The scaling of human mobility by taxis is exponential

Xiao Liang\textsuperscript{a}, Xudong Zheng\textsuperscript{a}, Weifeng Lv\textsuperscript{a}, Tongyu Zhu\textsuperscript{a}, Ke Xu\textsuperscript{a,*}

\textsuperscript{a}State Key Laboratory of Software Development Environment, Beihang University, Beijing 100191, People’s Republic of China

Abstract

As a significant factor in urban planning, traffic forecasting and prediction of epidemics, modeling patterns of human mobility draws intensive attention from researchers for decades. Power-law distribution and its variations are observed from quite a few real-world human mobility datasets such as the movements of banking notes, trackings of cell phone users’ locations and trajectories of vehicles. In this paper, we build models for 20 million trajectories with fine granularity collected from more than 10 thousand taxis in Beijing. In contrast to most models observed in human mobility data, the taxis’ traveling displacements in urban areas tend to follow an exponential distribution instead of a power-law. Similarly, the elapsed time can also be well approximated by an exponential distribution. Worth mentioning, analysis of the interevent time indicates the bursty nature of human mobility, similar to many other human activities.

Keywords:
Human mobility, Urban mobility, GPS data, Exponential distribution

1. Introduction

The emergence of location tracking devices (e.g., GPS navigator and mobile devices), and location-based services (LBS, e.g., Foursquare, Yelp check-in and Google places) provide unprecedented opportunities to study human mobility patterns from trillions of trails and footprints, which are of great

\textsuperscript{*}Corresponding author

Email addresses: liangxiao@nlsde.buaa.edu.cn (Xiao Liang), kexu@nlsde.buaa.edu.cn (Ke Xu)
significance in urban planning, traffic forecasting, marketing campaign, prediction of epidemics and designing of mobile network protocols.

Researchers observe that people’s daily activities (e.g., commuting between home and workplace, going shopping, and going vacation) follow reproducible mobility patterns by studying trackings of cell phone users’ locations. Similar results are also discovered from GPS trackings, wireless network traces, check-ins from location-based services and even movements of banking notes.

Be specific, Brockmann et al. observe that the distribution of displacements between consecutive reported sightings of the banking notes follows a power-law, and they conclude that human travel behavior can be described by Lévy walks with heavy-tailed pause time. Similarly, and observe that human trajectories data from GPS trackings could be approximated by Lévy flights. And researchers even notice obvious Lévy flights based on mobility patterns from trails of animals. Despite the prevailing Lévy walks, Gonzlez et al. discover existence of spatio-temporal regularity in human movements, indicating people are very likely to return to a few frequently visited locations. A high confidence in predicting human movements is found due to the underlying reproducibility of human mobility patterns by Song et al. The authors also propose a new model to characterize human mobility patterns. Han et al. demonstrate that the scaling law in human mobility could be explained by hierarchy of the traffic systems.

However, the datasets mentioned above also have their limitations. For example, banking notes perhaps are deposited in banks and then withdrawn after a long time, or transferred for many times between consecutive observations. As for trackings of cell-phone users, when people initiate or receive calls and text messages, they are probably on the way from their origins to destinations. Furthermore, the granularity of some datasets are coarse, and the trajectories are between cities that are far from each other, and the locations recorded may have large deviations from people’s actual movements.

In this paper, we study human mobility patterns for 20 millions of trajectories extracted from more than 10,000 taxis in urban areas of Beijing. Comparing to the other datasets mentioned above, the granularity of the taxis trails are in very fine granularity. Besides, the data might also reveal the effects of the urban traffic network on people’s movements.

The rest of the paper is organized as follows. In Section, we introduce the method of model selection. Section describes the data used in the
paper. We show our analysis and discuss the findings in Section 4. Finally, we conclude in Section 5.

2. Preliminary

Model selection is to identify the most appropriate model that is supported by the actual data from candidate models. Contrary to maximizing fit and null hypothesis tests, model selection criteria consider both fits with the data and complexity of models, and enable to compare multiple models at the same time. There are two criteria commonly used, which are Akaike information criterion (AIC) and Bayesian information criterion (BIC) [22, 23].

In this paper, we mainly employ AIC to compare two models: a power-law $y = Ax^{-\alpha}$ and an exponential $y = Be^{-\lambda x}$, where $A$ and $B$ are normalization constants. The steps of model selection are shown as follows.

1. Estimating the parameters of models using maximum likelihood method.
   The details about how to perform maximum likelihood estimates (MLE) of these models can refer to [24], [25] and [26].
2. Calculating the AIC scores for the models. The AIC score for model $i (i \in \{1, 2\})$ is given by
   \[ AIC_i = -2 \log L_i + 2K_i \]
   Here $L_i$ is the likelihood in which parameters are assigned with the estimated values from step 1 and $K_i$ is the number of parameters in the model $i$.
3. Determining the best models. The Akaike weights can be considered as relative likelihoods being the best model for the observed data. Let
   \[ AIC_{min} = \min_{i \in \{1, 2\}} \{AIC_i\} \]
   \[ \Delta_i = AIC_i - AIC_{min}, i \in \{1, 2\} \]
   Then, the Akaike weights are represented by
   \[ W_i = \frac{e^{-\Delta_i/2}}{\sum_{j=1}^{2} e^{-\Delta_j/2}}, i \in \{1, 2\} \]
   So the model corresponding with the largest Akaike weight should be selected as the best one.
3. Data description

To explore the urban movements, we use two GPS data sets, which were generated by over 10,000 taxis in Beijing, China, from Oct. 1st, 2010 to Dec. 31st, 2010 ($D_1$) and from Oct. 1st, 2008 to Nov. 30th, 2008 ($D_2$) respectively. The GPS data from every taxi were collected at about 1-minute intervals. In addition to location $l$ (longitude, latitude) and instantaneous velocity $v$, operational status $s$ (with passengers or without passengers) of taxis was also captured from GPS equipment at the same time. Thus, the GPS data for a taxi $k$ at time $t$ can be denoted by a tuple $(k, l, v, s, t)$. When a taxi was carrying customers, it offered the proxy to understand human mobility patterns in urban areas.

From both data sets, tens of millions of human trajectories can be extracted. More specifically, according to operational status collected, we can identify when and where customers got into and got off the same taxi. Therefore, a trajectory can be uniquely represented by $(k, l_O, t_O, l_D, t_D)$, which means that the customers departed from the origin $l_O$ at the time $t_O$ to the destination $l_D$ at the time $t_D$ with the aid of the taxi $k$. The tuples with the time $t$ between $t_O$ and $t_D$ for the taxi $k$ were associated with the trajectory. Here the displacement $\Delta L$ and the elapsed time $\Delta T$ for the trajectory can be calculated as follows:

$$\Delta l = |l_D - l_O|$$
$$\Delta T = |t_D - t_O|$$

If the next trajectory of the taxi $k$ is $(k, l_O, t_O, l_D, t_D)$, the interevent time $\tau$ that is the duration without passengers can be computed by

$$\tau = |t_O - t_D|$$

However, there were some abnormal tracks that need to be excluded from the results. For example, when $\Delta T < 1$ min and $\Delta T > 120$ min, the trajectory should be considered invalid because passengers seldom readily spend too short or too long time on taking taxis. Finally, we derive 12,028,929 trajectories in $D_1$ and 9,942,697 ones in $D_2$ as shown in Table\[I\]. It is worthy to note that our analyses are mainly based on $D_1$ whereas the $D_2$ intends to be compared with $D_1$ to detect some changes of trends.
Table 1: The numbers of trajectories and taxis in both datasets

|       | Number of trajectories | Number of taxis |
|-------|------------------------|-----------------|
| $D_1$ | Oct. 2010 3,932,107    | 11,686          |
|       | Nov. 2010 3,754,405    | 11,636          |
|       | Dec. 2010 4,342,417    | 11,562          |
|       | Total 12,028,929       | 11,686          |
| $D_2$ | Oct. 2008 5,111,144    | 10,695          |
|       | Nov. 2008 4,831,553    | 10,671          |
|       | Total 9,942,697        | 10,695          |

4. Statistical results and explanations

In this section, we first investigate the displacements between origins and destinations. Then the elapsed time of travels is analyzed and the correlation between displacement and elapsed time is revealed. Finally, the duration with no passengers (i.e., interevent time) is studied, which suggests human travel demands.

4.1. Displacement

For trajectories, the pairs of origin and destination reflect the purposes of human movements directly. As we know, a displacement is the distance of a line segment connecting the origin and destination. Contrary to the actual path traversed from the origin to destination in the city, the displacement is not influenced by geographic constraints and artificial interference. It is better to characterize the human mobility in urban areas.

Therefore, we measure the probability $P(\Delta l)$ with a displacement $\Delta l$ in the dataset $D_1$. As shown in Figure 1a, $P(\Delta l)$ increases suddenly in the beginning and reaches the peak when $\Delta l$ is about 2 km. After that, it decreases dramatically. The reason resulting in the rise at first is that the distances of human travels are seldom very short. Moreover, there are approximately 98% trajectories traversing a distance of less than 20 km, also suggesting that most movements occurred in urban areas. Intuitively, most individuals seem to be more apt to wander in the neighborhood of some places (e.g., homes, schools, and workplaces) in daily life. Consequently, the statistical distribution agrees with our experiences well.

Given the distribution of displacements, we partition it into two parts according to the displacement of 20km. For the first part, most displacements
occurred in urban areas, while for the latter part, these displacements often occurred between urban areas and suburbs. Because of economic consideration, few people choose taxis to traverse a large displacement. It seems that the distribution shows different trends in the two parts. Therefore, we utilize the AIC mentioned in Section 2 to compare two frequently used models: a power-law $P(\Delta l) \sim \Delta l^{-\alpha}$ and an exponential $P(\Delta l) \sim e^{-\lambda \Delta l}$ for the two parts. The detailed results for model selection are illustrated in Table 2. From the table, we can conclude the distribution of displacements can be well fitted by an exponential distribution with an exponential cutoff because of $W_{\text{exp}} \gg W_{\text{pow}}$ in the two parts. Moreover, the two different exponential fits observed in Figure 1a also support the conclusion further. We also notice that the exponential exponent for the first part is larger than the one for the latter part. It is reasonable because people travelling large displacements by taxis are less sensitive to taxi fares, resulting in decreasing slightly slower in the tail of distribution. In addition, it is interesting that the power-law exponents obtained for the first part in both datasets are not far from ones observed in [17] ($\mu = 1.59$) and [6] ($\mu = 1.75$). From above results, it can be inferred that displacements occurred in urban areas are distributed according an exponential rather than a power-law.
Furthermore, the distributions of displacements for both datasets are plotted respectively in Figure 1b. In order to reduce errors in the tail of distribution, we use complementary cumulative distribution function (CCDF) here. It appears that both distributions are almost coincident. Besides, the results of MLE for two data sets are very close to each other as shown in Table 2. These all indicate that human travel patterns have no obvious changes in recent years.

Table 2: Results of model selection for displacement in both datasets.

| Part        | Model       | $D_1$   | $D_2$   |
|-------------|-------------|---------|---------|
| First part  | Power law   | MLE for $\alpha$ | 1.4869  | 1.5108  |
|             |             | (95% CI)$^\S$ | (1.4859, 1.4880) | (1.5097, 1.5119) |
|             |             | $R^2$ †  | 0.9112  | 0.8950  |
|             |             | $W_{pow}^\dagger$ | 0        | 0       |
|             | Exponential | MLE for $\lambda$ | **0.2329**  | **0.2403**  |
|             |             | (95% CI) | (0.2328, 0.2331) | (0.2401, 0.2405) |
|             |             | $R^2$   | 0.9989  | 0.9995  |
|             |             | $W_{exp}^\dagger$ | 1        | 1       |
| Latter part | Power law   | MLE for $\alpha$ | 5.1048  | 5.2729  |
|             |             | (95% CI) | (5.0888, 5.1208) | (5.2519, 5.2939) |
|             |             | $R^2$ †  | 0.9119  | 0.9165  |
|             |             | $W_{pow}^\dagger$ | 0        | 0       |
|             | Exponential | MLE for $\lambda$ | **0.1698**  | **0.1768**  |
|             |             | (95% CI) | (0.1692, 0.1705) | (0.1760, 0.1777) |
|             |             | $R^2$   | 0.9707  | 0.9732  |
|             |             | $W_{exp}^\dagger$ | 1        | 1       |

$^\S$ A 95% confidence interval.

$^\dagger$ Coefficient of determination to measure the goodness of fit of a model.

$^\dagger$ Akaike weights representing relative likelihoods of models.

However, the observed shape of $P(\Delta l)$ may be caused by geographic heterogeneity (i.e., there are different statistical properties of human travels among distinct locations). We will intend to discuss the influences of geography on human mobility below. Here five representative local areas of circular regions with radius 1 km are selected, including Beihang university (BHU), Beijing Railway Station (BRS), Beijing Capital International Airport (BCIA), Xidan (a business district) and a residential district. These areas of-
ten have distinct transport features and population density. It is appropriate to exploit them to investigate the discrepancies caused by geographic heterogeneity.

The five distributions of displacements initiated in these regions for the $D_1$ dataset are plotted in Figure 2 separately. The obtained distributions, except BCIA, agree with each other very well and can be well approximated by the exponential fit, which also applies to the overall distribution of displacements as referred above. Also, most travels occurred in these areas have short displacements of less than 20 km. Nevertheless, movements initiated in BCIA often have larger displacements on average and show evident differences with other areas. The reason is that BCIA is located suburb of Beijing. Therefore, passengers who got off planes usually have to go to urban areas traversing long distances by taxis. At the same time, the tail of distribution appears to decay exponentially in the same trend with the others. In this paper we mainly focus on the movements in urban areas, so it can be concluded that the geographic heterogeneity does not affect our results on the observed human mobility patterns. The intrinsic travel demands in urban environments lead to the statistical pattern.

![Figure 2: Distributions of displacements in different areas. The black line represents the exponential fit with exponent 0.2329, which applies to overall distribution for $D_1$.](image)

It must be noted that our findings are not coincident with those obtained from bill notes [17] and mobile phones [6] which have demonstrated that the
distribution of displacements could be well approximated by a power-law or a truncated power-law. According to the characteristics of GPS data from taxis, there are probably two reasons that can be used to explain the inconsistency. Firstly, the movements involved in the datasets occurred mostly in urban areas and had small displacements. However, in other datasets, people travelled around the whole country by different transportation means and could traverse a long distance of more than 1000 km. The travels with long distances often happened between cities. So the displacements in urban environments decay faster than those measured from other datasets. Secondly, taxi fare increases with the distance passed by. When people intend to travel long distances, they may choose other public transportation means rather than taxis out of economic consideration. As a result, trajectories with long displacements may have lower likelihood to be captured by taxis. In summary, because of these two factors, the probability distribution of displacements in urban areas decays more quickly than those in other datasets and is inclined to be exponential. To what degree the two factors affect human travel demands in cities should be studied on more datasets further.

In addition, [2] study the travels of only 50 taxis collected from four cities in Sweden. They find the distribution of trail length follows a double power-law, implying both intracity and intercity movements each show a scale property. In their results, we notice that distribution in cities still follows a power-law in spite of economic effects. Compared with their dataset, our datasets are more comprehensive and cover the whole city fully. Also, through analyzing GPS traces of taxis in Lisbon, [13] illustrate that trip distance can be well represented by an exponential distribution. It is worthy to note that the exponential parameter they obtained ($\lambda = 0.26$) is not far from ours. [11] consider GPS data of private cars in Florence urban areas. It is observed that total distance of daily round trips for each vehicle agrees with an exponential distribution very well. They also identify vehicle stop positions and discover single trip length distribution deviates from an exponential and favors a power law gradually when trip length becomes longer. In summary, the results of urban mobility in [13] and [11] are consistent with ours. Thus, it can be conjectured that the phenomenon may not happen accidentally and exist in urban areas of cities widely.

4.2. Elapsed time

Elapsed time $\Delta T$ means the time that passengers spend on travelling from their origins to destinations. Given the origin and destination, the
elapsed time may be influenced by many factors such as current transportation contexts, length of path chosen and habits of driving, etc. We compute the elapsed time of trajectories in both datasets. The distribution of elapsed time from the dataset \( D_1 \) is shown in Figure 3a. Similar to displacements, the distribution of elapsed time increases when \( \Delta T \leq 7 \) min, and then decreases dramatically. There are about 98.9% trajectories in \( D_1 \) and 99.5% ones in \( D_2 \) with elapsed time of less than 60 min. As we know, short elapsed time was mainly caused by most trips with small displacements in urban areas, while long elapsed time was often caused by traffic jams and long trips between urban areas and suburbs. Likewise, we partition the distribution into two parts according to the elapsed time of 60 min. In order to decide good fits, the method of model selection mentioned in Section 2 is used as well. The detailed results are listed in Table 3, illustrating that the first parts of distributions can be well approximated by exponential fits in both datasets, while the latter parts of distributions in \( D_1 \) and \( D_2 \) are inclined to an exponential and a power-law respectively. Because we mainly focus on the movements in urban areas, it can be concluded from the first parts of distributions that elapsed time of trips in urban areas agrees with an exponential very well.

![Figure 3](image.png)

**Figure 3**: Elapsed time of trajectories. (a) The probability density function \( P(\Delta T) \) obtained for studied dataset \( D_1 \) in semi-log scale. The red dashed line indicates an exponential with the measured exponent \( \lambda = 0.0797 \). The blue dotted line represents an exponential with measured exponent \( \lambda = 0.0692 \). (b) The CCDFs of elapsed time for both datasets.

Furthermore, in order to explore the dynamic trends of elapsed time, we plot the distributions of elapsed time for both datasets respectively. As
| Part       | Model       | $D_1$       | $D_2$       |
|------------|-------------|-------------|-------------|
| First part | Power law   | MLE for $\alpha$ | 1.5549 | 1.7057 |
|           | $\alpha$   | (95% CI)$^\S$ | (1.5539, 1.5559) | (1.7046, 1.7069) |
|           | $R^2$      | †            | 0.8523 | 0.8318 |
|           | $W_{pow}$  | ‡            | 0      | 0      |
|           | Exponential| MLE for $\lambda$ | **0.0797** | **0.0912** |
|           | $\lambda$  | (95% CI)    | (0.0796, 0.0797) | (0.0911, 0.0912) |
|           | $R^2$      | †            | 0.9927 | 0.9868 |
|           | $W_{exp}$  | ‡            | 1      | 1      |
| Latter part| Power law   | MLE for $\alpha$ | 5.4924 | 5.7775 |
|           | $\alpha$   | (95% CI)    | (5.4602, 5.5246) | (5.7243, 5.8306) |
|           | $R^2$      | †            | 0.9965 | 0.9991 |
|           | $W_{pow}$  | ‡            | 0      | 1      |
|           | Exponential| MLE for $\lambda$ | **0.0692** | 0.0727 |
|           | $\lambda$  | (95% CI)    | (0.0688, 0.0696) | (0.0720, 0.0735) |
|           | $R^2$      | †            | 0.9984 | 0.9907 |
|           | $W_{exp}$  | ‡            | 1      | 0      |

$^\S$ A 95% confidence interval.

$^\dagger$ Coefficient of determination to measure the goodness of fit of a model.

$^\ddagger$ Akaike weights representing relative likelihoods of models.
shown in Figure 3b, it seems that the distribution in $D_2$ drops more quickly than that in $D_1$, indicating that passengers have spent more time on taking taxis on average. At the same time, the displacements people travelled have not changed too much as mentioned in Subsection 4.1. Besides, we can see from Figure 4 that the mean of elapsed time passengers spent on the same displacement in $D_1$ is basically longer than one in $D_2$. So it can be concluded that the transportation conditions in Beijing have become worse since 2008, which agrees with the facts very well. From Figure 4, we also notice that the rate of growth of elapsed time becomes slower especially when the displacement is larger than 20 km, which implies a higher average speed. It is reasonable since trips with large displacements are expected to be away from traffic jams in urban areas.

![Figure 4: Comparison of traffic congestion status between the two datasets. The red/blue point represents the mean of elapsed time for certain displacement.](image)

4.3. Correlation between displacement and elapsed time

The first parts of distributions of displacement and elapsed time both follow exponentials very well. In this subsection we will discuss the correlation between them. Note that we use the dataset $D_1$ for experiments below. The similar phenomena also apply to the dataset $D_2$.

For every individual movement, the displacement $\Delta l$ and the elapsed time $\Delta T$ have been measured. Therefore, there are a lot of trajectories with the
The same elapsed time $\Delta T$, which often correspond to different displacement $\Delta l$. The correlation can be shown in Figure 5. From the graph, we can observe that the mean of displacements increases with elapsed time. The growth rate becomes slower gradually when elapsed time is large. It demonstrate that the long elapsed time was often caused by traffic congestion leading to smaller average speed. Especially, when $\Delta T \leq 40$ min, the means can be well fitted by a linear function $\Delta l = \mu \Delta T$ with $\mu = 0.3326$. Here it must be emphasized that the relation between $\Delta l$ and $\Delta T$ is numerical approximation and does not hold in general. As we know from the above observations, displacements of 98% trajectories are less than 20 km and elapsed times of 95% trajectories are less than 40 min. Hence the relationship between exponential exponents of the first parts of both distributions can be approximately derived as follows.

$$E(\Delta l | \Delta T) = \mu \Delta T$$
Hence,
\[
\sum_{\Delta T} E(\Delta l|\Delta T)P(\Delta T) = \mu \sum_{\Delta T} \Delta T P(\Delta T)
\]
\[
E(\Delta l) = \mu E(\Delta T)
\]

Because the first parts of distributions of displacement and elapsed time are relevant with most trajectories and decay exponentially, we can obtain the expectations of both distributions approximately in the forms
\[
E(\Delta l) = \frac{1}{\lambda_l}, E(\Delta T) = \frac{1}{\lambda_T}
\]

So the relationship is given by
\[
\lambda_T = \lambda_l \mu
\]

From the Table 2 and 3, we can acquire \(\lambda_l = 0.2329, \lambda_T = 0.0797\). Also \(\lambda_T\) can be calculated from relationship \(0.2329 \times 0.3326 \approx 0.0775\). The value is very close to the MLE for \(\lambda_T\).

4.4. Interevent time

After carrying passengers from origins to destinations, taxis begin to wander or wait in the roads in order to seek new passengers. The interevent time often means the time spent on waiting for new customers. Intuitively, interevent time can be used to indicate degree of taxis’ busyness during certain period of time. In fact, short interevent time often means that there are more demands for travelling statistically. Therefore, to a large extent, it enables to reflect human travel demands indirectly.

In order to characterize human travel demands, we compute the interevent time \(\tau\) from trajectories of \(D_1\). The CCDF of interevent time from dataset \(D_1\) is shown in Figure 6a. From the graph, we can see about 98% of interevent times are no more than 200 minutes. When interevent time is below 200 minutes, the curve fits a power-law very well. Then, it decreases exponentially. The deviation from a power-law in the tail is caused by two reasons. On the one hand, long interevent time often occurred late at night when there were few travel demands. On the other, many taxi drivers stopped working to have a rest at midnight. Also, two different taxis are chosen randomly and the CCDFs of interevent time are plotted in Figure 6b and 6c respectively.
Both curves can be well approximated by power-laws and the two exponents are only slightly different. Moreover, we plot the distribution of power-law exponents of CCDFs for all taxis in Figure 6d. As shown in the figure, most taxis have similar power-law exponents around the mean value 1.19. It must be remarked that the exponent obtained is concerned with CCDF. So for probability density function (PDF), the exponent of distribution is very close to 2.

In summary, it can be concluded that durations of taxis without passengers (inactivity) is close to be distributed according an inverse-square power-law, while durations of taxis with passengers (activity) is well approximated by an exponential. The results resemble ones discovered in many animals with patterns of activity and inactivity where durations of inactivity follow inverse-square power-law distributions approximately while durations of activity are fitted by exponential distributions [27]. There may be some subtle relations between them deserving to be studied further.

Furthermore, we divide the taxi trajectories into two categories based on workday and rest day (including weekends and public holidays). Then we calculate the mean values of interevent time occurred at different hours, which are shown in Figure 7. As the graph indicates, there are more than 30 minutes of interevent time during the time slot of 23:00-5:00 in workday and rest day because people often stay at home for a sleep and seldom have needs to travel. We also notice that the interevent time during the time slot is shorter in rest day than in workday, which is caused that people often readily go out for entertainments in rest day. At the same time, people usually have a rest for lunch resulting in longer interevent time during the time slot of 11:00-12:00. As for workday, there are intensive trips occurred in time slots of 7:00-9:00 and 17:00-19:00 corresponding the rush time when people go to work and go off work. As for rest day, there are more travel demands in the afternoon or evening than in the morning. Therefore, it can be concluded that human travels in cities have characteristic of bursts, behaving as a large amount of movements emerge suddenly separated by long periods of inactivity because of strong periodic variations of travel demands in cities.

The results of interevent time demonstrate that human travel demands follow non-Poisson processes like many other human activities, for example, sending or receiving Emails, web browsing, library loans [28], etc. In contrast with an exponential distribution, a heavy-tailed distribution of interevent time allows for events occur frequently in a relatively short period of time,
Figure 6: Interevent time from the dataset $D_1$. (a) The CCDF for all taxis with exponent $\alpha = 1.12$. (b-c) The CCDFs for two taxis with exponents $\alpha$ are 1.01 and 1.35 respectively. (d) The distribution of power-law exponents of CCDFs for all taxis with mean $\mu = 1.19$, standard deviation $\sigma = 0.26$. 
then are inactive for a long time. So the periodic variation of travel demands in cities may be a part of reason to account for the results of interevent time.

5. Conclusion and future work

In this paper, we build models for 20 million trajectories collected from 10 thousand taxis in urban areas in Beijing. The main contributions of this paper is threefold: (i) models fitting the taxis’ traveling displacements in urban areas tend to follow an exponential distribution instead of a power-law, probably caused by the range of the movements and economic effects; (ii) similarly, the elapsed time can also be well approximated by an exponential distribution; (iii) bursty activities are observed in modeling the interevent time between the trajectories, which also help validate the bursty nature of human daily activities.

As future work, we are interested to further explore the two factors that affect the trajectories of taxis’ (i.e., the range of movements, and economic effects). Besides, we observe that the quality of the mobility data heavily relies on length of elapsed time for trajectories, and is dataset dependent. For example, elapsed time for movement of banking notes are normally long, and trajectories of short elapsed time indicate good data quality. To the opposite, elapsed time for trackings of cell phone users’ locations is usually short, and thus long elapsed time indicate high quality of the trajectories. So we are
interested to study to what extent the limitations of the data influence the 
modeling of the distribution of displacements. Last but not least, we would 
like to explore the relationship between mobility patterns modeled from taxis 
trajectories, and mobility patterns observed in other datasets.

Acknowledgements

We would like to thank the anonymous reviewers for their valuable sug-
gestions. We are also very grateful to Zhiyuan Cheng for helping us revise 
the manuscript. The research was supported by the fund of the State Key 
Laboratory of Software Development Environment (SKLSDE-2011ZX-02).

References

[1] H. D. Rozenfeld, D. Rybski, J. S. Andrade, M. Batty, H. E. Stanley, 
H. A. Makse, Laws of population growth, Proceedings of the National 
Academy of Sciences of the United States of America 105 (2008) 18702–
18707.

[2] B. Jiang, J. Yin, S. Zhao, Characterizing the human mobility pattern 
in a large street network, Phys. Rev. E 80 (2009) 021136.

[3] E. Agliari, R. Burioni, D. Cassi, Word-of-mouth and dynamical inhomoge-
neous markets: an efficiency measure and optimal sampling policies 
for the pre-launch stage, IMA J. Manage. Math. 21 (2010) 67–83.

[4] L. Hufnagel, D. Brockmann, T. Geisel, Forecast and control of epidemics 
in a globalized world, Proceedings of the National Academy of Sciences 
of the United States of America 101 (2004) 15124–15129.

[5] K. Lee, S. Hong, S. J. Kim, I. Rhee, S. Chong, SLAW: A mobility model 
for human walks, in: INFOCOM 2009, IEEE, 2009, pp. 855–863.

[6] M. González, C. Hidalgo, A.-L. Barabási, Understanding individual 
human mobility patterns, Nature 453 (2008) 779–782.

[7] C. Song, Z. Qu, N. Blumm, A.-L. Barabási, Limits of predictability in 
human mobility, Science 327 (2010) 1018–1021.
[8] D. Choujaa, N. Dulay, Predicting human behaviour from selected mobile phone data points, in: Proceedings of the 12th ACM international conference on Ubiquitous computing, Ubicomp ’10, ACM, Copenhagen, Denmark, 2010, pp. 105–108.

[9] Y. Zheng, Q. Li, Y. Chen, X. Xie, W.-Y. Ma, Understanding mobility based on GPS data, in: Proceedings of the 10th international conference on Ubiquitous computing, UbiComp ’08, ACM, Seoul, Korea, 2008, pp. 312–321.

[10] I. Rhee, M. Shin, S. Hong, K. Lee, S. Chong, On the Levy-walk nature of human mobility, in: INFOCOM 2008, IEEE, 2008, pp. 924–932.

[11] A. Bazzani, B. Giorgini, S. Rambaldi, R. Gallotti, L. Giovannini, Statistical laws in urban mobility from microscopic GPS data in the area of Florence, Journal of Statistical Mechanics: Theory and Experiment 2010 (2010) P05001.

[12] B. Jiang, T. Jia, Exploring human mobility patterns based on location information of us flights, 2011. ArXiv:1104.4578v2 [physics.data-an].

[13] M. Veloso, S. Phithakkitnukoon, C. Bento, N. Fonseca, P. Olivier, Exploratory Study of Urban Flow using Taxi Traces, in: The First Workshop on Pervasive Urban Applications (PURBA) 2011.

[14] M. Kim, D. Kotz, S. Kim, Extracting a mobility model from real user traces, in: INFOCOM 2006, IEEE, 2006, pp. 1–13.

[15] Z. Cheng, J. Caverlee, K. Lee, Exploring Millions of Footprints in Location Sharing Services, in: ICWSM 2011, Cholera.

[16] E. Cho, S. Myers, J. Leskovec, Friendship and Mobility: User Movement In Location-Based Social Networks, in: KDD 2011.

[17] D. Brockmann, L. Hufnagel, T. Geisel, The scaling laws of human travel, Nature 439 (2006) 462–465.

[18] G. Viswanathan, V. Afanasyev, S. Buldyrev, E. Murphy, P. Prince, H. E. Stanley, Levy flight search patterns of wandering albatrosses, Nature 381 (1996) 413–415.
[19] R. P. D. Atkinson, C. J. Rhodes, D. W. Macdonald, R. M. Anderson, Scale-free dynamics in the movement patterns of jackals, Oikos 98 (2002) 134–140.

[20] C. Song, T. Koren, P. Wang, A.-L. Barabási, Modelling the scaling properties of human mobility, Nature Physics 6 (2010) 818–823.

[21] X. Han, Q. Hao, B. Wang, Z. Tao, Origin of the scaling law in human mobility: Hierarchy of traffic systems, Physical Review E 83 (2011) 2–6.

[22] J. B. Johnson, K. S. Omland, Model selection in ecology and evolution, Trends in Ecology & Evolution 19 (2004) 101–108.

[23] T. Hastie, R. Tibshirani, J. Friedman, The elements of statistical learning, Springer, 2008.

[24] A. Clauset, M. E. J. Shalizi, Cosma Rohilla Newman, Power-law distributions in empirical data, SIAM Rev. 51 (2009) 661–703.

[25] A. M. Edwards, R. A. Phillips, N. W. Watkins, M. P. Freeman, E. J. Murphy, V. Afanasyev, S. V. Buldyrev, M. G. E. da Luz, E. P. Raposo, H. E. Stanley, G. M. Viswanathan, Revisiting Lévy flight search patterns of wandering albatrosses, bumblebees and deer, Nature 449 (2007) 1044–1048.

[26] A. Mashanova, T. H. Oliver, V. A. A. Jansen, Evidence for intermittency and a truncated power law from highly resolved aphid movement data, J. R. Soc. Interface 7 (2010) 199–208.

[27] A. Reynolds, On the origin of bursts and heavy tails in animal dynamics, Physica A: Statistical Mechanics and its Applications 390 (2011) 245–249.

[28] A.-L. Barabási, The origin of bursts and heavy tails in human dynamics, Nature 435 (2005) 207–211.