Exploring Social Interactions via Multi-Modal Learning

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ABSTRACT

Research shows that humans do not move in a completely random manner; instead, movement patterns for humans are predictable to some extent. Finding patterns in human mobility is of interest for many reasons, e.g., knowledge of future contacts made by humans carrying mobile devices can be used in making efficient routing decisions in mobile networks. We are interested in exploring social interactions among users, which is feasible thanks to the dataset released by Nokia for the Mobile Data Challenge (MDC'12).

We have recently developed a mobility model, SMOOTH, that is based on seven statistical features commonly found in pedestrian movements. While SMOOTH has been validated with a diverse set of movement traces, the MDC dataset is much richer than the datasets used in previous validations. We analyze the MDC dataset, determine appropriate values of input parameters to SMOOTH, and validate that SMOOTH can realistically simulate this Nokia dataset.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Store and forward networks

General Terms

Performance, Theory

Keywords

mobility model; mobile ad hoc networks; simulation credibility; performance evaluation; realistic mobility.

1. INTRODUCTION

Knowledge of future movement patterns may help predict social interactions among humans. For example, when a mobile node (or mobile phone) A needs to send a packet to mobile node B, one of the neighbors of node A can be used as a relay in the hope that the packet will ultimately reach node B. Thus, if we can predict (with some probability) which nodes will become A's neighbors that will also be a future contact for node B, then we can use this information in making smart routing/forwarding decisions. Our recently proposed mobility model, SMOOTH [8], is based on seven statistical features that are commonly found in human movements [1, 2, 4, 11, 12]; see Section 5 for the list of features. SMOOTH has been validated with a set of five location-based traces collected for diverse scenarios [11] and two contact-based traces collected for conference scenarios [3]. Unfortunately, the location-based traces from [11] did not capture contact information between a pair of mobile nodes. Similarly, the contact-based traces from [3] did not capture location information for a given mobile node. Thus, with the Nokia MDC'12 dataset, we are interested in both the location information of each mobile node and the contacts captured via the Bluetooth scans. Using this data, a meaningful interaction between a pair of mobile nodes can be extracted. Our analysis shows that humans do not move independent of each other; instead, movement patterns are influenced by their social contacts. In particular, there is a strong correlation between the locations visited by humans that belong to the same community and/or have similar interests.

With this work, our main contribution is providing an in-depth analysis of the MDC'12 dataset. For this purpose, we use a multi-modal learning approach. In other words, we apply several different methods to extract the statistical features present in human movement and analyze the dataset to explore social interactions among a pair of users. Finally, we simulate the scenario represented by this dataset on our recently developed mobility model, SMOOTH. We first extract appropriate SMOOTH input parameter values from the MDC dataset and then provide guidelines on how to simulate a similar scenario on SMOOTH. Through extensive simulations, we validate that SMOOTH is able to realistically simulate the Nokia MDC'12 dataset scenario. SMOOTH can then be used to create new movement scenarios that have the same statistical features as found in the Nokia MDC'12 dataset.

2. STATISTICAL FEATURES

As mentioned, seven statistical features are commonly found in human movement traces; see Section 5 for details on these seven features. For example, **feature1** says that humans do not move randomly; instead, humans order their visits to locations in some non-random manner. As a consequence, flights (i.e., the distance traveled between locations) by humans best fit a power-law distribution. Similarly, human movements are not independent of each other. In other

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words, humans that belong to the same community have a strong correlation between their movement patterns. In this section, we analyze the MDC'12 dataset to explore these features and extract the social interactions that exist between humans (i.e., users carrying mobile nodes).[1]

2.1 Nokia MDC'12 Dataset

The MDC'12 dataset [5] contains several files, including a **gps.csv** for each user that records the locations visited by the user and the timestamp for each visit. To extract *flights*[2] and *pause-times*,[3] we process the fields *userid*, *time*, *longitude*, and *latitude* from the gps.csv file. The contacts for each user are recorded in a **bluetooth.csv** file. Each user has a *mac_prefix* and a *mac_address* associated with his/her smartphone device. The data challenge consists of movement traces for 200 users; however, as part of the open track, we were released data for only 38 users. To process information for the 38 users, a *user_id.csv* file is provided that associates the user's id with a *mac_prefix* and *mac_address*. We process the bluetooth.csv file for each user and extract the contact information between a pair of mobile nodes in the MDC'12 dataset. (See [9] for details.)

2.2 Distribution Fitting via EasyFit

In this work, we use EasyFit[4] software for fitting distributions to the empirical data extracted from the MDC'12 dataset. EasyFit allows us to fit a large number of distributions and, thus, finds the best fit to the data. EasyFit uses three goodness of fit tests (i.e., Kolmogorov-Smirnov, Anderson-Darling, and Chi-Squared) to compare the empirical data with several other possible distributions and ranks the fitted distributions based on the statistics obtained via these three tests. Specifically, EasyFit provides the parameter values for each of the fitted distributions as well as indicates if the fitted distribution provides a good fit.

2.3 Flights and Pause-time Distributions

We first analyze the dataset to explore the distribution of flights and pause-times for the mobile phone users. For this purpose, we use the GPS data released for each user in the MDC'12 dataset. We initially define a location visited by a mobile node as the location defined by the GPS coordinates of the node; however, GPS data is noisy and, thus, needs to be processed to obtain improved locations visited by mobile nodes. We use three methods to remove noise: rectangular method, angle-based method, and pause-based method similar to [11]. Figure 1 shows the rectangular method used to aggregate several short flights (that each have a small change in direction) to a single flight. In addition, we extract the distribution for pause-times made by users at the visited locations. (See [9] for details on the methods and parameter values used for processing the locations and pause-times of mobile nodes in the dataset.) Previous research suggests that flights and pause-times for users best fit a power-law distribution [8, 11]. In this work, we validate previous efforts by comparing the MDC'12 flights and pause-time distributions with several other possible distributions via EasyFit; see Section 2.2 for details. Figures 2-3 show the results of our analysis; for each test, the distribution with rank 1 best fits the data. Thus, Pareto2 (a type of power-law) distribution best fits the aggregated flights and pause-time distributions extracted from the MDC'12 dataset; in Figure 2, Pareto2 is the best fit for all the three tests and in Figure 3, Pareto2 is the best fit for two tests out of three.

[1]We use the terms "mobile phone user", "mobile node", and "humans" interchangeably.
[2]A *flight* is defined as a straight-line distance covered between two consecutive locations.
[3]*Pause-time* is the amount of time a node pauses at a location.
[4]EasyFit: http://www.mathwave.com/products/easyfit.html

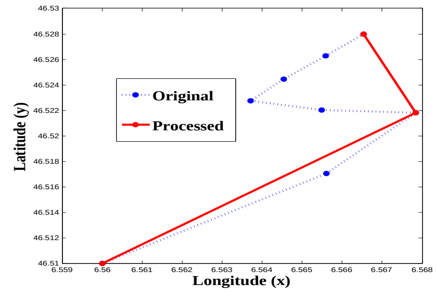


Figure 1: Rectangular method to process flights and remove noise in GPS data.

Goodness of Fit - Summary

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Exponential	0.33828	4	8775.9	4	18356.0	4
2	Exponential (2P)	0.33828	3	8495.3	3	18356.0	3
3	Gamma	0.86942	5	45687.0	5	2.7086E+5	5
4	Gamma	0.19186	2	3646.3	2	10933.0	2
5	Pareto 2	0.07534	1	2277.6	1	3217.3	1

Figure 2: Best fit analysis for the aggregated flights distribution extracted from the MDC'12 dataset.

Goodness of Fit - Summary

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Exponential	0.72275	3	51121.0	5	N/A	
2	Exponential (2P)	0.72275	4	51121.0	4	N/A	
3	Gamma	0.85081	5	44689.0	3	495.92	1
4	Gamma	0.3448	2	7624.2	2	17889.0	3
5	Pareto 2	0.17709	1	3461.2	1	16206.0	2

Figure 3: Best fit analysis for the aggregated pause-times distribution extracted from the MDC'12 dataset.

2.4 Contact Information

Social interactions of users carrying mobile phones are represented by the contact information extracted from their movement traces. Understanding contact information is crucial, as it determines the possibilities for data transfer between mobile nodes. In other words, if we know the distribution of contact time for a pair of users, we can make smart packet forwarding decisions. Contact information among mobile phone users can be characterized via the following three metrics:

- *Inter-Contact Times (ICT)*, which is the time between two consecutive contacts between a pair of mobile nodes and determines how often the users see each other.
- *Contact Duration (CD)*, which is the duration of a contact between a pair of mobile nodes and determines the amount of data that can be transferred during a contact of the mobile nodes.
- *Contact Number (CN)*, which is the number of times a pair of mobile nodes are connected and determines the number of times mobile nodes can relay each other's data.

To extract contact information for users, we first analyze the MDC'12 dataset to obtain these three aggregated distributions. Specifically, we process the Bluetooth contacts recorded by each user during scanning. We then used EasyFit to find the distributions that best fit each of the three extracted contact distributions (i.e, ICTs, CDs, and CNs).

Goodness of Fit - Summary

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Exponential	0.62232	3	3726.2	4	11122.0	4
2	Exponential (2P)	0.62309	4	4073.6	5	11255.0	5
3	Gamma	0.7009	5	1360.6	3	7077.4	3
4	Gamma (3P)	0.34813	2	414.77	2	2751.3	2
5	Pareto 2	0.0832	1	23.867	1	428.06	1

Figure 4: Best fit analysis for the aggregated ICTs distribution extracted from the MDC'12 dataset.

Goodness of Fit - Summary

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Exponential	0.45014	3	1412.7	4	4946.0	3
2	Exponential (2P)	0.45673	4	2066.8	5	5639.4	4
3	Gamma	0.55717	5	767.56	2	2627.9	2
4	Gamma (3P)	0.19024	2	1094.7	3	N/A	
5	Pareto 2	0.09634	1	16.703	1	412.89	1

Figure 5: Best fit analysis for the aggregated CDs distribution extracted from the MDC'12 dataset.

Goodness of Fit - Summary

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Exponential	0.36457	3	33.978	2	90.658	3
2	Exponential (2P)	0.39797	4	294.59	5	134.07	4
3	Gamma	0.5891	5	36.946	3	57.144	2
4	Gamma (3P)	0.30616	2	103.28	4	N/A	
5	Pareto 2	0.17041	1	2.3768	1	8.6759	1

Figure 6: Best fit analysis for the aggregated CNs distribution extracted from the MDC'12 dataset.

Figures 4-6 show the EasyFit results for the aggregated ICTs, CDs, and CNs distributions and rank the fitted distributions based on the fits provided. As shown, Pareto2 provides the best fit for the aggregated ICTs, CDs, and CNs distributions extracted from the MDC'12 dataset. We can now predict the time remaining until the next contact between user A and user B and, thus, make smart routing decisions in mobile networks. All of the distributions we fit have statistically significant differences with the empirical distribution of the data; however, Figure 7 shows that the Pareto2 distribution fits the data fairly well, with the difference being statistically significant because of the large amount of data.

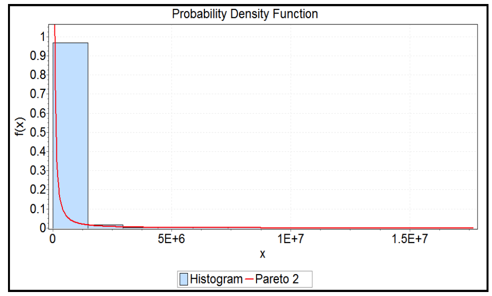


Figure 7: Comparison of the empirical aggregated ICTs distribution extracted from the MDC'12 dataset and the fitted Pareto distribution.

Goodness of Fit - Summary

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Exponential	0.28258	2	0.43368	2	N/A	
2	Exponential (2P)	0.40537	5	4.7535	4	N/A	
3	Gamma	0.21846	1	0.37271	1	N/A	
4	Gamma (3P)	0.34986	4	5.6232	5	N/A	
5	Pareto 2	0.28327	3	0.4348	3	N/A	

Figure 8: Best fit analysis for the aggregated ICTs distribution extracted from the MDC'12 dataset.

Fitting Results

#	Distribution	Parameters
1	Exponential	λ=3.0749E-4
2	Exponential (2P)	λ=4.6037E-4 γ=1080
3	Gamma	α=1.3545 β=2401.0
4	Gamma (3P)	α=0.66977 β=2610.8 γ=1080.0
5	Pareto 2	α=84.931 β=2.7487E+5

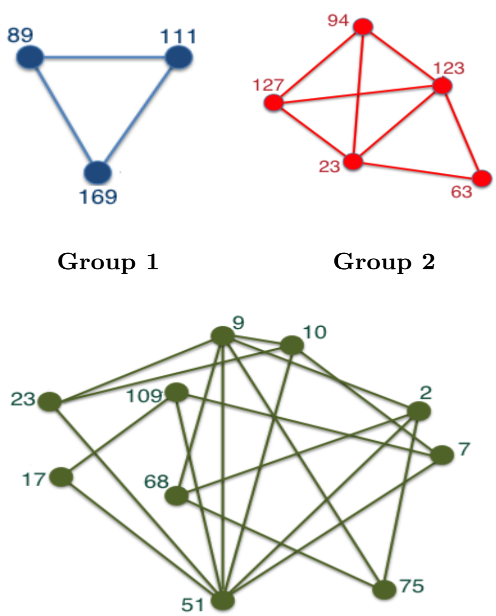
Figure 9: Best fit values for the aggregated ICTs distribution extracted from the MDC'12 dataset.

Passarella et al. [10] state that the ICTs distribution for individual pairs of nodes may not follow a power-law distribution. We, therfore, analyzed the MDC'12 dataset for the individual ICTs distributions. Figure 8 shows the results from fitting the ICTs distribution for the pair (89, 111) via EasyFit. As shown in Figures 8-9, a Gamma distribution with α=1.3545 and β=2401.0 provides the best fit. We note that results for other individual pairs in the MDC'12 dataset are similar. Figure 7 plots the histogram of the aggregated ICTs with the fitted Pareto2 distribution.

3. SOCIAL INTERACTIONS

Our investigation into the dataset shows that some contacts are more frequent than others. For example, in the MDC'12 dataset, user 2 contacts user 75 more frequently than user 2 contacts user 51 and user 68. Thus, we are interested in exploring if a community structure is exhibited in this dataset. We, therefore, analyzed the dataset and extracted the clustering behavior among users. For this purpose, we used the K-clique algorithm implemented in cFinder.[5] The K-clique algorithm uses the contacts made by the users to explore social interactions between the users. Figure 10 illustrates the groups of users extracted by the K-clique algorithm. The users that are not included in any of the groups are users with no visible association with these three groups.

Since the groups shown in Figure 10 represent the users with social interactions between them, it is interesting to explore how these social interactions affect the movement patterns of the involved mobile nodes. For example, Figure 11 shows the locations visited by the three users in Group 1. As shown, there is a visible overlap between the visited locations. We also provide statistical proof of the overlap in Table 1, by listing the percentage of overlap between locations visited by every pair of users in Group 1. Specifically, the first row in the table indicates that 74.9% of locations visited by user 89 are visited by user 111 and 41.52% of locations visited by user 111 are visited by user 89. Our analysis illustrates that the movement patterns of humans are not completely independent of each other; instead, the locations visited by socially-interacting humans exhibit some correlation.



Group 1 Group 2

Group 3

Figure 10: Groups of users identified.

[5]cFinder: http://www.cfinder.org/

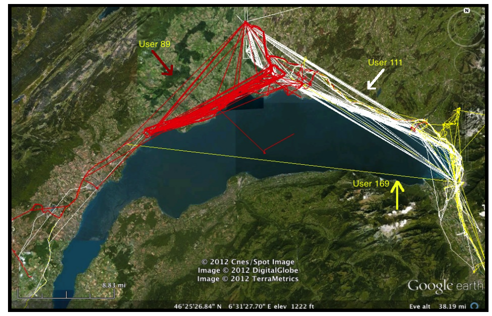


Figure 11: Locations visited by the three users in Group 1 (see Figure 10) have significant overlap. Each user's movement is a different color.

User Pair	% of overlap
(89, 111), (111, 89)	74.9%, 41.52%
(111, 169), (169, 111)	72.61%, 64.35%
(89, 169), (169, 89)	74.9%, 36.8%

Table 1: Percentage of overlap between locations visited by users in Group 1 (see Figure 10).

4. MOVEMENT PATTERNS OVER TIME

We analyze the dataset to extract the change in movement pattern of mobile nodes over time. Specifically, we extract the number of distinct locations visited by a mobile node over time. Song et al. [12] found that humans tend to revisit locations that they have visited in the past. In particular, the probability to explore a new location is given by:

$$prob\_explore(n) = aD_n^{-b} \quad (1)$$

where D_n is the total number of distinct locations visited by mobile node n so far, and $a \approx 0.6$ and $b = 0.21 \pm 0.02$ are the constants derived from the empirical data analyzed in [12]. As the number of distinct locations visited by a user increases, the probability to explore decreases. In other words, the movement path for the user becomes less explorative and, therefore, more predictable. We analyze the MDC'12 dataset and found that the values of parameter a and b (in Equation 1) are 0.98 and 0.0008, respectively. Figure 12 shows the value of parameter b obtained from the MDC'12 dataset. We note that the calculated values for a and b are quite different than the values suggested in [12]. The values of a and b are dependent on the dataset as well as how a "previously visited" location is identified. In [12], the authors track the cell phone towers a user is connected to during its movement. Thus, if a user reconnects to a previously visited cell phone tower, it is recorded as a visit to a "previously visited" location. In this work, we define X as a "previously visited" location if it is within 5 meters of a location Y previously visited by the user. In other words, the scale in our work is much more precise than in [12].

5. SMOOTH

The evaluation of real human walks shows that seven statistical features are commonly found in human movement [1, 2, 4, 11, 12]. Quoting from [8]:

- **feature1:** The flights (i.e., a straight-line distance covered between two consecutive locations) distribu-

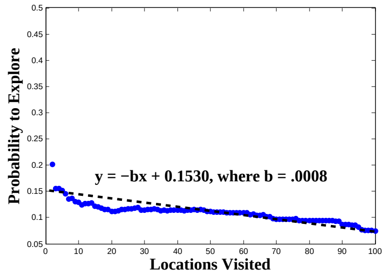


Figure 12: Analysis of data to obtain parameter b used in Equation 1.

tion of mobile nodes follows a truncated power-law (TPL).[6]

- **feature2:** The ICTs (inter-contact times) (i.e., the amount of time between two successive contacts of the same pair of nodes) distribution of mobile nodes follows TPL.
- **feature3:** The pause-times (i.e., the amount of time a node pauses at a location) distribution of mobile nodes follows TPL.
- **feature4:** The distribution of mobile nodes is non-uniform in the network.
- **feature5:** Mobile nodes do not move randomly in the network; instead, their movement patterns can be predicted to some extent due to the regularity present in their movement. (See the next two features for details.)
- **feature6:** A mobile node explores a new location, i.e., a location not previously visited, with probability (say *prob_explore*) inversely proportional to the total number of distinct locations it has visited so far.
- **feature7:** A mobile node visits a previously visited location with probability given by (1-*prob_explore*).

In [8], we propose a *simple* trace-based mobility model that is *realistic*. SMOOTH is realistic since it generates synthetic traces that match well with real human movement. Other *simple* mobility models proposed thus far do not mimic real human movement and other *trace-based* mobility models proposed thus far are not simple to use. Compared to several trace-based mobility models (e.g., TLW [11], SLAW [6], SWIM [7], etc.), the synthetic traces generated by SMOOTH are more credible; that is, SMOOTH is the only model that captures all seven of the statistical features commonly found in human movement. (See [8] for more details.)

5.1 Validating SMOOTH

SMOOTH [8] has been validated for a diverse range of scenarios; however, in addition to the issues listed in Section 1, the duration of these scenarios is limited to only a few hours ($\leq$ 1100 hours). The MDC'12 dataset is significantly larger and, therefore, is less susceptible to bias when compared to the other datasets used to validate SMOOTH. Thus, in this section, we provide results on simulating the MDC'12 dataset scenario with SMOOTH. Specifically, we first analyze the MDC'12 dataset to determine values for the input parameters to SMOOTH. Table 2 lists the input parameters to SMOOTH and their values extracted from the dataset. (See [8] for a complete description of each of the input parameters to SMOOTH and Section 2 for details on how we extracted these values.) We then used these values for simulating the MDC'12 scenario with SMOOTH and extracted the ICTs, CDs, and CNs distributions. In addition, we simulate a smaller scenario, shown in Table 2, that is similar to the MDC'12 Scenario. Figure 14 compares the aggregated ICTs, CDs, and CNs distributions obtained, respectively, from the MDC'12 dataset and the distributions obtained by simulating these two scenarios with SMOOTH. As shown, SMOOTH imitates the social interactions among users in the MDC'12 scenario very well. (See [9] for details.)

[6]The truncated power-law (TPL) distribution follows power-law upto a certain time after which it is truncated by an exponential cut-off.

Scenario	MDC'12 dataset	Small Scenario
Duration (days)	365	365
Nodes	38	38
Area (m^2)	60000x60000	1000x1000
Range (m)	25	25
Clusters	3	3
(α, f_{min}, f_{max})	(1.1, 1m, 5000m)	(1.1, 1m, 300m)
(β, p_{min}, p_{max})	(0.6, 10s, 7882033s)	(0.6, 10s, 7882033s)
(a, b)	(0.98, 0.0008)	(0.98, 0.0008)

Table 2: Input parameter values of SMOOTH for the MDC'12 dataset. The Small Scenario is a smaller version of the MDC'12 Scenario.

6. CONCLUSIONS

In this work, we provide an in-depth analysis of the MDC'12 dataset using a multi-modal learning approach, and we simulate the dataset with our realistic mobility model (SMOOTH). We make the following conclusions from our work:

1. Flights, pause-times, and ICTs for users in the MDC'12 dataset follow the Pareto2 distribution with exponents 1.1, 0.6, and 0.44, respectively.
2. Humans do not move independent of each other; instead, there is a strong correlation between locations visited by users that are socially interacting.
3. Values for parameters a and b are different than the values derived from the dataset used in [12].
4. SMOOTH is shown to, once again, do an excellent job in simulating real scenarios.

A detailed report of all the methods used in this work and the associated Matlab code can be found on our research group webpage, *http://toilers.mines.edu.*

7. FUTURE WORK

Our analysis of the MDC'12 dataset shows that users belonging to the same group are socially interactive. These social interactions, however, may not be of a similar nature. While some users in a group may be involved in professional interactions, other users may be personally related. Therefore, we are interested in analyzing the MDC'12 dataset for the *type* of social interactions that may exist among users. In the MDC'12 dataset, for example, user 94 visits 1.75% of the locations visited by user 23; however, user 23 visits 67.44% of the locations visited by user 94. With this observation, we may conclude that user 94 does not move as often as user 23. For example, perhaps user 94 is a bank teller and user 23 is visiting the bank as a customer; in

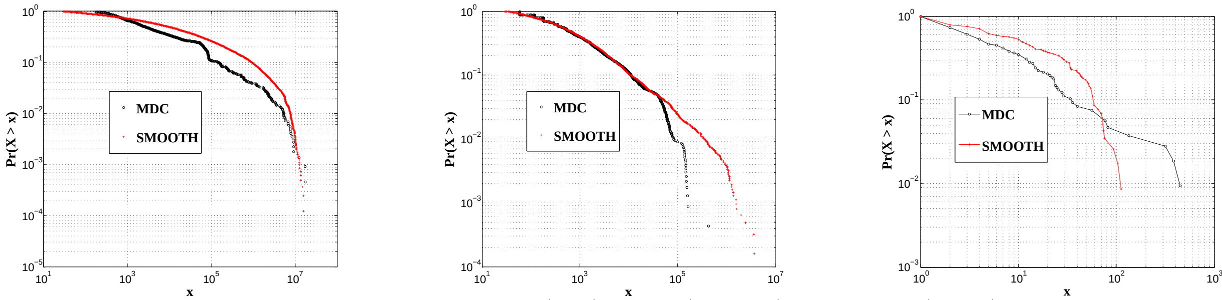


Figure 13: Comparison of the aggregated ICTs (left), CDs (middle), and CNs (right) distributions extracted from the MDC'12 Scenario and the synthetic traces generated by SMOOTH for the MDC'12 scenario (Table 2).

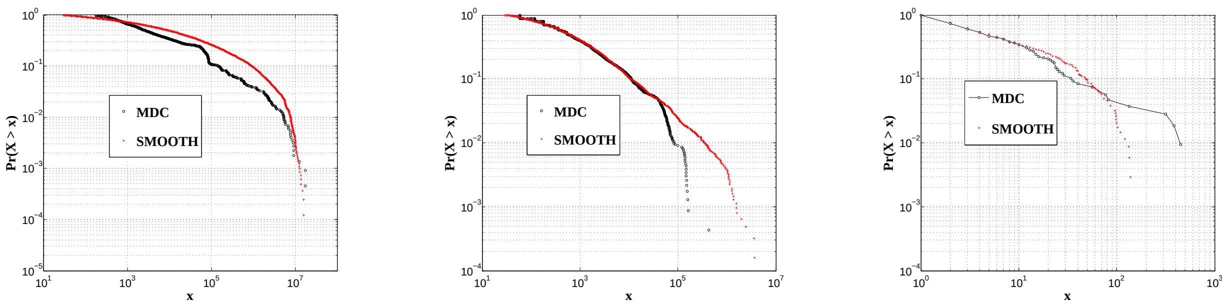


Figure 14: Comparison of the aggregated ICTs (left), CDs (middle), and CNs (right) distributions extracted from the MDC'12 Scenario and the synthetic traces generated by SMOOTH for the Small Scenario (Table 2).

other words, perhaps user 94 only has a few locations that are visited (e.g., bank, store, home) and user 23 visits two of them (e.g., bank and store). Similarly, we note that user 2 contacts user 75 more frequently than user 51 contacts user 68. Thus, based on the contact information (e.g., frequency of contacts, duration of contacts, etc.) and/or the amount of overlap between the locations visited by the users, we are interested in investigating the type of interactions between a pair of users. As discussed in Section 4, the values for parameters a and b in Equation 1 are based on the dataset as well as the definition used for a "previously visited" location. We are interested in exploring the values for a and b by defining the "previously visited" location similar to [12] and then comparing our results with [12].

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