Multi-modal Modeling of Urban Mobility

Manu Bansal, Ankur Gupta, Manu Jose, Saurabh Trivedi, Mario Gerla

Computer Science Department,
University of California, Los Angeles
Los Angeles, CA, USA
{manub, ankgupta, mjose, strivedi, gerla}@cs.ucla.edu

Abstract—Design and efficacy of a routing protocol for mobile ad-hoc networks strongly depends on the underlying mobility pattern of the mobile nodes. Counter to the perception of mobility being random in time and space, we show that spatial modality is a key trait of human mobility. Most of the mobility of an individual can be captured by a small fraction of all locations, called spatial modes, visited by the person. Further, we show that there is strong predictability of spatial modes in time. We combine these properties into a mobility model that accurately captures more than 90 % of the mobility of a typical individual.

Any realistic mobility model must either derive out of real traces or be compared back to them. In developing our mobility model, we extensively analyze publicly available cell tower connectivity traces of urban users. We apply the technique of multidimensional scaling to fill in missing location information in the traces with high reliability. We believe this approach will make available a wealth of connectivity traces for mobility analysis which are otherwise considered unfit for the task.

Keywords—mobility modeling; trace analysis; ad-hoc networks; vehicular networks

I. INTRODUCTION

With the advent of Mobile and Vehicular Ad-hoc Networks (MANETs and VANETs), several new applications have emerged, such as vehicular urban sensing and delay-tolerant content delivery [18]. These applications depend on network data exchange through physical contact of mobile nodes in urban environments. It is well known that the performance of routing protocols in such environments critically depends on the underlying motion characteristics of the constituent nodes [16][13]. It is our goal in this study to develop a provably realistic mobility modeling framework.

A wealth of mobility models has been proposed in literature. These are reviewed in §II. These models range from purely social survey-based models to purely random mathematical processes. At one end of the spectrum, the models are very realistic, but are tedious to represent and use in network simulations. On the other end, some models are overly simplistic and unable to faithfully represent the true nature of mobility and, at the same time, distinguish them among each other. We use the term mode to refer to the most frequent value of a random variable, as in statistics. A spatial mode is thus defined to be a frequently visited location of the user (described in §V-A). Further, we show that these modes are highly predictable in time. They are visited in what we call activity modes. Activity modes are groups of spatial modes that frequently occur together or back-to-back in a travel cycle of the user (described in §VI-C).

In achieving the goal of developing a necessarily realistic mobility model that is usable in network simulations, we are faced with several challenges. The prime challenge is validation, i.e. to be able to claim that our modeling is, indeed, true to reality. We ensure this by starting with a real mobility trace for all our deductions. Lack of rich traces with GPS information makes the problem harder. We surveyed the publicly available traces at CRAWDAD [17] and found MIT Reality Dataset [7] most suited to our purpose. This trace captures the mobility of 100 users in and around the MIT Media Laboratory over a period of nearly 1 year. The trace records cell-tower association information with a very high degree of completeness in time. However, precise GPS information is not available in the trace. Despite this, we choose to use the trace due to its richness in time, the number of users and the environment it represents. Detailed description of the dataset can be found at [17]. To solve the challenge of missing GPS information, we have successfully applied the technique of Classical Multidimensional Scaling. This allows us to fill in the required location information with a high degree of reliability without depending on any external information.

Further, we want to develop a model that requires only a small parameter set to describe the mobility of a population of users. Thus, we need to identify trends in the mobility patterns that can be parametrized to generate models for many users. The key trait of our characterization is the recurrent theme of modality in mobility. We show that users have a few spatial modes that capture most of the their mobility and, at the same time, distinguish them among each other. We use the term mode to refer to the most frequent value of a random variable, as in statistics. A spatial mode is thus defined to be a frequently visited location of the user (described in §V-A). Further, we show that these modes are highly predictable in time. They are visited in what we call activity modes. Activity modes are groups of spatial modes that frequently occur together or back-to-back in a travel cycle of the user (described in §VI-C).

Once the spatial modes are identified together with activity modes, the motion of users is predictable with accuracy rates up to 90%, and is captured by standard classifiers.

Our key contributions can be summarized as follows:

• Developing a set of techniques to reliably utilize cell-
tower connectivity traces for mobility modeling.
- Establishing the existence of modality in spatial and temporal characterization of mobility.
- Exploiting modality to use standard classifiers for modeling and predicting mobility with a very high degree of accuracy.

The rest of the paper is structured as follows. In §II, we place our work in perspective with respect to prior work in mobility modeling. In §III, we describe our approach to smoothen out the data over cell-hopping and jittery mobility. In §IV, we show how to localize cells using information from cell-association transition sequence using multidimensional scaling. In §V, we analyze the pre-processed data to validate the hypothesis of existence of a few spatial modes. In §VI, we analyze the predictability of temporal patterns in mode selection. We conclude in §VII with some future directions.

II. RELATED WORK

The earliest and most popular class of mobility models is synthetic random mathematical models. An important example is the Random Waypoint Mobility Model [16]. A related model for group mobility is the Reference Point Group Mobility Model [13]. These models are easy to simulate and analyze mathematically. It should be noted, however, that they face a time-decay phenomenon when simulated without caution. There is a body of literature solving this problem for a wide class of random models [2] [20] [27].

The simplicity of random models comes at the cost of realism. It has been argued that these models are not the best representations of human mobility. Hotspot-based models reveal the power-law characteristics of visit point distributions that are observed in real traces [24]. The work in [24] studies aggregate statistics of a population of mobile nodes in an urban environment, as well as time-aggregated statistics of visit patterns for individual nodes. These results are derived through analysis of real traces. We wish to make a distinction between two lines of contributions made through [24] and similar works: 1) discovery of macroscopic mobility statistics, and 2) development of models that exhibit these characteristics. Some recent works have focused on the first aspect of finding properties through rich cell-phone connectivity traces of a large population [25] [10]. Some of the previous works, including simulators, have focused primarily on the second aspect of building a model that could be configured to exhibit the requisite properties [28] [14] [3]. Concepts to design mobility models include modeling of social behaviors [6], modeling scenario motion constraints [21] [15] and modeling macroscopic traffic flow constraints [19]. A major difficulty in using such models is to reliably and efficiently configure them to mimic the target scenario. More often than not, the target properties are not clear as it is still an active area of research. Even when they are, it is usually tedious to configure model parameters. Techniques involved include specifying full daily itineraries of every user in the system and specifying many hotspots on the plane of motion. The configuration can be so tedious as to render the model useless or to severely limit the realism of simulation. Hence, there is a need for a parsimonious model that bridges the two lines of work, as has been emphasized in [22].

The requirement of succinct yet realistic model makes the problem unwarrantably hard. This has motivated another line of work, where the goal is to identify and cater to only those properties of mobility that have a significant impact on network performance under study, thus relaxing the model on other aspects [1]. Striking a balance between all three components of a model is still an open playground. Some surveys summarize the wide constellation of mobility modeling [11] [5].

Our work is set in the vision of realistic and succinct mobility modeling. Towards this end, we employ real trace analysis to discover properties of mobility that lend itself to succinct modeling. Our key-premise is that the mobility of a user is actually predominantly represented by a very few states, which we call modes, in both space and time behaviors. Choosing to trade-off slight accuracy can hugely cut down the state representation. To the best of our knowledge, such a multi-modal approach in every dimension of mobility has not been applied fruitfully before this paper.

III. TRACE SMOOTHING

The location of a mobile node is unique at any given instant, but the mapping between location and cell tower is not, i.e., a stationary user can be in the range of more than one tower. This frequently leads to a cell-hopping behavior in response to time-varying signal qualities from the visible towers. The hopping interval can be as small as few seconds. The result is splitting of cell association time among hoppers.

In the Reality traces, we observed strong presence of such cell-hopping behavior, especially between the principal cell IDs. The magnitude of distortion caused by hop-splitting is expressed in Table I. It shows the fraction of time slices that are recognized as part of a hopping sequence by our algorithm and, therefore, attributed to both the involved cell IDs. These fractions are computed with respect to total time attributed to the two involved cell IDs individually, including the common portion. The individual fractions with respect to the entire trace duration with and without accounting for hopping are also shown.

Table II shows example transition sequences involving cell-hopping. cellId is the absolute cell ID, cellIdx is a locally indexed version of cellId and cellIdSx is the cellIdx value after smoothing over hopping sequences. A value of 0 represents no-signal, −2 represents phone turn-off and −1 represents phone turn-on. The desired labeling of cell IDs for such a sequence is a single cell ID, representative of
the current location of the node. Our smoothing procedure involves detection of hopping sequences and relabeling of hop time-slices to discretize cell associations. The two steps are described ahead.

A. Cell-hopping detection

A hopping pattern is detected by the recurrence of a cell ID within a short time interval, \( R \), of its previous occurrence, indicating a rapid re-association. The intuition is that a travel pattern starting and ending at the same location (same cell ID) visiting other locations (intermediate cell IDs) in a small time interval is either impossible or unreasonable. The smallest cell in an urban area has radius on the order of 100m and for a reasonable average vehicular travel speed is 10m/s (\( \approx 22 \text{mph} \)), it would take about 10s to exit a cell if the cells were disjoint. Movement out of the home cell to return to the same cell corresponds more likely to an errand rather than simple commute without stay. A vehicular commute would reasonably involve a stay of at least a couple of minutes at the destination cell, thus ruling out recurrence of the home cell within a few minutes.

Based on the traces, \( R = 5 \)min effectively detects hopping sequences. This parameter also naturally provides a handle for smoothing out short errands that make the mobility jittery without affecting the macroscopic pattern. An example scenario is motion in a lunch break from the primary work location cell ID. We choose not to distinguish such intervening cell IDs by choosing \( R = 40 \)mins and relabeling the corresponding time slices to belong to the home cell ID. The notion of home cell ID is ambiguous in a strong hopping pattern as in Table II.

B. Cell discretization

Figure 1 shows various overlapping-cells scenarios. A node in the region of intersection will experience cell-hopping behavior among the component cells. To label the intersecting region as a unique location, it must be ascribed to one of the components. Also, some cell IDs may always or majorly be seen as hoppers with other cell IDs. We merge such cell IDs into one of the containing hoppers. We use the following rules to merge cells and round-off an intersection to a single cell ID.

With a slight abuse of notation, let \( A \) denote the total time spent at cell ID \( A \), including any time spent hopping or in intersection with another cell ID determined through smoothing. Similarly, let \( A_0 \) denote the time spent solely at \( A \), and let \( A \cap B \) denote the time spent in the intersection of cell IDs \( A \) and \( B \), which will extend to intersections of any number of cell IDs. The following rules are used to discretize cell association times:

1) **Independent and weak cells.** A cell ID \( B \) is independent if \( B_0 \geq 0.5 \times B \), weak otherwise.

2) **Rounding.** An overlapping region \( A \cap B \ldots \cap K \rightarrow \max(A, B, \ldots, K) \).

3) **Dissolve.** A weak cell ID \( A \) is dissolved and merged into \( B \) such that \( A \cap B > A \cap C \) for all cell IDs \( C \neq A, B \). Thus, \( A_0 \rightarrow B \).

The above set of rules merges cell IDs in a manner that preserves a small cell ID that is not majorly involved in hopping and is, therefore, an important feature of the user’s mobility, while strengthening a big cell ID by absorbing smaller majorly intersection cells into it. Such small cell IDs are not significant in characterization of the location distribution and only act to split up the time spent at the important locations.

IV. Localization and Clustering

The data traces we use in this work do not have GPS location information. However, the temporal pattern of cell association can be used to deduce the relative localization of cell IDs to a high degree of reliability for the purposes of mobility characterization. We next describe our localization procedure.
A. Adjacency from transition sequence

A sample of the data trace is shown in Table II. The trace has a row for every cell ID transition, including transitions to and from lack-of-signal or phone-turn-off. A consecutive pair of cell IDs indicates that the two cells are adjacent and, possibly, overlapping. Further, if two cells A and B are not neighboring, travel from A to B will involve going through intermediate cells. The minimum number of intermediate cells in the trace provides an estimate of their separation. While this separation may not be the true geographical separation in the event that there does not exist a direct path between the two cells, or the the user never traversed it, this estimate can be interpreted as the effective distance between A and B for this user. Thus, it naturally incorporates the separation on map in addition to the geographical separation.

We first build the symmetric adjacency matrix by considering the pairs of contiguous cell IDs. We then compute the all-pair shortest paths on this adjacency, which reveals all the reachability estimates that could be derived from the trace. To further improve our estimates, we combine the adjacency information from all users before computing the shortest paths.

B. Multidimensional scaling

Given a set of points whose pair-wise distances are known, it is possible to embed them in a space of appropriate dimension so that the distances are preserved. The minimum number of dimensions needed for such an embedding depends on the distances. The general technique used to solve this problem is Multidimensional Scaling [4]. A multidimensional scaling algorithm tries to minimize the disparity between the pairwise distances of candidate set of point locations and the input pairwise distances. Variants of the algorithm use different metrics to measure the disparity, the most common of which are strain and stress. An optimization search is performed on the disparity metric to find the optimal point localization to within a desired error bound.

If the distances describe a point-set on a 2-dimensional plane, it must be possible to embed them back in two dimensions. Based on the intuition that the shortest-path distance matrix we computed above describes points on a map, we use Classical Multidimensional Scaling in MATLAB [26] to embed a user’s visited cell-towers in two dimensions. The output for a particular user is shown in Figure 2. Lines connecting points show the edges in the adjacency matrix used to generate the distance matrix for these cell-towers.

![Cell-tower localization for a particular user using Classical Multidimensional Scaling. Circles represent cell-tower locations in 2D plane; edges represent the seed adjacency matrix.](image)

**Figure 2.** Cell-tower localization for a particular user using Classical Multidimensional Scaling. Circles represent cell-tower locations in 2D plane; edges represent the seed adjacency matrix.

### Table III

<table>
<thead>
<tr>
<th>cell</th>
<th>top ev</th>
<th>normalized ev</th>
<th>bottom ev</th>
<th>normalized ev</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>41376</td>
<td>1</td>
<td>-629.97</td>
<td>-0.015225</td>
</tr>
<tr>
<td></td>
<td>31734</td>
<td>0.76696</td>
<td>-4642.7</td>
<td>-0.11221</td>
</tr>
<tr>
<td></td>
<td>12508</td>
<td>0.30231</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The remarkably low distortion in adjacency edges indicates that the point set is reliably embedded in two dimensions. Points that are adjacent according to the adjacency matrix (joined by an edge) are successfully placed closed on the 2D plane. The accuracy of embedding is further verified by analyzing output eigenvalues of the scaling algorithm. These are shown in Table III for the same user.

V. SPATIAL MODES

A. Existence of spatial modes

We begin the multi-modal modeling of user mobility by establishing the notion of spatial modes. We study the visit frequency distribution of each user over the data trace period. The visit points and temporal weights on these points
are fairly uniformly distributed in the Random Waypoint mobility model over the entire space of motion. Further, these distributions are homogeneous over the population of simulated users. On the contrary, we observe a strong localization trend where users tend to spend most of their time at a few locations from the entire visit point set. Further, these locations vary across users, marking a heterogeneity in spatial modes. Even for a single user, the locations are highly patterned in the simulation space, as seen in Figure 2 and Figure 3.

![Figure 3](image3.png)

**Figure 3.** Existence of spatial modes. More than 70% users have less than 10 modes accounting for 90% of their entire time.

After analyzing the data for all 100 users, we have the following spatial mode statistics:

1) The mean number of modes that account for 90% of a user’s mobility is 7.7.
2) The mean number of modes with more than 1% of stay time is 7.6.
3) More than 70% of all users have less than 10 modes accounting for 90% of their mobility.

These characteristics directly establish the existence of spatial modality.

**B. Temporal mode preference**

The identification of existence of strong modality in spatial visit preference enormously simplifies the problem of mobility prediction by down-sizing it to a few locations per node. All our further study of mobility is based on spatial modes. We next study the temporal visit patterns of the modes which, once characterized, will allow us to predict the mode of the user in space and time, thus fully characterizing the mobility.

Our intuition is that the mobility of a user is strongly periodic with a period equal to 24-hours, corresponding to the daily life cycle. Further, the mobility is strongly characterized by roughly two locations, corresponding to the home and work places, i.e. most of the time is spent on these two axis locations. To dwell into this notion, we plot the time spent at top-k modes by the hour of the day, aggregated over the entire duration of the trace. This is show in Figure 4. Each color represents a particular mode. The one at the bottom is the most frequent mode, with decreasing frequency as one goes up in the stack of bars. The top bar represents the state of no-signal, while the bar below it represents all locations other than the top-k modes.

There are four remarkable properties of the daily pattern of mode visit. First, all top-k modes show a clear bias to either the day-time hours or the night-time hours. Each mode shows a uni-modal time spread, marked by an S-shaped distribution with a single maximum and a single minimum.

While the jump of frequency to and from favorable slab of the day is not entirely sharp, the spread is still small, usually on the order of 2-3 hours. Second, all modes show a time-selectivity. The only modes that are spread over the entire 24-hour span are the no-signal and other-locations modes, which contribute to a small fraction of the users entire daily time expenditure. Third, the transition timings of various modes are highly correlated, either positively or negatively. Thus, the modes “line-up.” Fourth, for either of the two slabs of the 24-hour span, there are multiple modes with non-trivial weights.
The first three observations corroborate our work-home pivot intuition. They indicate a strong correlation of spatial mode of a mobile user with respect to the hour of the day, and set the stage for predictive models. The fourth observation, however, runs counter to expectation, as it splits the pivots into more than one location. In the next section, we develop machine-learning based prediction models and tackle the pivot split problem.

VI. PREDICTIVE MODELS FOR SPATIO-TEMPORAL MODES

With the establishment of spatial modes that are strongly predictable in time, we are now set to build predictive models for the position of a node in space and time. We approach this as a classification problem. The challenge is to select descriptive features that determine the spatial mode in time to sufficient accuracy. As discussed in §V-B, the hour of the day alone does not lend to a sufficient model as the presence in any hour is split into multiple modes. However, the lining-up property of different modes suggests that the predictability is high up to a bag of modes that are time-correlated. We use this predictability as a benchmark for our mode prediction algorithms. Subsequent sections describe the benchmark setup and activity-sequence based classifier models that lead to such prediction performance.

A. Prediction benchmark

The hour-wise frequency distribution of top-k modes for a particular user is shown in Table IV. This distribution corresponds to a plot of the kind shown in Figure 4. We sharpen the distribution slabs by bagging together the modes that are positively correlated in time. For a particular user, this bagging results in bags (1, 4, 5) and (2, 3, 6), where the index $k$ refers to the $k^{th}$ most-frequent mode of that user. The CellIdx values for these modes are (630, 928, 1152) and (673, 916, 1140). The corresponding plot is shown in Figure 5.

To begin with, classification is performed with hour-of-day as the only attribute and spatial mode as the output class. As our data is expressed as a transition sequence, we first convert it to a uniformly sampled time series with a time-interval of 5 minutes. The classifiers are trained on random sample made up of 50% of the trace data, and tested on the remaining. We use four classification techniques - Bagging, Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) and Neural Networks (NNet) [12][8]. Bagging is implemented in Weka [9], while the remaining classifiers are implemented in R [23]. Performance results are tabulated in Table V.

Two metrics are used to study the prediction performance. Accuracy measures the fraction of test instances correctly classified. The so-called confusion matrix describes the break-up of classifier outcome, tabulating the distribution of classification outcomes for each class. The rows of a confusion matrix represent the class of an instance being classified while the columns represent the outcome class. Our results indicate a benchmark of roughly 80% classification accuracy.

Table V
CLASSIFIER BENCHMARK: PERFORMANCE ON MODE-BAG PREDICTION. ACCURACY MATRIX.

<table>
<thead>
<tr>
<th>Bagging</th>
<th>LDA</th>
<th>NNet</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>81.182%</td>
<td>82.3%</td>
<td>82.3%</td>
<td>82.3%</td>
</tr>
</tbody>
</table>

B. Multiple modes per time

We perform raw classification on the data with hour-of-day as the only attribute, where each of the top-k mode is maintained as a separated class. Results are summarized in Table VI. As expected, the classifier performance is poor, owing to the fact that each hour-of-day is made up of contributions from multiple modes. Clearly, this is an insufficient model for mobility of a user. We present a modified model in the next section that boosts up the predictability remarkably.

C. Modality of activity sequences

The split of most hours of the day into multiple modes is counter-intuitive, especially for night hours. Day hours can be explained through a distributed nature of work location, but night hours can only be explained by there being multiple locations where the user resides on a regular basis. A natural question to consider is whether there is a correlation between the prevalent modes at two different hours, or whether the modes occur in arbitrary grouping even over short time spans. To answer this, we look at activity sequences, defined as contiguous sequences of a given length of modes visited by the user over the entire trace duration. The frequency distributions of these sequences for two lengths for a particular user are shown in Table VII.

The key observation is that for 3-mode sequences, only a total of 4 sequences have significant occurrence frequency out of a total of 6 choose 3 = 20 possible sequences. The figure of 4 is obtained by counting a sequence A-B-A as being same as B-A-B. In our table, both of these sequence occur because the sequence frequency is computed using a sliding window over the top-k mode transition sequence. This indicates that there is modality even among activity sequences, so that only a few sequences of modes occur together with high frequency. Further, as indicated by
comparing the 2- and 3-mode sequences, all the important 3-mode sequences happen to be activity loops rather than being simple sequences. Thus, in a particular activity mode, the user’s mobility is primarily centered around two modes. Together with the establishment of only a few spatial modes, this is a strong characterization of the mobility. This is verified by the phenomenal classification performance upon adding the activity-mode as an attribute to the classifier. These results are shown in Table VIII and Table IX. The data now has two attributes - hour-of-day and activity-mode, where activity-mode identifies a particular high-frequency activity sequence.

**D. Merits of multi-modal approach**

The ingredients of our multi-modal approach can be summarized as follows:

1) **Spatial modality.** Most of the time spent by a mobile user can be captured in a small fraction of all visit points of that user.
2) **Temporal modality.** All spatial modes are uni-modal in hour-of-day, so that they follow a single-peaked distribution over the day. Further, they line up frequency transition boundaries.
3) **Activity modality.** Over an epoch of communication interest (at most a single day), the user is contained to one of few activity loops. Each activity loop entails a subset of spatial modes.
4) **Modes are sufficient.** The parametrization of mobility through modes captures more than 90% of the entire mobility of a user. Further, these modes predict the location of user in space and time to an extremely high degree of accuracy (about 95%).

Previous works have argued in favor of high degree of predictability of the mobility of a typical urban user [25] [10], as opposed to the notion of mobility being largely random. We have shown a constructive methodology meets those predictability expectations.

**VII. Conclusions and Future Work**

Our work has focused on the premise of modality in all aspects of urban mobility. This concept has allowed us to express the mobility to a very high degree of accuracy with a small state description. As a by-product of using public
domain cell-phone connectivity traces for mobility study, we have developed techniques that will make similar traces lacking GPS feasible for mobility studies, thus opening up a wealth of data.

We believe that this work is a novel first step in mode-modeling. In light of simultaneous discovery of statistical aggregate behavior properties, there is a natural motivation to relate individual node modal properties to aggregate phenomena. We have focused on the aspects of mobility that are predictable, trading off some of the unpredictable traits for accuracy. Characterization of the randomness outside modality will complement our work. We have used classifiers as the work-horses of mobility prediction. Abstracting out the commonalities in classifier configurations across users will help characterize a generative process for the whole population in a succinct representation, which is the ultimate goal of mobility modeling.

ACKNOWLEDGMENT

We are deeply thankful to Prof. Stott Parker for his insights on datamining techniques applicable to our work. We acknowledge the early explorations of Swapnil Barai, Sharad Jain and Vamsi Krishna which raised our confidence in the multi-modal approach. We thank Dr. Nathan Eagle for promptly sharing the MIT Reality Dataset and providing additional information about it. Thanks are also due to anonymous reviewers whose comments improved this work.

This research was sponsored by the U.S. Army Research Laboratory and the U.K. Ministry of Defence and was accomplished under Agreement Number W911NF-06-3-0001. The views and conclusions contained in this document are those of the author(s) and should not be interpreted as representing the official policies, either expressed or implied, of those of the author(s) and should not be interpreted as representing the official policies, either expressed or implied, of the U.S. Army Research Laboratory, the U.S. Government, the U.K. Ministry of Defence or the U.K. Government. The U.S. and U.K. Governments are authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon.

REFERENCES