Evolution Analysis of a Mobile Social Network

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Abstract. Smart phones and ubiquitous wireless connections are helping people to build and maintain mobile social relationships. We present an in-depth and complete evolution analysis on the user activities and social graph of a mobile social network using data obtained from Nokia Friend View. Our results show that (1) user activities in Friend View are highly correlated and the power law fitted exponents for user activities distribution are slowly becoming larger over time, which appears to be contrary to the famous "rich get richer" assertion in the preferential attachment model because users in Friend View regard the reciprocity as important during the interaction and (2) both undirected friend network and directed comment network in Friend View are small-world and scale-free networks over time with slowly decreasing clustering coefficient. However, compared to online social networks where users have a large number of friends but loose weakly-tied subgroups, users in Friend View tend to have close strongly-tied cohesive subgroups. The results can help us understand users' social activities and interactions over time in mobile social networks.

Keywords: Mobile social network analysis, small-world evolution

1 Introduction

Due to the mobility of users and the ubiquity of the mobile phone, social networks are now being created and maintained using the mobile phone, which are called mobile social networks. Mobile social networking applications such as Loopt, Foursquare and Gypsii use location of users in order to provide services such as finding people and places nearby, providing relevant content based on location, and creating specific topic channels from which other people can subscribe to.

Previous work have studied the structure and properties of online social networks (OSN) [1-4] and their evolution [2, 3, 5-7]. However, many researchers use crawled datasets to analyze and model different types of social networks and therefore these results are subject to bias due to the incomplete social information on users about linkage and activity from using only one or two snapshots of networks. Very few deals with in-depth social network analysis of a mobile social network except for [8] and study its evolution from beginning to end. There are still, however, many questions that have not been addressed. How do the activities and interactions of users in mobile social networks change and evolve over time? What is the correlation between users' activities and interactions and how does this correlation evolve over time? Is a mobile social network still a small-world and scale-free network over time and how does the social graph evolve? If we can address these questions, it can help us understand more about users in mobile social networks, thus improving the user experience and mobile social services provided to the user.

In this paper, we perform an in-depth analysis of a mobile social network and study its complete evolution using data obtained from Friend View, which is a service that was created by Nokia Research Center to allow mobile users to find others, update their status and location, add friends, and keep updated with others. We study the number of users' activities such as posting status messages, making comments to others' status, and making friends along with the network properties such as degree, shortest path length, network density and clustering coefficient in the friend network and comment network and show how they evolve. Results illustrate that user's activities in Friend View are highly correlated and the power law fitted exponents for user activity distributions are slowly becoming larger over time, meaning fewer people are being connected with those that have high degree of activity (or the most popular users), therefore new Friend View users appear to not necessarily connect to the users with most activity. This appears to be contrary to the famous "rich get richer" assertion in the preferential attachment model in which new users are more likely to get connected to those that have a high degree of connection. We believe the reason for this behavior is because users in Friend View regard the reciprocity during interaction as important, and not the amount of activity. Also, Friend View remains a small-world and scale-free network that has decreasing clustering coefficient over time. In addition, the comment network is more closely connected compared to the friend network in Friend View and other OSNs.

Our contributions are the following. First, we study the complete evolution of a mobile social network based on the entire lifetime dataset (which we believe we are the first to do) from beginning to end, while other researchers do complete evolution for only OSNs and evolution analysis using the snapshots of crawled datasets. Second, we discover that the power law fitted exponents for user activity distribution slowly becomes larger over time, which appears to be contrary to the "rich get richer" assertion in the preferential attachment model mostly associated with current social network models. Third, the friend network and comment network are both small-world and scale-free networks over time with assortative mixing pattern.

The paper is organized as follows. Section 2 describes related work that have studied the properties and evolution of OSNs and mobile social networks. In Section 3, we introduce and describe the user interface, and overall usage statistics of Nokia Friend View. We study the evolution of Nokia Friend View in Section 4 and quantify the evolution of user activities, the friend network and the comment network and show how the assortative mixing pattern evolves. Finally, we conclude in Section 6.

2 Related Work

There has been much work in studying the properties and structure in OSNs such as Digg [9], Twitter [3, 10], MySpace and YouTube [11], Wealink [2], Yahoo! 360 and Flickr [4], Cyworld [1], and Xiaonei (now RenRen) [12], using social network measures such as degree, network density, clustering coefficient, number of users, number of links, and network diameter. These researchers compare and contrast their results with other OSNs. For example, comparisons have been made between Twitter, WWE blogging network, and Brightkite [8] and have been discovered to be small-world networks. Our work differentiates from them in that we study the evolution of users' social activities and the structural properties in a mobile social network.

Wilson et al. [13] studied user interactions in the Facebook to answer the question as to whether social links are valid indicators of real user interaction. Cha et al. [14] used Flickr user interactions and favorite photo activities to study how far and quickly information was propagated in OSN. Our work differs in that we do not focus on exploring users' interaction and social activities in a static network, but rather to investigate how users' social activities change and evolve over time.

A social network evolves over time, so recently, there has been increasing work on studying the evolution of OSN. Many researchers have used crawled datasets from OSNs in order to model the evolution of a social network. For example, Kumar et al [4] analyzed the structure of Yahoo! 360 and Flickr networks and Barabasi et al. [6] analyzed scientific collaborations over time, and together using social network analysis, they each created a model of evolution and used simulation to test the model. Sanchit Garg et al. [15] analyzed the social content aggregator FriendFeed and suggested that proximity bias plays an important role in the link formation process. Viswanath et al. [16] studied the evolution of activity between users in Facebook to capture how social links can grow stronger or weaker over time and found that although the links of the activity network change rapidly over time, many graph properties of the activity network remain unchanged. Hu et al. [2] studied the evolutions of degree, network density, clustering coefficient and modularity, in order to reveal the properties and evolutionary patterns of the Wealink. Our work, however, differs in that we do not attempt to create a model of evolution or do simulation, but rather we examine the structural evolution of both the undirected friend network and the directed comment network respectively in a mobile social service.

With the proliferation of GPS location becoming standard in mobile phones and the convenience of internet access over 2.5G and 3G cellular networks as well as Wi-Fi networks, location-based social networks on mobile phones are now becoming a reality. Social networks are now being created using the mobile phone and use location to tailor specific content (such as Brightkite) and people (such as BuddyCloud and Aka-Aki), and are also used for search (such as Loopt) and communication (such as Gypsii). For example, a mobile micro-blog [17] was created for sharing and querying geo-tagged content through mobile phones. CenceMe [18] used sensor-enabled mobile phones to share information in a mobile social network and used context for detecting and recognizing user's everyday activities. Cluestr [19] is a group and community aware mobile social network that allows users to efficiently select contacts to address them as a group. However, there exists few work into analyzing the user behavior and network properties of mobile social networks because it is difficult to obtain this data. Perhaps one of the first analytical studies into mobile social networks is that of Dodgeball [20], where the author provided an ethnographic study using qualitative analysis (participant observation, user observations and in-depth interviews). Li and Chen [8] have conducted quantitative analysis of a commercial location-based mobile social network (Brightkite). Dong et al. [21] used the mobile phone call logs from users in a city to build a large mobile social network and analyzed the network properties. Our work differs from [8, 21] in that we study the evolution of user's activities and evolution of properties of both the undirected friend network and the directed comment network in a mobile social network.

3 Friend View and Dataset Description

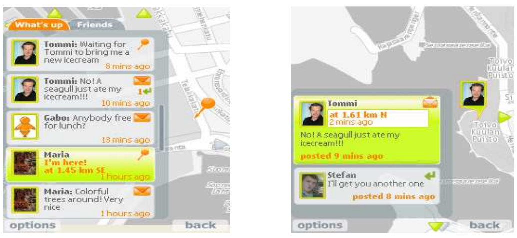
3.1 Friend View User Interface

Friend View is a location-enhanced micro-blogging application launched in Nokia Beta Labs in the beginning of November 2008, and was discontinued at the end of September 2009 because it was an experimental project. It allows users to post messages about their status with location about where they are from GPS-enabled Nokia S60 phones and share their activities with close friends. In the Friend View, users can keep up with all their friends' locations and recent status messages on a map in the What's up tab (Figure 1 (a)), and make comments to related conversations started from status messages (Figure 1 (b)). Users can add friends by specifying an e-mail address, finding a new friend in the Friend View directory, or adding a new friend who has commented on a status message originated by the user's friend.

3.2 Dataset Overview

We obtain the entire complete dataset from the Friend View project team that consists of the time that all users joined Friend View, status messages posted with or without GPS location, comments users received and made, and their list of friends. The dataset contains full information about users' activities in 11 months from the beginning of November 2008 to the end of September 2009. For privacy and security reasons, all the data used in this paper are appropriately anonymized. Since much work has studied the structure of a static snapshot of a dynamic and evolving social network by crawling a subset [1, 8, 16], we believe that in-depth analysis about the entire lifetime of the Friend View dataset provide interesting and reliable results.

During the 11 months of operation, a total of 34980 users are registered to Friend View, with 8443 users having friends, and a total of 20873 friendship links being created. A total of 62736 status messages are posted by 16176 users, providing an average of 3.88 status messages per user. 37599 status messages from 13597 users



(a) (b)

Fig. 1. User interface (a) status messages from friends, (b) comments to a friend's status.

have GPS location (we see this location information as a kind of checkin that is popular in current location-based social networks such as FourSquare, Gowalla), 9363 status messages that come from 2395 users receive comments, and 22251 comments are posted from 2283 users, providing an average of 3.91 status messages with comments per user and 2.38 comments per status message. An average of 9.75 comments is made per user for the status messages that have comments.

On average, the interactions or activities (status messages and comments) are low compared with other OSNs like Facebook. In our opinion, this reflects the fact that mobile location-based social networks are still not as widely used, due to the privacy concerns of sharing one's location to all (as have been witnessed with Google Buzz). In addition, despite the convenience of using the mobile phone anytime and anywhere for posting status and making comments, it is still easier and faster to write statuses and comments with a full-sized keyboard than with a keypad or small keyboard on the phone. Nonetheless, since we have the entire dataset, we can perform a complete evolution analysis of Friend View which we present in the next section.

4 Evolution of Friend View

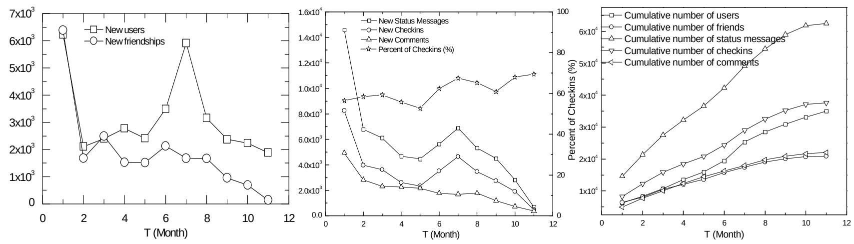
We analyze the evolution in Friend View and compares with OSNs. We extract 11 snapshots of the dataset with an interval of one month. We first present the usage and social activities evolution of Friend. Then we examine the social network evolution of Friend View by considering the graph's properties from both the user's friend network and comment network and compare them with that of OSNs.

4.1 Usage evolution

The evolution of new users and friendships made and users' social activities including statuses, checkins and comments are shown in Figure 2 (a) and (b). In Figure 2 (c), the evolution of the cumulative number of users and users' activities are illustrated.

The growth patterns for the number of new users and new friends are similar in shape in Figure 2 (a). The highest number occurs during the beginning when many users join Friend View and are eager to try out the service, and then overall dramatically decreases until the end of the service, with the exception of a few spikes. In the 6th month (April 2009), the number of new users increases and it is interesting to note that in the 7th month (May 2009), the number of new users encounters a huge spike and almost reaches the level from the beginning. We are not sure why this exists, however it may be as a result of a touch version of Friend View that was released.

The cumulative growth patterns for the number of users and friends in Figure 2 (c) appear to follow an S type of shape, but are less steep than those in ONSs such as Wealink [2] and Cyworld [1]. The cumulative trends start small, rapidly accelerate and then stabilize. In the case of the cumulative number of users, it still continues to grow while with the cumulative number of friends, it appears to plateau off during the 10th and 11th months. The cumulative number of status messages, checkins and comments also follow a similar distribution, with the cumulative number of



(a) (b) (c)

Fig. 2. Evolution of the number of new users, friendships, activities and the cumulative results.

comments closely resembling the cumulative number of friends. This may be due to the Friend View interface which allows users to add commenters as friends.

As shown in Figure 2 (b), the growth patterns for the number of user activities such as posting status messages, uploading GPS locations when checking in at a place and commenting on others' statuses and checkins, share similar trends with Figure 2 (a). At the first release, users were excited with the mobile location-based service and were very active in the networks. With the huge spike of new users joining Friend View in the 7th month (May 2009), the number of status messages and checkins also encounter a relatively huge spike, although it did not reach the level from the first month. However, we see no increase for new comments from May 2009 compared with that from April 2009. From that, the social activities in Friend View reached a saturation point from which it reduced progressively. It is interesting that, the percent of checkins over status messages is stable and rises up gradually from 56% in the beginning to about 70% in the end. Therefore, users did not lose their interest in sharing where they were with close friends when they posted their current status.

We now examine if there are any interesting user behavioural relationships between the various user activities by performing a correlation analysis. Table 1 gives the Pearson correlation coefficient between different pairs of users' social activities. The Pearson coefficient between a user's number of status messages and number of checkins is 0.87, indicating strongly that a user in Friend View that posted many status messages is also likely to share many locations. This explains why the percent of checkins over status messages remains high when users' activities decline. Users that posted many status messages are also very likely to receive many comments (Comment In) about their status messages/checkins (Pearson coefficient = 0.58 for status messages and 0.55 for checkins) and make many comments to (Comment Out) others' status messages/checkins (Pearson coefficient = 0.5 for status messages and 0.47 for checkins) and associate with many friends (Pearson coefficient = 0.38 for status messages and 0.27 for checkins). Users who post many comments are very likely to receive many comments for their status messages/checkins with Pearson coefficient between comments out and comments in being 0.95. In a word, the

Table 1. Pearson correlation coefficient between user's activities

	Status	Checkins	Comments In	Comments Out	Friends
Status	1				
Checkins	0.87583	1			
Comments In	0.57724	0.5483	1		
Comments Out	0.50489	0.47416	0.95431	1	
Friends	0.37636	0.27109	0.29547	0.27732	1

correlation coefficients in Table 1 could explain the similar patterns and trends in Figure 2 for users and friendships and for user's behavior patterns of social activities.

4.2 Social activity evolution

We present the distribution of users' social activities including the number of users' status messages, checkins, comments received, comments made and friends. These distributions are based on the whole dataset and are shown in log-log scale as illustrated in Figures 3 (a)-(e). As expected, the distributions follow a power law with different fitted exponents. The majority of users have a small number of activities in Friend View, for example, many users posted one, two and three status messages /checkins. However, we do encounter few users in the long tail of the distribution that have excessive number of status messages/checkins that amount in the hundreds and even thousands. Although the maximum number of comments a user received and made and the maximum number of friends a user had are not very large (smaller than 200), the distributions are more perfectly fitted by power law.

Additionally, we analyze and show in Figure 3 (f) the distributions of the number of comments received and made and the number of users' friends based on the cumulative dataset up to the month indicated on the x- axis and find how the distributions change and evolve. The comments and friends that users are involved in are more important for the social interactive communities formed in Friend View in that they reflect real user activity rather than social linkage alone [13]. We do not show all the three distributions (number of comments received and made and number of users' friends) at each cumulative month here but find that they normally can be fitted as a power law distribution. In Figure 3 (f), we plot the evolution of the power law exponent for each distribution. During the evolution of Friend View, generally, the absolute values of power law exponent for the three distributions are slowly becoming larger, although not too much. Large absolute slope of power law fitting line in log-log scale may imply that more users appear in the head of distribution curve's long tail and relatively more users have small number of comments received and made and small number of friends. It seems to be opposite to the famous "rich get richer" assertion in the preferential attachment model [22], where new users are more likely to comment and link with those that have high degree. Two possible reasons for this may be: (1) users in Friend View interact with each other through mobile phones and so it is difficult for them to find out the popular users to add as friend and select interesting activities to join and (2) users in the directed comment network of Friend View regard the reciprocity in comment interaction as important [13]. This explanation can be confirmed in Section 4.4.

4.3 Social network evolution

We study the evolution within the friend network and comment network using the cumulative dataset between the beginning of Friend View to the T month since its release. The friend network is an undirected graph formed based on a pair of friends, while the comment network is a directed graph based on users making comments to

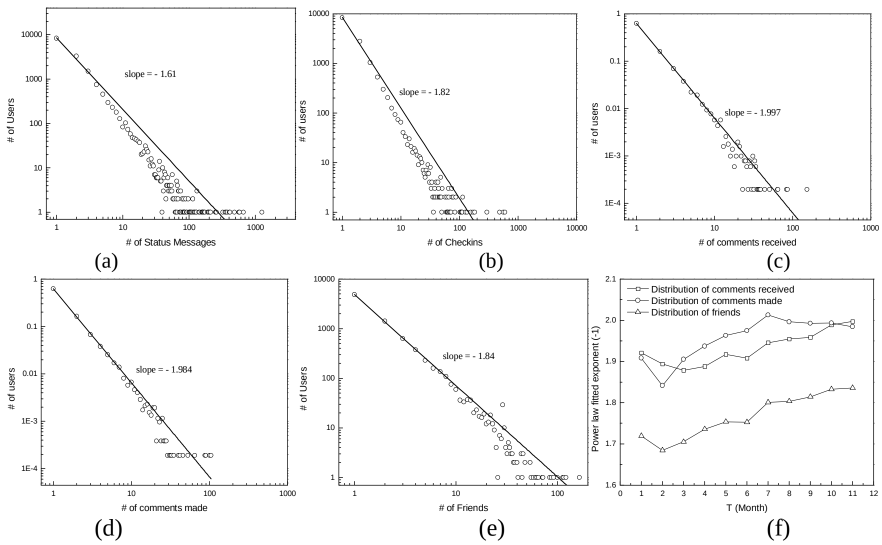


Fig. 3. User activity distribution (based on whole dataset) with power law fitted exponent for (a) Status messages, (b) Checkins, (c) Comments received, (d) Comments made, (e) Friends and (f) Power law fitted exponent evolution for comments received, comments made and friends.

others's statuses. To study how the friend and comment social graphs change and evolve over time, we analyze the shortest path length and network clustering coefficient, as well as the network density, so to understand if the friend and comment networks are always small-world and scale-free networks over time.

Figure 4 shows evolution for the average shortest path length for both the friend network and comment network. The friend network has an average shortest path length of around 6 (with a slight decrease from 6.0 to 5.8 during the first three months and then slightly rises from 5.8 to 6.4 over time), indicating each user can reach another user at an average of only 6 hops. This exactly corresponds to six degrees of separation, a general property of social networks [23, 24]. Similar work but for OSNs, the average shortest path length were presented to be slowly rising from 5.5 at the beginning to 7.5 near the end for Wealink [2] (similar to Friend View), be slowly decreasing from 6.6 at the beginning of March 2007 to 4.4 at the beginning of March 2008 for Purdue University network in Facebook [25] (different to Friend View). Average shortest path length of other undirected friend networks in one or cumulative snapshots are reported to be 3.72 for Xiaonei [12], 6 for MSN Messenger [26].

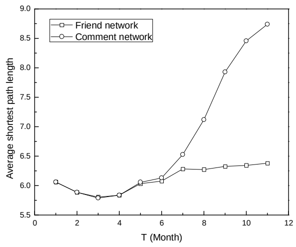


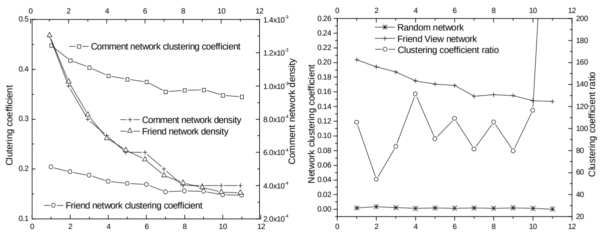
Fig. 4. Evolution of the average shortest path length for friend and comment networks.

In Figure 4, the average shortest path length of the comment network is almost the same to that of the friend network for the first five months. Then, it deviates and directly rises to 8.8. This may be explained by Figure 2 which shows that the number of new comments slowed down over time. Similar work in [25] shows that the average shortest path length over time for a conference network in Twitter [25] quickly decrease from 5.5 on 12/07/09 to 4.2 on 12/18/09 (different to Friend View). Average shortest path lengths of other directed networks in one or cumulative snapshots are 6.01 for Flickr [4], 8.26 for Yahoo! 360 [4], and 6.84 for Sina blog [12].

Figure 5 (a) shows the evolution of clustering coefficient and network density for both the friend network and comment network. The clustering coefficient can provide evidence of the existence of subgroups based on the property that social networks have many connected triads exhibiting a high degree of transitivity [27]. It shows that the two properties for the two networks are positively correlated with each other (Pearson coefficient is 0.98457 for comment network and 0.98457 for friend network) and both follow a similar declining curve, which is similar to the results of the Wealink [2] but different to the results of Facebook and Twitter [25]. This means that the Friend View friend network and comment network both become less dense and less clustered (fewer subgroups) over time, as we demonstrated in [28]. The reason is users form larger subgroups over time as more users join Friend View [28]. However, compared to OSN where users have a large number of friends but loose weakly-tied connections, users in Friend View tends to have close strongly-tied cohesive subgroups, because the decreasing clustering coefficient for both the friend network and the comment network are still considerably larger than that of OSNSs such as Sina Blog [12] and Xiaonei [12], Wealink [2], and Facebook and Twitter [25].

In addition, in Figure 5 (a), network density of the friend and comment network are almost similar to each other over time. In the first five months, the friend network was slightly denser than the comment network and in next months, the comment network was slightly denser than the friend network. However, the clustering coefficient of the comment network was apparently larger than that of the friend network, which means that users in the comment network were more cohesively connected than users in the friend network. An explanation is that, user A receives a comment from user B and then visits user B's status list where user A finds an interesting comment from user C, so user A visits user C's status and makes a comment.

Figure 5 (b) shows the evolution for the clustering coefficient of the corresponding random network of the friend network, and the order of magnitude of the friend



(a) (b)

Fig. 5. Evolution of (a) clustering coefficient and network density and (b) clustering coefficient of the friend network and its randomized version and coefficient ratio over randomized version.

network's clustering coefficient is higher than that of the corresponding random network [29]. We do not show the related curve for the comment network due to the fact that the comment network has considerably larger clustering coefficient than the friend network (0.345 for the comment network compared with 0.147 for the friend network at the end of Friend View's service and similar pattern during each timeslot) and obviously smaller number of users involved than friend network (2283 users in the comment network compared with 8443 users in the friend network at the end and similar pattern during each timeslot). The clustering coefficient of the comment network is an order of magnitude higher than its corresponding random network. From Figure 5 (b), it is clearly shown that the clustering coefficient for the Friend View friend network is significantly higher than for the random network although it decreases over time. At the same time, from Figure 4, since the average shortest path length is small and is around 6, then we can conclude that the Friend View friend network is indeed a small-world network over time [24]. Besides, from Figures 3 (e) and (f), the friend network degree distribution follows a power law with rising slope over time, so the friend network is also a scale-free network over time. Similar results can be also inferred for the comment network of Friend View.

4.4 Assortativity evolution

We additionally want to know if there exists a cordrelation between the undirected connection of adjacent users in the friend network and directed connection in the comment network in Friend View, and how the correlation evolves over time. Assortativity is often used to characterize the correlation and defined as the Pearson correlation coefficient of the degrees of each side of a link. A positive assortativity indicates that nodes with large degree in the network tend to be connected by other similar nodes with many connections, and vice versa. We plot the assortativity coefficient for the friend and comment network in Figure 6.

First, all the assortativity coefficients for the friend and the comment network are always positive over time, so the two networks both have an assortative mixing pattern, confirming the conventional wisdom that social networks are assortative mixing [30]. Second, however, the assortativity undergo noticeable decline during the first three months, and then remain stable and smooth except that the assortativity coefficients for comment in-in and comment out-out dropped sharply to the same level of comment in-out. Therefore, during evolution, both friend network and comment network of Friend View still have an assortative mixing pattern, unlike Wealink transitioning from the initial assortativity to subsequent disassortativity [2]. Thirdly, for the friend network, users with many friends tend to make friends with others who also have

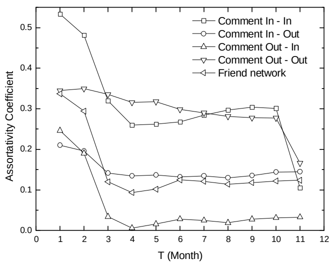


Fig. 6. Evolution of assortativity coefficient for friend network and comment network.

a lot of friends. In the comment network, obviously, users who post many comments tend to make comments to status/checkin of others who also make many comments out as we see a large assortativity coefficient for comment out-out (similar to that of Sina blog [12]). Users who received many comments for their status/checkin tend to make comments to status/checkin of others who also receive many comments as we see a large assortativity coefficient for comment in-in (contrary to that of Sina blog [12]). That is to say users in the comment network tend to connect with counterparts through comment activities. The reason is that users in the directed comment network of Friend View regard the reciprocity as important for interaction, which is different to that of the active users in the directed Sina blog which just tends to connect celebrities and do not require the celebrity's response [12].

5 Conclusions

We study the complete evolution of a mobile social network based on the entire lifetime dataset from Friend View which we believe we are the first to do from beginning to end, while others do evolution for only OSNs and evolution analysis using crawled datasets. We discover that Friend View does not follow the "rich get richer" scheme in the preferential attachment model of social networks, but rather power law fitted exponents for user activity distribution are slowly becoming larger over time. We find that the friend network and comment network in Friend View are both small-world and scale-free networks with assortative mixing pattern over time.

By analyzing the evolution of mobile social network, it helps to understand its operation and user behaviour, thus helping to identify which time periods to focus on for improving its growth. Besides, we can create a dynamically social interface that highlights the people in the network that have a certain property like degree and visualize their ties, in similar fashion to Vizster [31]. The result can also enable new applications that utilize the social graph for recommending people to help facilitate closer ties. It is our belief that we can create an analytical framework that can be used to study any mobile social network in comparison with other social networks.

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