uncorrelated function of the node degree k: $s(k) = \langle w \rangle k$ [29]. The value of $s(k)$ is the averaging out-strength s_i for the nodes with the same degree k, and the standard deviation is plotted. The result of the real data is very similar to that obtained in a randomized weighted network. We maintain the topology of the original network and shuffle the weights globally to get the randomized network [30].

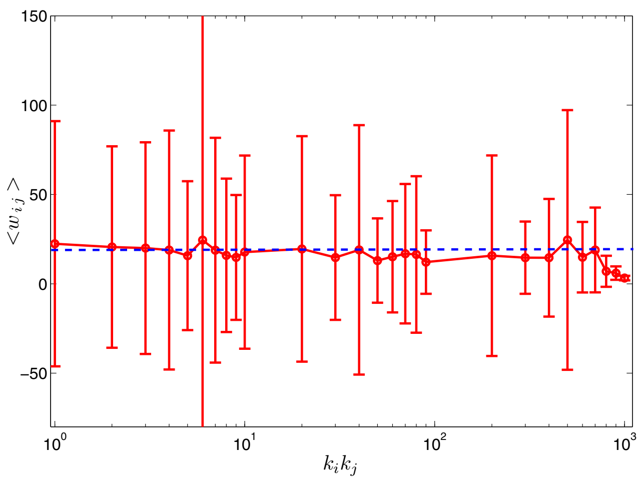

Figure 3. (Color online) The weight $\langle w_{ij} \rangle$ is almost constant for about three decades of $k_i k_j$, where k_i and k_j are the end-point node degrees. The value of $\langle w_{ij} \rangle$ is the averaging result for the links with the same $k_i k_j$, and the standard deviation is plotted. The result confirms that there are no correlations between the weight and two corresponding end-point node degrees.

III. Pairwise interaction pattern

A. Heterogeneous communication pattern

For a given node i with degree k_i and out-strength s_i, the disparity in the weights can be evaluated by the quantity $Y_i = \sum_{j \in N_i} [w_{ij}/s_i]^2$, where N_i is the set of first neighbors of i [31], [32]. By this definition, Y_i has an implicit dependence on the value of k_i. If all edges have comparable weights, $Y(k)$ (that is, the disparity averaged over all nodes with the degree k) will be scaled as $1/k$. In other words, the value of the weight w_{ij} is of the same order s_i/k_i. In contrast, if only one or a few weights dominate over all the others, $Y(k)$ is independent of k and $Y(k) \simeq 1.0$ [33]. The result of $Y(k)$ for the short message communication network has been shown in Fig. 4. It is clear that the curve of $Y(k)$ is far larger than $1/k$, which suggests that the users show a strong heterogeneous communication pattern. This observation is consistent that most users mainly have heavy communication with just one of their friends [9].

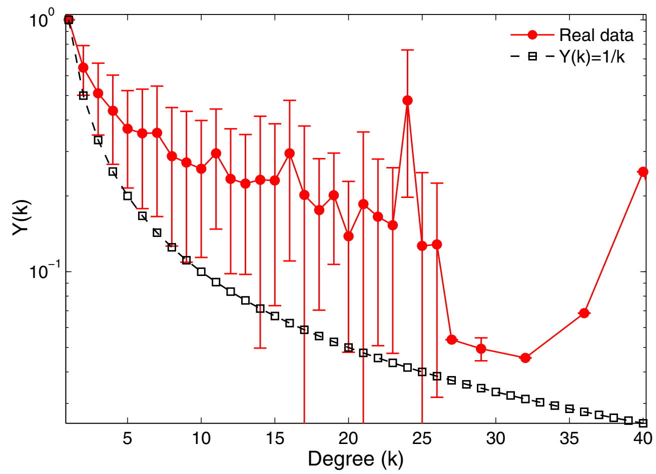

Figure 4. (Color online) Measured $Y(k)$ as a function of k is shown and compared with its theoretical low-boundary $1/k$ and upper-boundary 1.0. The value of $Y(k)$ is the averaging Y_i for the nodes with the same degree k, and the standard deviation is plotted. The value of $Y(k)$ is the disparity averaged over all nodes with the degree k [33]. Because the curve of $Y(k)$ is far larger than $1/k$, the intensity of the users' communication is highly heterogeneous among their network neighbors.

B. Principal communication component

In the previous study, it has been found that about 50% of the users send more than 90% of their messages to just one friend [9]. We define the statistic $R_{ij} = n_{ij}/N_i$ to measure the intensity of communication between users i and j. The value of R_{ij} is the ratio of the number of message n_{ij} that i sends to j to the total messages N_i sent by i. For user i, it is very easy to find the maximal value R_i^{max} from his short message records. The value of R_i^{max} close to 1.0 indicates that the user mainly communicates with one particular partner. For many individuals who only send one or two short messages, the values of R_i^{max} are obviously very high (1.0 or 0.5). Therefore, we only list the values for active users who send more than five short messages in Fig. 5. The result of R_i^{max} is stable for all the active users (meaning about 70% messages are sent to the most closest person), which clearly reveals that most of the users indeed have only one major active communication partner.

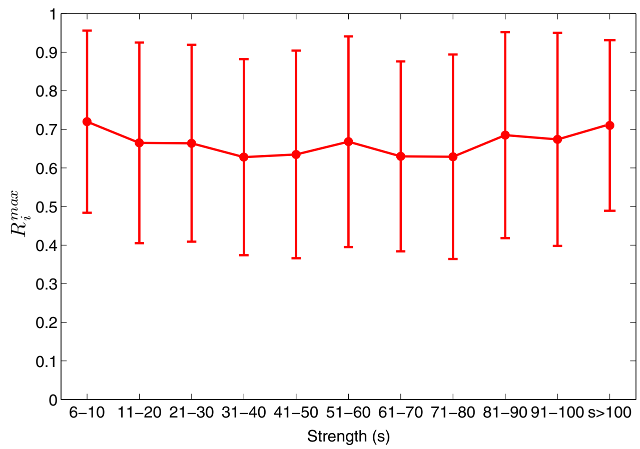

Figure 5. (Color online) The values of R_i^{max} for active users. The active users are the persons who send more than five short messages. We see that about 70% of short messages from each user are sent to one particular associate, which clearly reveals that most of the users indeed have only one major active communication partner.

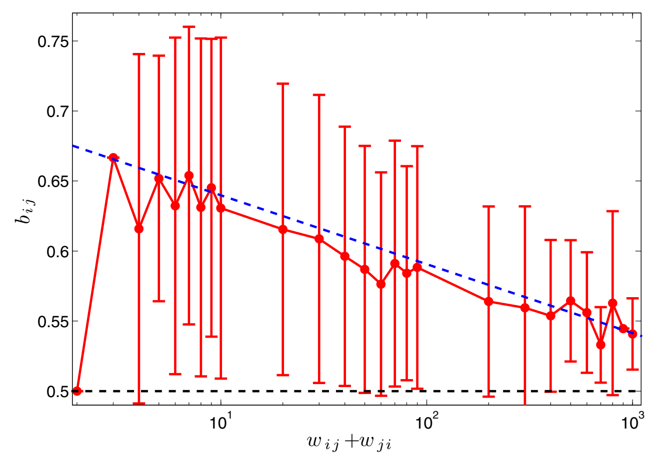

Figure 6. (Color online) The values of weighted reciprocal coefficients b_{ij} as a function of edge weights for all the users. The weighted reciprocal coefficient is defined as $b_{ij} = max(\frac{w_{ij}}{w_{ij}+w_{ji}}, \frac{w_{ji}}{w_{ij}+w_{ji}})$, where w_{ij} is the total number of short messages that user i sends to j [26]. All the values of b_{ij} are below 0.7 and decrease with $w_{ij}+w_{ji}$ increasing, which indicates that the information flow has a symmetric (reciprocal) trend in the short message commutation network. The blue dash line is just drawn to guide our eyes.

C. Reciprocity of communication

Our data analysis also shows that mutual (reciprocal) links are dense in the communication network. A traditional way of quantifying the reciprocity is to compute the ratio of the number of links pointing in both directions $L^{\leftrightarrow}$ to the total number of links L: $r = \frac{L^{\leftrightarrow}}{L}$ [34], [35]. The value of r for a real network lies in the range of $[0, 1]$. However, this definition is not very useful for the weighted network built by the short message communication events, for we have removed all unidirectional edges and the reciprocity according to the above definition would be 1.0.

For a weighted network, we aim to determine not only whether the communication between a pair of users is one directional or mutual [24], but also the bias of the information flow strength of the two different directions [25], [26]. Here we use the definition in [26]: $b_{ij} = max(\frac{w_{ij}}{w_{ij}+w_{ji}}, \frac{w_{ji}}{w_{ij}+w_{ji}})$. The weight w_{ij} is the total number of short messages that user i sends to j during the whole month period. Note that b_{ij}=b_{ji}, and the distributions of b_{ij} for all edges in the network are in the range of $[0.5, 1.0]$. The weight of each edge allows us to study the reciprocity of the edge instead of the full network. The value of 0.5 means that the edge is symmetric (reciprocal), and in contrast the value of 1.0 means that the information flow is completely unidirectional.

The dependence of b_{ij} on the value of $w_{ij}+w_{ji}$ is shown in Fig. 6. This result is an obvious evidence that there is a reciprocal trend for short message communications, for all the values of b_{ij} are below 0.7. In addition, the more reciprocity property for the higher $w_{ij}+w_{ji}$ also implies that a more symmetric pairwise relationship might trigger more communication events, and vice versa.

D. Pairwise structure of rich nodes

The rich-club phenomenon is another significant topology property [36], [37] and it can dominate other statistics of complex networks [38], [39]. In many real-life weighted networks, the rich-club effects based on degree and strength are not trivially related [30], [40]. The topology structure of the 100 highest weight edges in the short message communication network is shown in Fig. 7(b). We also compare this result with that of the U.S. air transportation network [41]. In the air transportation network, the 100 highest weight edges connect each other and form an inter-connected group [Fig. 7(a)]. Compared with the tendency of the rich-club effect in the air transportation network, the short message communication network shows many isolated pairwise connections, so our results illustrate that the short message communication network has no rich-club property.

Although we do not calculate the rich-club coefficient using quantitative methods [30], [36], [37], [40], the very fragmented local subsets again prove the pairwise interaction pattern in the short message communication network. Our simply qualitative method not only measures the relationship among the edges with the highest weights but also roughly represents the connection of the nodes with the strongest strengths. Because all users send most of their short messages to one major active communication partner [Fig. 5], the nodes with the strong strengths in the short message communication network have a similar connection relationship like Fig. 7(b).

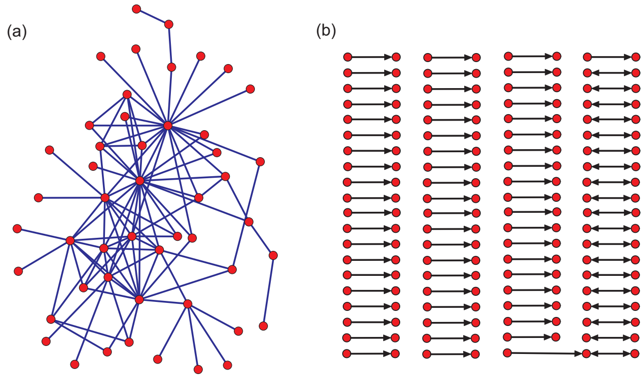

Figure 7. (Color online) The topological structure of the edges with the 100 highest weight in the air transportation network and the short message communication network. To simplify the representation of the structure, here we do not show the weight of each edge. Compared with the strong inter-connection of the air transportation network, the short message communication network shows many isolated pairwise connections. (a) The air transportation network is obtained by considering the 500 United States airports with the largest amount of traffic from publicly available data [41]. Nodes represent airports and edges represent air travel connections among them. The weights are given by the number of seats available on the scheduled flights. (b) The short message communication network is obtained by considering the short message sending/receiving relationships among the members of a company in China [9]. Nodes represent individuals and edges represent short message communication among them. The weights are given by the number of short messages.

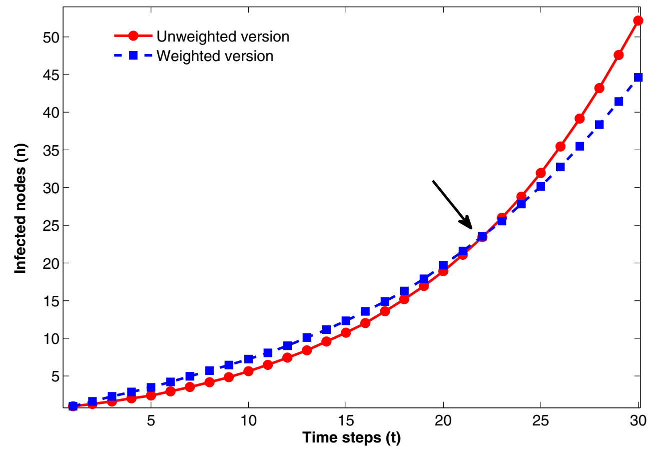

Figure 8. (Color online) The number of infected nodes as a function of time t in the short message communication network. Here we use the Susceptible-Infected (SI) model to simulate information spreading dynamics. The result is the average from selecting the node whose out-strength is larger than 100 as the start node. In the weighted version, it is assumed that the probability for a node i to pass on the information to its neighbor j in one time step is given by $P_{ij} = xw_{ij}$, and $x = 0.003$ [5]. We also compare the above result with that obtained in an unweighted version (all the tie weights are considered equal) of the short message communication network using the same average spreading rate.

IV. Impact of pairwise interaction pattern

We have known the accurate interaction pattern among individuals, and the next step is to explore how the interaction pattern affects spreading behaviors in electronic person-to-person communications.

A. *Impact on information spreading*

To show how the pairwise interaction pattern affects spreading behaviors, we use the Susceptible-Infected (SI) model to simulate information spreading dynamics [5], [6]. For the weighted short message network, each infected individual i can pass the information to his direct neighbor j with the probability $P_{ij} = xw_{ij}$ at each time step, where the parameter x controls the overall spreading rate [5]. We also compare the above result with that obtained in an unweighted version (all the tie weights are considered equal) of the short message communication network using the same average spreading rate. Recently, it has been found that information transferring is significantly slower in the weighted network than in its unweighted version [5].

We now study a special spreading process in which a rich strength node has the initializing information, since a node with a higher strength has a higher probability to transfer information to others. On the large scale, information is transferred faster in the unweighted network than the weighted version, which is essentially coincident with the result in [5], because the rich isolated multipolarization phenomenon means that there are many bottlenecks for global information spreading in the weighted network [Fig. 7]. On the contrary, the weighted version has a faster spreading speed than the unweighted version on the small scale [Fig. 8]. This finding implies that for real information spreading, previous works may underestimate the spreading speed of local information. However, the pairwise interaction leads to the result that most messages are only sent to the most closest person, so it is difficult for a pair of intimate individuals to transmit their common local information to a large range (to be a global information). In summary, the pairwise pattern promotes local information spreading among a pair of friends and in contrast also suppresses global information spreading.

B. *Impact on human dynamics*

We also confirm a strong correlation between the pairwise conversation and human dynamics. There are two important time periods with which to describe human dynamics: the waiting time and the interevent time. The waiting time τ_i is the interval between receiving and then sending a short message for user i, and the interevent time t_i is the time interval between sending two consecutive messages. The effect of bursts on hindering information propagation has been well studied [2], [3], [13], [19], yet there are few works to study the effect of the conversation mechanism within human crowds [9]. For the mobile phone call data, recently Miritello *et al.* found that group conversations enhanced local information spreading, because the interaction among individuals can trigger more information spreading behaviors [7].

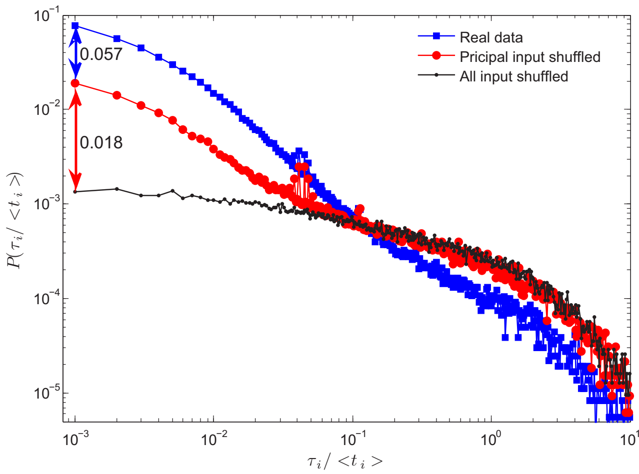

Figure 9. (Color online) The distribution of the waiting time rescaled by the average of the interevent time. The waiting time τ_i is the interval between user i receiving a message and then sending a short message to another user. The interevent time t_i is the time interval between sending two consecutive messages for user i. Here $\langle t_i \rangle$ represents the average of the interevent time t_i of the active user i. The active users are the persons who send more than five short messages. For the case of "principal input shuffled", we only shuffle the receiving time-stamps of short messages from the one major active communication partner. For the case of "all input shuffled", we shuffle the receiving time-stamps of short messages from all the users.

In this study, we verify again that τ_i depends on the group conversations in Fig. 9. Using the similar framework in [7], we compare the results of τ_i for only shuffling the receiving time of short messages from the one major active communication partner and shuffling all the receiving time. Both most short messages being sent to one particular person [Fig. 5] and the weighted reciprocal coefficients being high [Fig. 6] indicate that there are no frequent cascading information spreading in the short message dataset. Therefore, the event that user i receives the information from user m ($m \to i$) is not a trigger for i to communicate with other people like user n ($i \to n$ and $m \neq n$). However, we find that the pairwise interaction is the basic pattern of group conversations ($i \to j$, and then $j \to i$). The pairwise interaction is the most significant impact on human dynamics, for it can greatly reduce the waiting time between a pair of close friends [Fig. 9].

V. Conclusion

In summary, we have found a strong pairwise interaction pattern in the weighted communication network by analyzing the network topology and interaction strengths. The pairwise interaction, which has not been reported in other communication datasets by unweighted network analysis, is the basic conversation pattern among individuals and it has a significant impact on human dynamics of communication behaviors: reducing the waiting time in electronic person-to-person communications.

Our finding suggests that the short message service promotes local information spreading and slows down global information cascading spreading. Basically, anyone can transfer information to anyone, for human society has a famous small-world property [42], [43]. However, interaction strengths play distinct roles for information spreading [5]. It is believed that weak ties have a strong impact for long-range information spreading and strong ties are significant for local information spreading [44]. In the short message dataset, most information is local (especially tends to happen between a pair of users), and the global cascading spreading is not frequent. Our results are coincident with the fact that the short message communication system is not designed for spreading global information such as rumor and news, but is self-organizing to support us to spread or exchange local information in daily life.

The collective communication behaviors of all the customers in a company belonging to the same mobile phone operator have been analyzed based on the weighted network theory. Our work is helpful for mobile phone operators to design new service plans and tariff strategies. For example, it is valuable for a mobile phone operator to provide a special tariff for a pair of users with frequent communication relationships. Furthermore, because the number of the user's friends obeys a power-law distribution [14], it is a remarkable fact that most users have only one major active communication partner (70% messages are sent to the same person). Therefore, our findings also can be used to optimize communication services.

For a self-organizing complex system (e.g., the short message communication system in this study), it is well known that "the whole is greater than the sum of its parts" [45], so dividing a large-scale complex system into multiple sub-systems (or individuals) is not helpful for the comprehensive understanding on the whole complex system [46]. The pairwise interaction pattern suggests that human dynamics not only depend on individuals' rhythm [47], but also are strongly affected by the complicated interplay among intimate friends. Nevertheless, our work is a step in an ongoing effort to bridge the gap between individual microscopic interactions and macroscopic social systems.

Acknowledgment

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