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ORIGINAL ARTICLE

Influence of social relations on human mobility and sociality: a study of social ties in a cellular network

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Abstract Personal networks can influence human behavior in many aspects. This article presents a correlation analysis of social tie strength and individual behavior concerning mobility and sociality. The study uses a large-scale mobile phone data (110,213 subjects) from which behavior indicators for both mobility and sociality are inferred and used for the analysis. Mobility diversity, dispersion, and range are considered as mobility behavior indicators. Call frequency, call duration, and degree (number of social ties) are considered for sociality. The results show that people tend to have a more similar behavior with their closer ties for most of considered individual behavior indicators, except for the mobility dispersion.

Keywords Social influence · Mobile phone data · Human mobility · Sociality · Cellular social network

1 Introduction

With today's high mobile phone penetration and emerging mobile sensing technologies, mobile phones have become personal sensors that collectively generate a huge amount of individual 'digital traces' from which community and city-level behavioral signatures can be inferred. It opens up a unique opportunity for behavioral studies to sense and observe human behavior where human being is also part of the sensing infrastructure. This new sensing paradigm has triggered an increasing interest in the use of mobile phone records as a proxy for various types of social and spatial interactions. Geographers and others have started to use this new data source to gain new insights on spatial structures and population geography in high space-time resolution. For example, Reades et al. (2009) have examined concentrations of people in a city, population distribution due to nonrecurrent mass events such as a pop festivals (Reades et al. 2007), the use of private or public spaces by individuals (Calabrese et al. 2010), and the use of location-based services as a form of insight into complex and rapidly changing spatial phenomena (Ratti et al. 2006, 2007). Human geographers such as Ahas et al. (2006) studied commuting as well as tourist patterns (Ahas et al. 2007, 2008). The use of such data is seen in mobility studies to shed light on the displacement (Lambiotte et al. 2008; Licoppe et al. 2008) and mobility paradigm (Sheller and Urry 2006). In the complexity and network science field, researchers such as Barabasi and his colleagues explored statistical mechanisms governing the formation of the complex networks of human communication in cellular networks. For example, the work of Song et al. (2010a, b) links mobility discussions with statistic physics, while that of Candia et al. (2008) illustrates individual human dynamics using mobile phone records as the main instrument. Other examples in relevant research fields include spatial friendship network structures (Eagle et al. 2009), event-based social networks (EBSNs) (Liu et al. 2012), and transport and incidents management (Steenbruggen et al. 2013), and many other recent research projects (Blondel et al. 2015).

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According to Barabási (2009), new data availability can enable social sciences to break through previous analytical limitations to understanding social and spatial systems. In this study, we make use of longitudinal mobile phone call detail records (CDRs) to investigate on the influence of social ties on people's behavioral characteristics in mobility and sociality. This study has been inspired by our previous investigations about how people's mobility is influenced by the geography of their social ties (Phithakkitnukoon et al. 2012b) and the impact of weather condition on social interaction (Phithakkitnukoon et al. 2012a) and daily activity patterns (Phithakkitnukoon et al. 2013).

Recent studies have shown that social influence is a key factor in many aspects of human behavior, for example acceptance of mobile entertainment (Liu et al. 2010), adoption of information technologies (Vannoy and Palvia 2010), sharing of song choices (Seeburger et al. 2012), and inequity aversion (McAuliffe et al. 2013). In the same time according to the social-activity travel hypothesis (Axhausen 2006), location choice for common activities depends on the home location of the social network's members engaged in the shared activity (Carrasco et al. 2008). In general, people tend to maintain relations with geographically close peers. This tendency is falling with the physical distance, as it has been observed, for example, in a cellular (Lazarsfeld and Merton 1954) as well as online friendship networks (Liben-Nowell et al. 2005). Social networks play a key role in generating social activities and travels (Van den Berg et al. 2013). Different travel surveys indicate that social activities account for 15–30 % of all trips (Van den Berg et al. 2013). This topic has become an important issue for transportation and human mobility studies (Toole et al. 2015). Our work reflects this trend and aims to further extend our understanding of the social influence on human behavior particularly in the aspect of mobility and sociality. In our study, we also analyze the similarity between mobility and sociality in personal networks mobilizing the concept of homophily. The homophily in social networks has been described long ago in sociology (Lazarsfeld and Merton 1954). Homophily is the principle that a contact between similar people occurs at a higher rate than among dissimilar people. Thus, people tend to forge close relationships with people of a similar social status, position, age, gender, or worldview (McPherson et al. 2001). Our study further investigates on how similar are people connected by phone interactions in their behaviors and not only in their social characteristics, concerning mobility (i.e., the way they travel), and sociality (i.e., the way they interact), based on logging records of mobile phone usage.

2 Methodology

2.1 Dataset

This study used a set of anonymized call detail records (CDRs) of mobile phone users in Portugal that provides fine-grained longitudinal mobility traces and communication logs over 1 year, from April 2006 to March 2007. The data accounted for approximately 13 % of the population and were collected for billing purposes from all 308 municipalities of Portugal by a European telecom operator. To safeguard personal privacy, individual phone numbers were anonymized by the operator before leaving their storage facilities and were identified with a security ID (hash code). The CDR comprised the voice call information: timestamp, caller's ID, callee's ID, call duration, caller's connected cellular tower ID, and callee's connected cellular tower ID. The dataset did not contain information relating to text messages (SMS) or data usage (Internet). The location of the mobile phone user was recorded as the nearest connected cellular tower location when the users made or received a call. The dataset provided us with social and spatial characteristics of the mobile phone users over an extensive temporal window of observation. There are over 6500 cell tower locations in total, and each on average serves an area of 14 km^2, which reduces to 0.13 km^2 in urban areas such as Lisbon and Porto.

To ensure a fine-grained longitudinal data that captures behavior in both mobility and sociality, we selected only those mobile phone customers whose locations were recorded at least five times each month (i.e., at least five calls made/received each month); this led to the consideration of 110,213 subjects from the dataset. This filtering was hoped to exclude mobile phone users who were inactive or disconnected users during the period of our observation. Consequently, inactive users (low sociality) who made and/or received calls less than five times per month on average were excluded from our analysis. Nonetheless, the average number of close friends (or support clique) was shown to be about 3–5 people (Dunbar and Spoors 1995; Hill and Dunbar 2003). So, for a regular mobile phone user who calls each of his or her close friends once a week on average would still be included in our analysis based on our threshold.

Following Onnela et al. (2007), we only considered reciprocal communications in inferring the social network for each subject. On average, over 1 year, there are approximately 49 reciprocal links per subject; each subject spends 467 min on the phone each month (approximately 6 min daily) and is connected with 173 calls monthly (approximately 8 calls daily) across 98 different cell towers.

2.2 Analysis

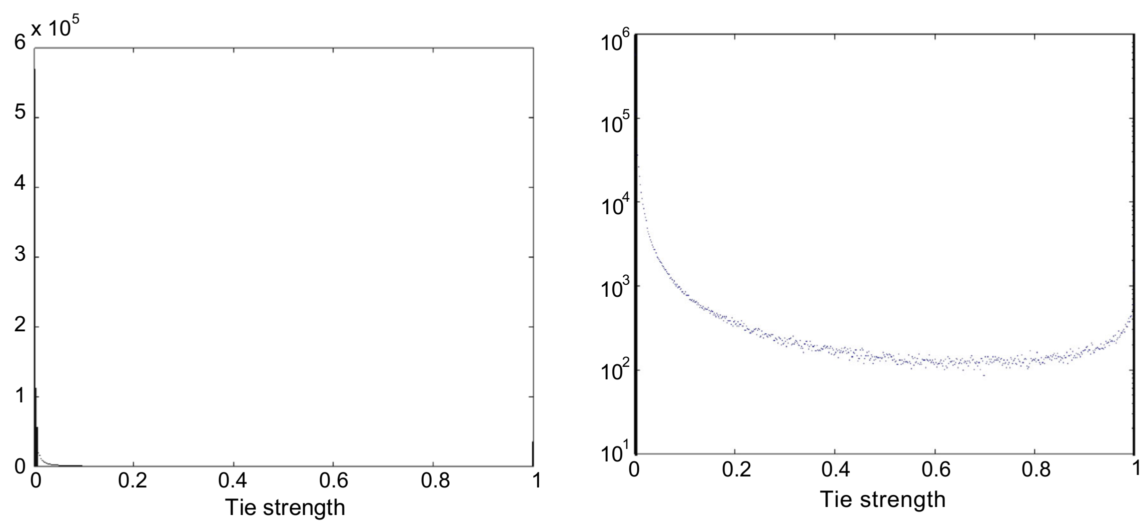
We were particularly interested in how much social relation influences human behaviors, specifically mobility and sociality. To quantify the level of social relationship (or tie strength), we adopted the theory developed by Mark Granovetter in his milestone paper of 1973 (Granovetter 1973) in which he defined the strength of a tie as ‘a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services’ (Granovetter 1973, p. 1361). We adopted a similar approach to Onnela et al. (2007) using the amount of time spent in communication and reciprocity as proxies. With our CDR data, for each subject, a tie strength was calculated as a normalized call duration for each of their associated social ties, as given by Eq. (1).

$$s(i) = \frac{c(i)}{\frac{1}{N}\sum_{i=1}^{N} c(i)} \tag{1}$$

where $s(i)$ is the social strength of tie i, $c(i)$ is the total call duration with tie i, and the denominator is the total amount of call duration of all associated ties where N is the number of associated ties. Hence, $s(i)$ is between 0 and 1, where 1 implies the strongest strength and 0 implies the weakest strength. Figure 1 shows the histograms of the strength of subjects’ social ties in our dataset in both linear and logarithmic scales. The average tie strength across our subjects was 0.05 with a standard deviation of 0.17.

We inferred behavior concerning mobility and sociality from the data using relevant parameters. For mobility, three parameters were used as proxies namely diversity, dispersion, and range. Mobility diversity refers to the total number of different locations visited by the person. Mobility dispersion measures the amount of variation (or randomness) in mobility, which was defined as a Euclidean norm of mobility variations in latitude and longitude directions, i.e., $\sqrt{s_{\mathrm{lat}}^2 + s_{\mathrm{lon}}^2}$, where s_{lat} and s_{lon} are standard deviations in latitude and longitude directions, respectively. Mobility range simply infers the travel distance range of the person’s mobility, which is defined as the distance (in kilometers) from the person’s home location to the farthest location the person ever visited. Home location was estimated using the method developed in our previous study (Phithakkitnukoon et al. 2012b), which is based on the spatial distribution of the call activity intensity during nighttime. The home locations estimated using this method have been shown to be reasonable proxies according to the comparison with the Portuguese census data (Phithakkitnukoon et al. 2012b). Figure 2 shows the histograms of mobility diversity, dispersion, and range in which means and standard deviations are also given. On average, people visit 98 different locations having a variation in their trips of 0.43 km and with a range of about 300 km.

For sociality indicators, we used call frequency, i.e., number of calls made and received per day, call duration, i.e., amount of talk time per day, and degree, i.e., number of social ties. Based on all 110,213 subjects in our study, we found that the average call frequency is 5.63 times per day (standard deviation = 5.42), the average call duration



(a) **(b)**

Fig. 1 Histograms of social tie strengths ((mean, std.) = (0.05, 0.17)). **a** Tie strengths (linear) and **b** tie strengths (log)

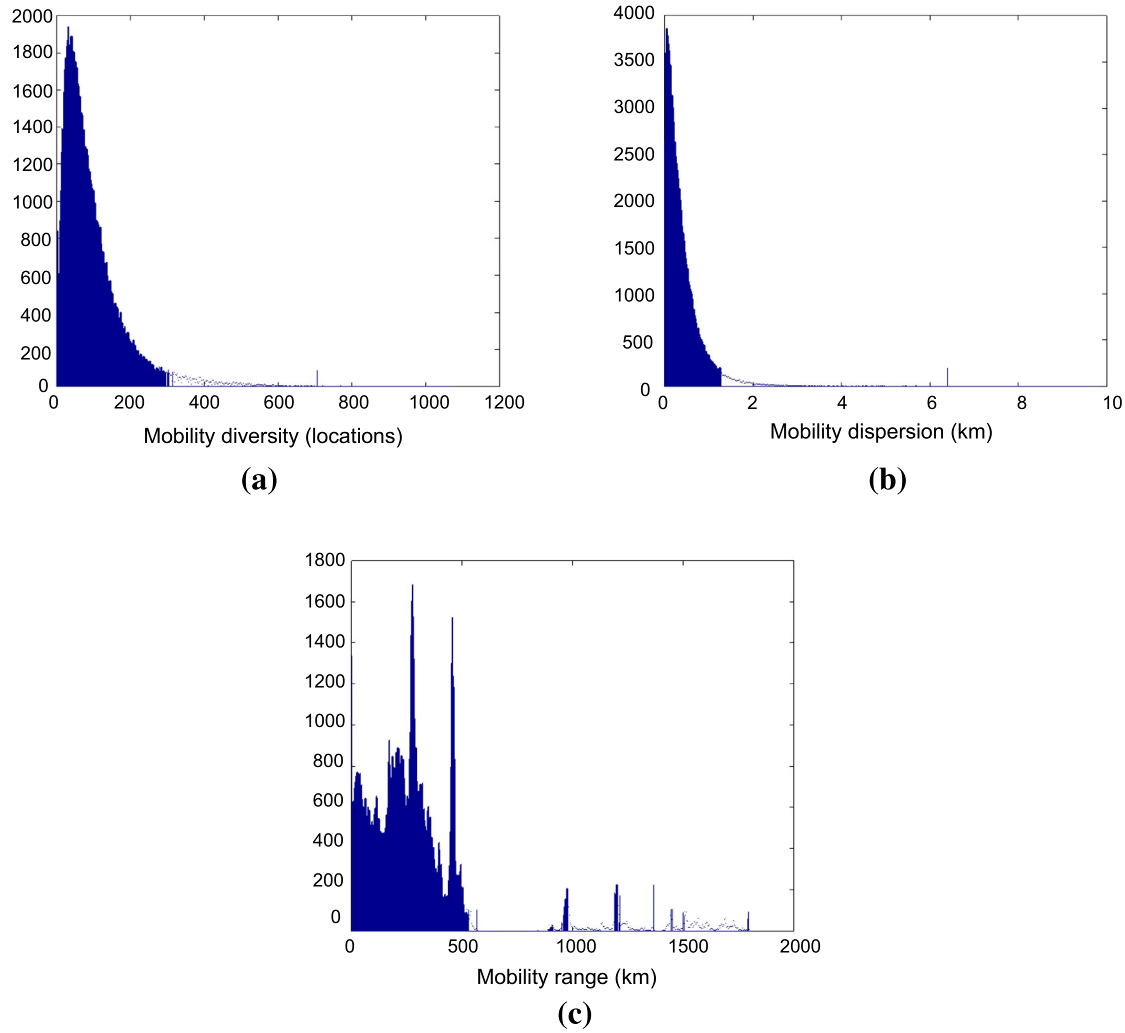


Fig. 2 Histograms of mobility diversity, dispersion, and range (mean, std.). **a** Mobility diversity (97.90, 88.06), **b** mobility dispersion (0.43, 0.58), and **c** mobility range (300.09, 294.02)

is 911.10 s (or 15.18 min) per day (standard deviation = 1218.70 s or 20.33 min), and the average degree is 44.03 (stand deviation = 43.34). The distributions of these sociality indicators are shown in Fig. 3. This means that, on average, the subject connects to the cellular network about five times daily, spends about 15 min on the mobile phone daily, and has about 44 social ties (or friends).

3 Results

To observe the relationship between the tie strength and mobility behavior, we examined dissimilarity in individual behavior indicators with respect to the tie strength. For each subject's social tie, we computed tie strength and the difference in each behavior indicator between the subjects and his/her ties. For mobility diversity, the result shows that people tend to have similar behavior with their closer social ties, as shown in Fig. 4a, i.e., the higher tie strength, the lower level of dissimilarity. The dissimilarity in mobility diversity on average varies from nearly 100 different visited locations to below 50 locations from the lowest to the highest tie strength levels. The relationship can be described by a fitted exponential equation, $y = 112.37 - 0.39x - 31.67$ with the correlation coefficient, $r = -0.85$. For mobility diversity, the same relationship was not observed, as shown in Fig. 4b with a low correlation coefficient, $r = -0.17$.

This suggests that the randomness in people's trip distances is not significantly correlated with the strength of their ties. Mobility range, on the other hand, appears to be correlated with tie strength as the dissimilarity decreases as tie strength becomes higher (Fig. 4c), with $r = -0.78$ and a fitted curve $y = 93.89 - 3.33x + 145.88$. The average

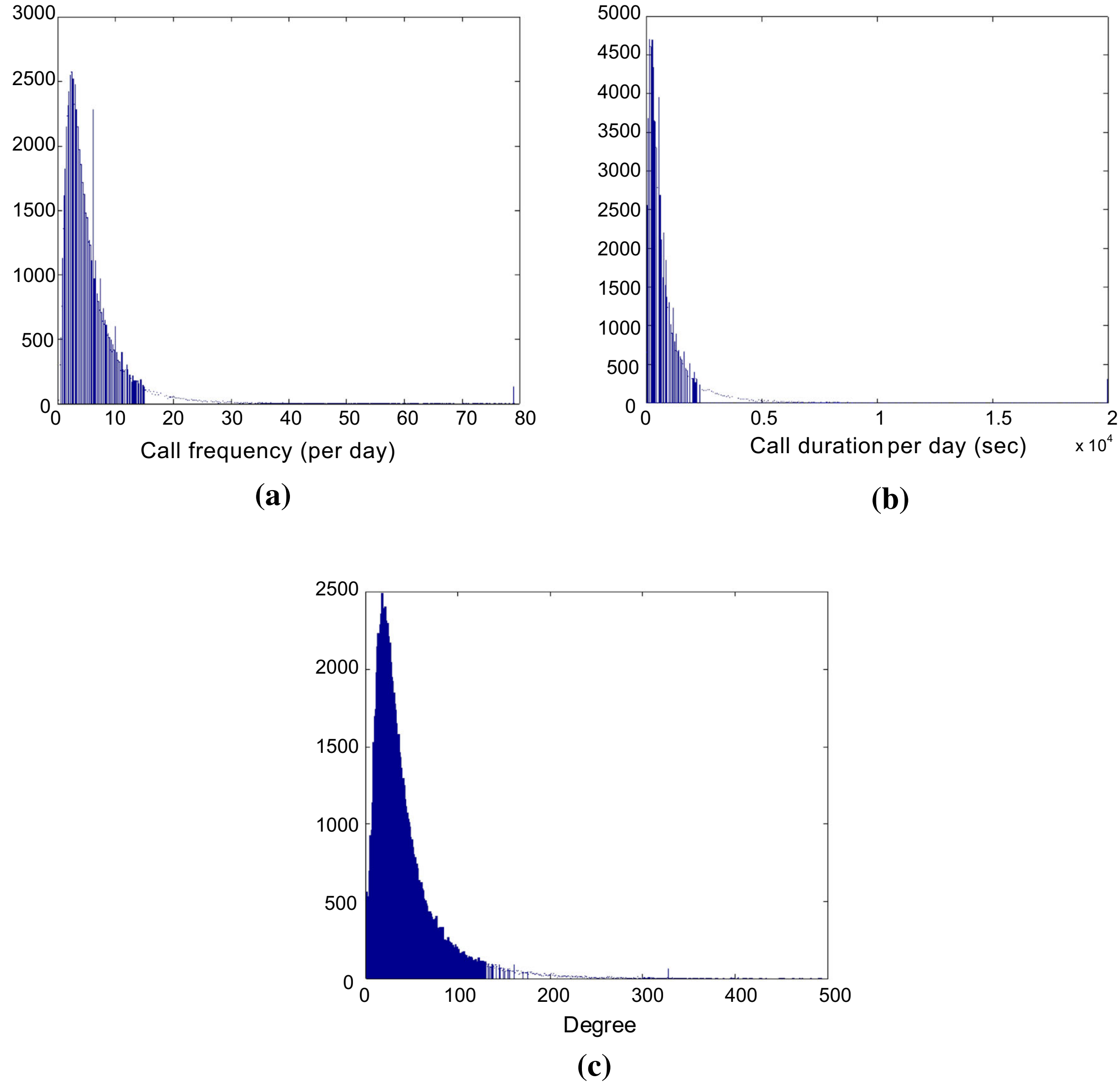


Fig. 3 Histograms of call frequency, call duration, and degree (mean, std.). **a** Call frequency (5.63, 5.42), **b** call duration (911.10, 1219.70) ≈ (15.18, 20.33 min), and **c** degree (44.03, 43.34)

range difference between the weakest and strongest tie strengths is about 100 km.

3.1 Sociality

Similar to the mobility behavior, individual behavior indicators concerning sociality are examined with respect to social tie strength. For call frequency, the result (Fig. 5a) suggests that the level of activeness in sociality as measured by call frequency is more similar to that of closer social ties, with $r = -0.75$ and fitted curve $y = -6.34x + 8.19$. Likewise for the call duration, behavior in the form of amount of time spent with social ties appears to be more similar to behavior of closer ties (Fig. 5b). The average difference in call durations ranges from about 1000 s (≈16 min) to about 250 s (≈4 min). The fitted curve is $y = 1703.5 - 0.55x - 710.22$ with $r = -0.83$. For degree, a closer tie strength also suggests a similar size of degree, i.e., number of ties (Fig. 5c. The difference in degrees on average varies from nearly 200 ties to about 20 ties, from the weakest to the strongest tie strengths. In other words, our closer friends tend to have a similar number of friends that we have.

4 Conclusion

With its sensing capabilities, mobile phone has become our personal behavior sensor that continually collects data streams from which our individual behavioral patterns can

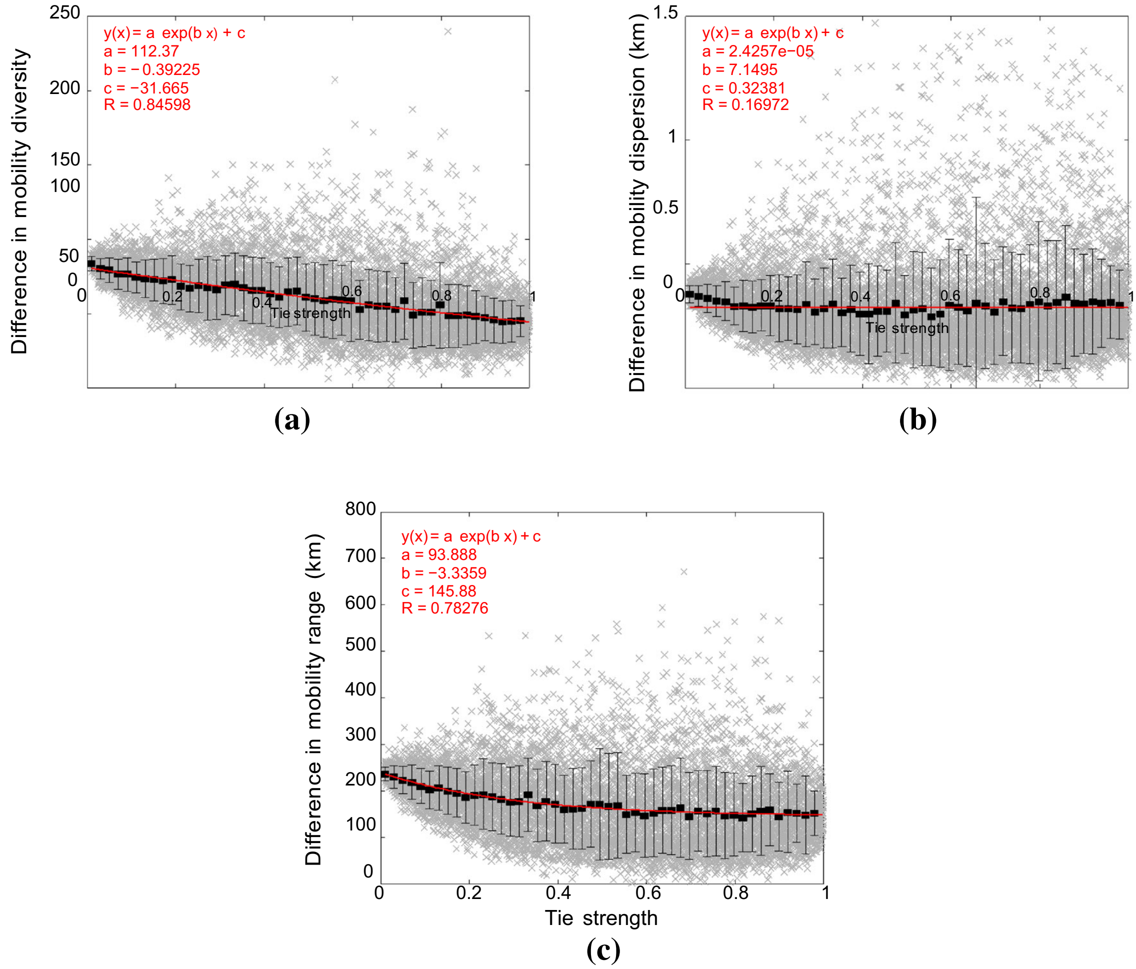


Fig. 4 Relationship between social tie strength and mobility behavior indicators. **a** Tie strength and mobility diversity, **b** tie strength and mobility dispersion, and **c** tie strength and mobility range

be inferred. Collectively, these data streams create a behavioral metadata that can provide deep insights into how our social and urban systems function. This means that mobile technologies can themselves be also used to study the relationship between social relation and behaviors such as mobility and sociality. In this study, we were particularly interested in understanding how social relation can influence people's behaviors concerning mobility and sociality. For mobility, we used diversity, dispersion, and range as behavior indicators. For sociality, call frequency, call duration, and degree were used as behavior indicators. We examined the correlation between social tie strength (which was based on amount of time spent in relationship, i.e., cumulative reciprocal talk time) and each of individual behavior indicators. Our results show that people tend to have a more similar behavior with their closer ties, as we observed a strong correlation between the social tie strength and most of considered individual behavior indicators, except for the mobility dispersion.

These results shed a new light on homophily and assortativity in social networks (Newman 2003). We observed that people are closely connected with similar mobile and sociable others. Of course, it is difficult to say whether we actively seek for others behaving the same or, to the contrary, as our personal networks are similar in some social dimensions, our behavior characteristic has beforehand been a close one. The correlation study cannot arbitrate on this point. However, some research indicates that homophily facilitates engaging in a new behavior. For example, in a controlled experiment setting, it was shown that homophily significantly increased overall adoption of a new health practice in obese individuals (Centola 2011). Thus, we can speculate on a kind of mutual influence, or contagion process where the closest ties adjust step by step their sociality but also mobility range and diversity. In fact, homophily effect and social influence are frequently confounded and difficult to separate in non-experimental studies (Shalizi and Thomas 2011).

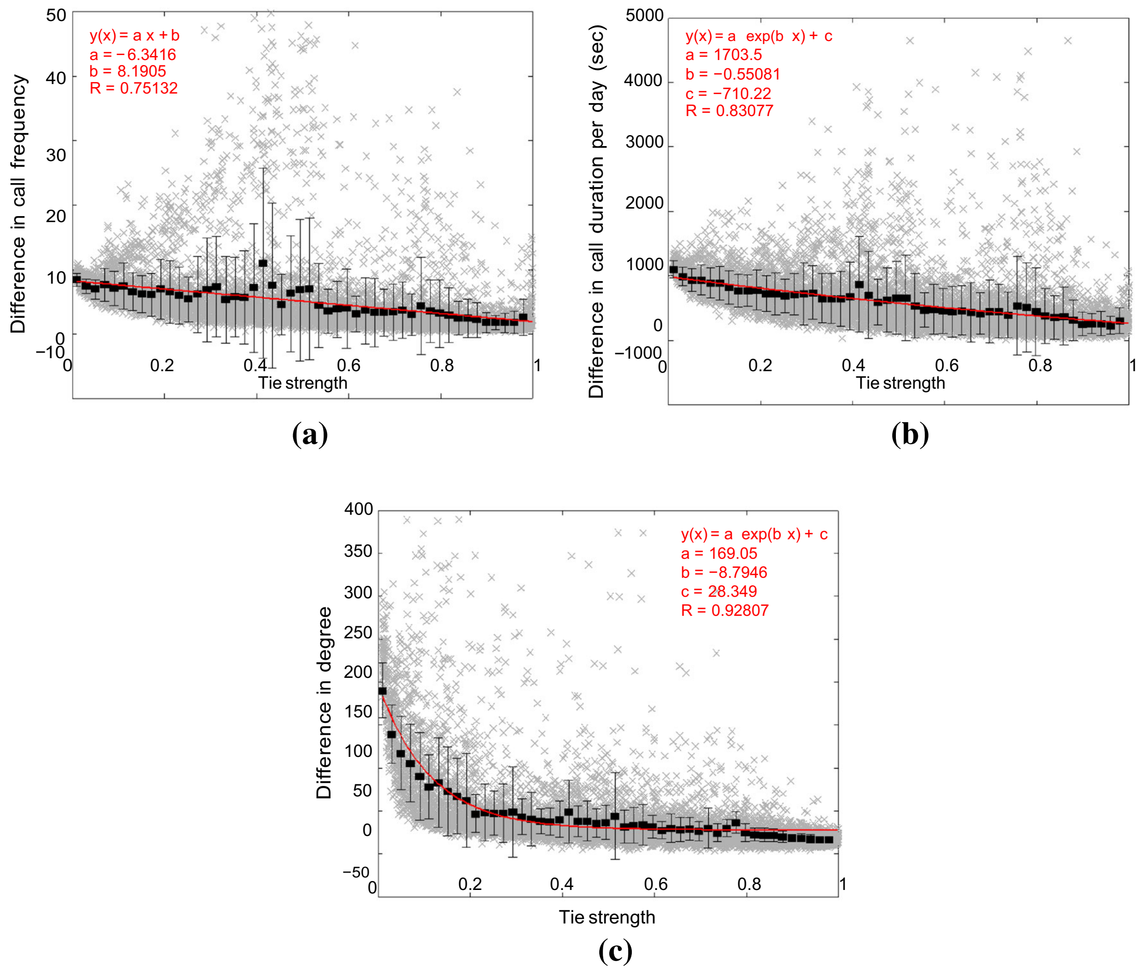


Fig. 5 Relationship between social tie strength and sociality behavior indicators. **a** Tie strength and call frequency, **b** tie strength and call duration, and **c** tie strength and degree

Nonetheless, there are some limitations to the observations we present in this study. The first of these is the discontinuous nature of the location traces in our dataset. Since individuals are located only when connections with the cellular network are established, we can only identify a subset of all locations visited. Yet, we believe that the longitudinal nature of our data compensates for this to some extend. The second limitation is the coarse spatial resolution of the location information, which is determined by the granularity of cellular tower coverage. Although a much higher spatial resolution can be achieved using traditional surveys, in practice such surveys are typically conducted for small samples of the whole population and for very limited periods of time. A final limitation is the subjects themselves who are mobile phone users that can only provide us a partial view of their social behavior and networks. Nonetheless, we believe that the study still offers useful piece of knowledge that helps us better understand of our human behavior through utilization of our current mobile and pervasive technologies.

This study reflects on the trend of big data analytics that helps further extend our understanding of social influence, and we hope that our findings suggest new ways to use mobile phone data to investigate the interplay between people's social relation and their behaviors. One of the implications of our findings is transport modeling, which has ignored the social dimension of travel in the past, as there was no empirical literature to lean upon. The use of opportunistic sensing approach allows us to capture fine-grained longitudinal data that captures behavior in both mobility and sociality, and this allows us to better understand their interrelationship that can help facilitate transport modeling and even further formulate hypotheses to guide the limited empirical work undertaken so far and to stimulate future studies and development. Though our findings suggest that people of a closer relationship tend to have a similar behavior, a question that still remains is how much the friendship does actually influence behavior and how much people with a similar behavior (or personality) themselves attract each other to forging a friendship.

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