Evaluating Mobility Models for Temporal Prediction with High-Granularity Mobility Data

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***Abstract*—A mobility model is an essential requirement in accurately predicting an individual's future location. While extensive studies have been conducted to predict human mobility, previous work used coarse-grained mobility data with limited ability to capture human movements at a fine-grained level. In this paper, we empirically analyze several mobility models for predicting temporal behavior of an individual user. Unlike previous approaches, which employed coarse-grained mobility data with partial temporal-coverage, we use fine-grained and continuous mobility data for the evaluation of mobility models. We explore the regularity and predictability of human mobility, and evaluate location-dependent and location-independent models with several feature-aided schemes. Our experimental results show that a location-dependent predictor is better than a location-independent predictor for predicting temporal behavior of individual user. The duration of stay at a location is strongly correlated to the arrival time at the current location and the return-tendency to the next location, rather than recent k location sequences. We also find that false-positive predictions can be reduced by adaptive use of mobility models.**

***Keywords*-human mobility; mobility model; mobility prediction; human factors;**

I. Introduction

Building a human mobility model that characterizes movement patterns is an intellectual challenge in mobile computing [1]. The mobility model provides an accurate prediction of individuals' future location, which is an essential requirement for various mobile applications [2], [3], [4]. To understand the nature of human mobility, a wide range of approaches has been proposed for the development of a mobility model [3], [4], [5], [6], [7]. Previous works mainly focused on prediction of *spatial movement* (i.e., how well a future location is predicted) [5], [6]. However, most studies predicted future location without knowledge of *temporal behavior* (i.e., when movement to the next location will take place and how long a user will stay in that location) [7]. Indeed, uncovering the temporal features of human mobility is challenging because temporal behavior includes considerable uncertainty compared to spatial movements [4], [8]. In this paper, we explore spatio-temporal features for predicting temporal behavior of an individual user, which are important for the development of mobile applications.

We argue that the granularity of mobility data used in the literature is too coarse to precisely capture daily movement patterns. In analyzing human mobility, previous studies used GPS trajectories [5], connected radio beacons [1], [3], [6], or communications patterns [1], [9]. A GPS signal is usually not available in indoor or urban environments, where people spend approximately 87% of their time [8], [10]. Thus, GPS fails to distinguish nearby places in indoor environments at room-level accuracy. The mobility resolution determined by the cell-tower connections is coarse, ranging from a few hundred meters in urban areas to a few kilometers in rural regions. Such coarse resolution has limited ability to capture human movements at a fine-grained level. Our experimental data from the Seoul area revealed that the average number of places in most associated cell-tower regions is 11 ± 2. In other words, mobility data captured by a cell-tower considers 11 distinct locations as one place and therefore misses the transition between these places. In addition, mobility data derived from communication patterns offers only partial coverage. In previous studies, wireless network traces were recorded by an active network connection only in corporate regions [3], [6]; Voice calls and text messages were captured in short bursts [1], [9]; e.g., the average inter-event time of individual data was 1.5 hours [9]. Hence, analysis using fine-grained mobility data is essential to explore the important factors that remain to be uncovered in mobility prediction.

Our work explores the following research questions:

- How much regularity and predictability is inherent in human movements?
- Which features are strongly correlated to temporal behavior?
- Which mobility model is best for the prediction of temporal behavior?

Here, the key technical challenges are: (1) to quantify the predictable regularity in human behavior, (2) to define meaningful features for extraction of useful information, and (3) to predict next location with duration of stay. To address these challenges, we analyzed *fine-grained mobility data*, defined as follows: a place is recognized with room-level accuracy in indoor as well as outdoor environments, and the movement patterns are recorded every two minutes for an entire day. We deployed our mobility monitoring system [8], [11] to collect fine-grained mobility data from 10 users over a period of two months. Using this data set, we first explored the regularity and the predictability in human mobility. We then evaluated a variant of mobility models with several feature-aided schemes. We estimated the upper bound of each mobility model and demonstrated the performance of temporal prediction by comparing the accuracy and cost. We extensively evaluated the effect of using location sequences, arrival times, temporal periodicity, and the size of dataset. Finally, we presented the important factors in reducing false-positive cases in mobility prediction.

This paper makes the following contributions:

- We provide an extensive analysis of the regularity and predictability of fine-grained mobility data (Section III).
- We thoroughly evaluate the prediction accuracy and cost of several mobility models using long-term user traces (Section V).
- We present the effect of using feature-aided schemes and important features for reducing false-positive cases (Section V).

II. Related Work

Extensive research has been done on mobility models to predict individual mobility. The basic concept is to compare a current pattern with historical data and to extract similar patterns for predicting the next location. The key feature is how to generate the residence-time distribution from historical data. Most studies [3], [4], [6] used Markov-based models. Lee and Hou used a semi-Markov process with first-order Markov predictor to build a steady-state distribution and a transition-probability matrix from wireless network traces collected across a campus [3]. They analyzed correlation between time and location, and validated the efficiency of temporal prediction for network bandwidth provisioning. Song et al. evaluated the performance of various mobility predictors with time-aided and fallback mechanisms, using campus-wide wireless network traces [4], [6]. They reported that simple Markov predictors performed better than complex predictors for location prediction in practice [6], and that accurate temporal prediction with high-granularity requires more sophisticated and expensive mobility data than the association history of wireless network users [4].

NextPlace used nonlinear time series analysis of arrival time to predict temporal behavior [7]. Compared to Markov predictor, NextPlace uses a location-independent predictor and the continuous similarity of time series vectors. Jyotish used type-of-day (e.g., weekday and weekend) to filter redundant information from historical data [12]. Instead of predicting temporal behavior at current location, Jyotish chose the most visited location at a specific day and time bucket based on presence probability (e.g., most visited location at 8-10 a.m. on weekdays). We chose a Markov-based model as location-dependent predictor and NextPlace as location-independent predictor for the evaluation. We also apply the return tendency of human behavior to these models to extract useful information from historical data.

III. Motivation

We explore regularity and predictability in human mobility to elaborate our motivation. We analyze fine-grained mobility data collected from 10 graduate students. We deployed our mobility learning system, named LifeMap [8], [11], to collect real user traces over a two-month period in Korea. LifeMap monitors a user's mobility every two minutes, using GSM, WiFi, and GPS. The system automatically recognizes visited places with room-level accuracy using WiFi fingerprinting. The basic idea is that the radio signals from surrounding WiFi access points (APs) are similar when a user is stationary [8]. When a user stays at a place, LifeMap generates place signatures including location, arrival time, residence-time, attached cell towers, and the WiFi fingerprints. Our previous work [8] reported that LifeMap correctly monitored 93% of visits within a detection delay of approximately 150 seconds. LifeMap cannot trace user mobility when a user is located in an area that does not have WiFi coverage. The collected data reveals that participants spend about $2.1 \pm 1.7\%$ of their time in non-WiFi regions. In other words, the uncertainty of our data set is only 2.1% across the entire period. Consequently, the collected data is sufficient for use as high-granularity mobility data.

A. Spatial and Temporal Regularity in Human Behaviors

We first set forth the spatial regularity in human mobility. In collected data traces, participants spent $85 \pm 3\%$ of their time staying in place, while they spent $13 \pm 3\%$ of their time moving. This indicates that, in order to predict the majority of temporal behaviors, the mobility predictor should focus on predicting the stay-duration in places, rather than the travel time in-transit. Thus, we focus on the accuracy of predicting duration of stay.

People mainly stay in a limited number of highly-frequented places. To represent such regularity, we define two notions: the place is a *frequented place (f-place)* if a user visits this place more than three times; *top-n place* is a set of n most visited places during the entire collection period. The number of f-places for each user ranges from 8 to 35 (median 20). The propotion of f-places to all places is $11 \pm 2\%$, but the combined residence-time in all f-places comprises $94 \pm 3\%$ of the total residence-time. Specifically, the participants spend $57 \pm 18\%$ of residence-time in the top-1 place and $83 \pm 12\%$ of residence-time in the top-2 places (usually home and workplace). In addition, $69 \pm 7\%$ of transition is toward known f-places. This finding indicates that humans tend to return to a few selected f-places. Since the duration of stay is directly related to departure to the next place, the mobility predictor can accurately predict stay-duration if the method utilizes this observed return-tendency.

We investigate temporal regularity in human mobility to explore the correlation between time and location. We use three types of time buckets: day-bucket is 1440-length buckets (24-hour$\times$60-minute); weekday- and weekend-buckets

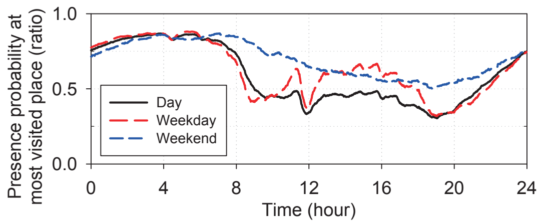


Figure 1. Temporal regularity according to different types: day, weekday, and weekend bucket. For example, 0.87 at 4 in dashed weekday line means that a user is located in one specific place at 4 a.m. during 87% of weekdays.

use two different day buckets according to type-of-day. We then measure the number of visits at the most visited place in every bucket. Figure 1 shows the average probability of being at a most-visited place. The results indicate that humans tend to spend most of their time in a few places with temporal regularity. In detail, the participants spent their nights (0-7 a.m.) at home during 83±3% of days, and they spent 57±7% of time during work hours at the workplace on weekdays. This shows the routine life-patterns of most individuals: people spend most of their time at home or at the workplace, and actively move around during daytime hours.

B. Predictability in Human Behaviors

We explore the predictability of spatial movement and temporal behavior in human mobility. From movement history (the notation is defined in Section IV), the predictability of stay-duration s_i at location l_i is defined as follows:

$$f_p(l_i, s_i) = \begin{cases} 1 & \text{, if } \Pr(|s_x - s_i| < \varphi \mid l_x = l_i) > 0 \\ 0 & \text{, otherwise} \end{cases},$$

where $x < i$ and φ is a given threshold. In other words, we consider that the duration s_i is predictable if s_i is previously observed in historical data within the given time difference. Here, we set φ =5-minute. Similarly, the predictability of the spatial movement from l_i to l_{i+1} is defined as follows:

$$f_p(l_i, l_{i+1}) = \begin{cases} 1 & \text{, if } \Pr(l_{x+1} = l_{i+1} \mid l_x = l_i) > 0 \\ 0 & \text{, otherwise} \end{cases}.$$

f_p indicates the upper bound of predictability in a history-based predictor. High predictability means that most of the pattern was previously observed.

Figure 2 presents the average f_p of all users. The optimal predictor filters out redundant information with minimal decrease in predictability. The result indicates that (1) people tend to follow their previous mobility patterns, and (2) temporal behavior is less predictable than spatial movements. To explore the effect of location sequences, we estimated the predictability of a high-order Markov predictor. The order-k Markov predictor extracts stay-duration patterns by matching k most recent locations, which is a widely-used technique for mobility prediction [3], [4], [6]. The use of a longer location-sequence rapidly reduces the predictability of temporal behavior (from 66% to 31%), while spatial movement shows relatively high predictability (from 74% to 57%), as illustrated in Figure 2. This result reveals

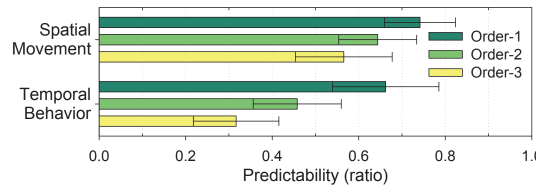


Figure 2. Average of the predictability of all users.

that the context of previously visited locations excessively filters out information necessary for predicting stay-duration. Thus, an alternative method is required to extract the useful information without loss of predictability.

IV. Mobility Model

We describe location-dependent and location-independent models for temporal behavior prediction: how long a user will stay in place and when movement to the next location will occur. We then show three feature-aided techniques for extracting meaningful patterns: a time-aided scheme, a fallback mechanism, and a return-probability-aided scheme.

A. Location-dependent Model

The basic assumption of a location-dependent model is that people tend to remain at the same place for similar durations on each visit. For example, a user may spend about one hour at a cafeteria, irrespective of whether they visit at 12 p.m. or 6 p.m. The Markov predictor $\mathbb{M}$ is widely used as a location-dependent model [3], [4], [6]. Consider a user's movement history $H = (l_1, t_1^a, s_1), \cdots, (l_n, t_n^a, s_n)$, in which t_i^a is the arrival time and s_i is the stay-duration at location l_i. From H, we extract the location history $L = l_1, l_2, \cdots, l_n$, and the finite set of m visited places. From L, the recent k location context is $L(n-k+1, n) = l_{n-k+1}, \cdots, l_n$. Then, the order-$k$ (or $O(k)$) Markov predictor generates the residence-time distribution S at the current location l_i, defined as follows:

$$S_i = \textstyle\sum_{j=1}^{m} (p_{ij} S_{ij}),$$

where $p_{ij} = \Pr(l_{x+1} = l_j \mid L(x-k+1, x) = l_{i-k+1}, \cdots, l_{i-1}, l_i)$ and S_{ij} is the form of a discrete histogram distribution from the stay-duration set $\mathbb{S}_{ij} = \{s_x \mid L(x-k+1, x+1) = l_{i-k+1}, \cdots, l_{i-1}, l_i, l_j\}$. Indeed, p_{ij} is the weight of visit frequency from location l_i to l_j, and S_{ij} is the residence-time distribution from l_i to l_j. Here, $\sum_{j=1}^{m} p_{ij} = 1$ and $\int_0^\infty S_i(t)dt = \int_0^\infty S_{ij}(t)dt = 0$ or 1. In brief, the Markov predictor extracts historical patterns by matching recent k location sequences.

B. Location-independent Model

A location-independent model uses temporal features without location information. The basic assumption is that people tend to spend similar staying time at similar times of day. For instance, a user tends to leave places at 6 p.m., whether the user is at a workplace or a cafeteria.

We used a variant of NextPlace [7] as a location-independent model. NextPlace uses nonlinear time series analysis to extract similar patterns from historical data. From H, NextPlace extracts arrival time history $A = t_1^a, t_2^a, \cdots, t_n^a$ and current context $c = A(n-k+1, n) = t_{n-k+1}^a, \cdots, t_{n-1}^a, t_n^a$. Then, S is a form of discrete histogram distribution from the stay-duration set $\{s_x \mid f(A(x-k+1, x), c) < \sigma\}$, where f is the similarity function of two vectors and σ is a given threshold. We use the maximum norm for f and $\sigma = 10\%$ of deviation, as suggested in [7]. The model considers the similarity between sequences of arrival time without location information.

C. Feature-aided Schemes

The major roles of feature-aided schemes are: (1) to extract the useful information from extensive data, and (2) to compensate the *none-prediction* (i.e., $\int_0^\infty S_i(t)dt = 0$). We describe three techniques: the time-aided scheme, the fall-back mechanism, and the return-probability-aided scheme.

The time-aided scheme uses a paired state of location and arrival time (l_x, t_x^a) with quantized time buckets (e.g., hour interval) [6]. This scheme assumes that the stay-duration is dependent on the arrival time at a place. For example, a user entering the workplace at 10 a.m. may remain for 2 hours, whereas arrival at the same location at 1 p.m. derives a stay duration of 5 hours. To generate residence-time distribution, the time-aided Markov predictor uses the stay-duration set $\mathbb{S}_{ij} = \{s_x \mid L(x-k+1, x+1) = l_{i-k+1}, \cdots, l_{i-1}, l_i, l_j$ and $A(x-k+1, x) = c\}$, where A is the history of arrival time and c is recent k arrival time sequences. We apply time-aided schemes to location-dependent models because location-independent models already use the sequence of arrival times. The fallback mechanism uses the low-order predictor if the high-order predictor has no prediction result. For example, the Markov model uses $O(k-1)$ predictor if $\int_0^\infty S_i(t)dt = 0$ in $O(k)$ predictor.

The return-probability-aided scheme $\mathbb{R}$ uses the temporal periodicity of location visits. The insight is that people tend to return to visited places with temporal periodicity [1], and that stay-duration is correlated to the return-tendency of the next place. For example, a user will tend to return home at 9 p.m. irrespective of whether he is currently at the workplace or cafeteria. From a user's movement history H, we extract historical visit sequence at location l_j, $H_j = (l_j, t_1^a, s_1), \cdots, (l_j, t_k^a, s_k)$. From H_j the return probability R_j at l_j takes the form of a discrete histogram distribution from the temporal periodicity set $\{d_x \mid d_x = t_{x+1}^a - (t_x^a + s_x)$ where $1 \leq x \leq k-1\}$, in which $(t_x^a + s_x)$ is the departure time. Then, $\mathbb{R}$ generates the residence-time distribution S at location l_i, defined as

$$S_i = \sum_{j=1}^{m} p_{ij}(S_{ij} \times R_j),$$

where $p_{ij} = \Pr(l_{x+1} = l_j \mid l_x = l_i)$ and S_{ij} is the form of a discrete histogram distribution from the stay-duration set $\mathbb{S}_{ij} = \{s_x \mid l_x, l_{x+1} = l_i, l_j\}$. Let t^c be current time and t_k^d be a last departure time observed for l_j; we set the origin of R_j by the non-visited time (i.e., the sum of $t^c - t_k^d$ and the average transition time from l_i to l_j). Here, $\sum_{j=1}^{m} p_{ij} = 1$ and $\int_0^\infty S_i(t)dt = \int_0^\infty S_{ij}(t)dt = \int_0^\infty R_j(t)dt = 0$ or 1. Consequently, $\mathbb{R}$ allocates high provision probability to a time-slot when the user will return to the next place following temporal periodicity.

Table I

DESCRIPTION OF DATA SET

User	Sex	Age	Day	Place (f-place)	User	Sex	Age	Day	Place (f-place)
U1	F	30s	206	215 (27)	U6	M	20s	124	285 (31)
U2	M	20s	110	82 (12)	U7	M	30s	174	281 (27)
U3	M	20s	119	103 (13)	U8	M	30s	102	107 (8)
U4	M	30s	250	286 (27)	U9	M	20s	255	268 (35)
U5	F	20s	113	134 (13)	U10	M	30s	58	87 (10)

V. EVALUATION

We evaluated several mobility models in terms of fundamental accuracy of provision probability. We used fine-grained mobility data collected by 10 users, as described in Section III. The data traces include 1,848 places and 9,418 stays, as described in Table I. Note that a subset of this data is available in the CRAWDAD research communities [13].

In this section, $\mathbb{M}$ denotes the Markov model and $\mathbb{N}$ denotes the NextPlace model. The subscript denotes the order-k (e.g., $\mathbb{N}_2$ is $O(2)$ NextPlace). We omit the subscript of order-1 (i.e., $\mathbb{M}$ is $O(1)$ Markov). The superscript T denotes the time-aided scheme (e.g., $\mathbb{M}_2^T$ is a time-aided $O(2)$ Markov model). We quantize the arrival time into hour-interval in a time-aided scheme [4]. Suffix $\mathbb{R}$ denotes the return-probability-aided scheme (e.g., $\mathbb{MR}$ is a return-probability-aided Markov model). In NextPlace, we use a discrete histogram distribution of stay-duration set, although work in [7] suggests the use of simple average time.

A. Metrics

We explore the provision probability derived from the mobility model to evaluate the fundamental accuracy of prediction. The residence-time distribution S forms a probability density function in minute-interval. $S(t)$ indicates the provision probability at t minute in S. We define five performance metrics: *correct provisioning* f_c, *uncertainty* u, *rank of provision probability* r, *detection delay* d, and *accuracy of location prediction* f_a.

The correct provision f_c and uncertainty u indicate the shape of the residence-time distribution. f_c is the predicted probability around the actual stay-duration. f_c of stay-duration s_i in the generated residence-time distribution S_i is defined as follows:

$$f_c(s_i, S_i) = \int_{s_i-\varphi}^{s_i+\varphi} S_i(t)dt,$$

where φ is the given time threshold. We set φ =5 minutes. The optimal model generates $f_c = 1$, which means that the model allocates all probability around the ground-truth of stay-duration.

Uncertainty u is the number of the time bucket in S_i, which has a positive probability, defined as follows:

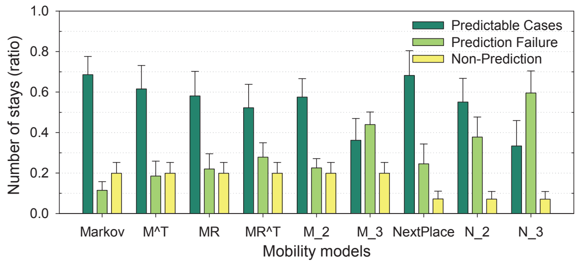


Figure 3. Number of stays according to prediction results.

$u(S_i) = \sum_1^{|S_i|} u_t$, where $u_t = \begin{cases} 1 & \text{, if } S_i(t) > 0 \\ 0 & \text{, else} \end{cases}$

A large u means that the model predicts temporal behavior for a wide range of buckets. Both f_c and u directly affect the performance of prediction related to resource allocation [4], [8]. A large u derives inefficient use of resources, since resources would be allocated to a wide range of buckets. Otherwise, a high f_c means that the application allocated greater resources around the moment of actual movement.

Rank r and delay d reveal the accuracy of temporal prediction using S. r is the accuracy of prediction if the application uses the PDF form of S, while d is the accuracy of prediction if the application uses the CDF form. r is the relative rank of provision probability for time s_i. Optimal r is 1, which means that $S(s_i)$ has maximum provision probability in the distribution (top-1 bucket in S). r indicates that the model guarantees correct prediction of the stay duration within top-r buckets. We set $r = \infty$ if $S(s_i) = 0$.

Delay d is the time difference between predicted duration of stay and actual duration. We use mobility monitoring application [8] to estimate d. To predict a user's behavior, the application allocates a given resource by using S. We assume that the given resource comprises 144 sensing opportunities (i.e., once every 10 minutes) per day. The application can then use sensing opportunities if the cumulative probability from time a to time b exceeds the given probability unit p (i.e., $\int_a^b S_i(t)dt > p$). Given k sensing opportunities, the application senses at time t_i and a user departs the place at time t^d, then the detection delay d is $\min_{1 \le i \le k} |t_i - t^d|$.

The accuracy of location prediction f_a is the ratio of predicted probability of actual next location to f_c. f_a of stay-duration s_i in S_i is defined as follows:

$$f_a(s_i, S_i) = \frac{p_{ij} \int_{s_i-\varphi}^{s_i+\varphi} S_{ij}(t)dt}{f_c(s_i, S_i)},$$

where the numerator is provision probability derived from stay-duration patterns to actual next location l_j. f_a is directly related to the location prediction with given departure time. The optimal model generates $f_a = 1$, which means that the mobility model correctly predicts the next location at the actual departure moment. Otherwise, a model with low f_a has a lack of location prediction.

In summary, the better mobility model generates high correct-provisioning f_c, small uncertainty u, low rank r, small delay d, and high accuracy of location prediction f_a.

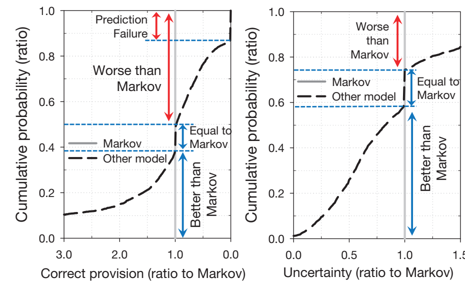


Figure 4. Example of detailed information in CDF form. The left-most curve indicates better performance in all metrics.

B. Performance of Mobility Models

We first explore the predictability of each mobility model. We apply fallback mechanism to all models to set the equal upper bound of predictability. The order-k $\mathbb{M}$ and $\mathbb{N}$ used order-(k-1) models until order-1. $\mathbb{M}^T$ and $\mathbb{MR}$ used an order-1 model as a fallback. Figure 3 presents the propotions of three potential outcomes: *predictable case* means that the model generates positive probability for the actual duration of stay ($f_c > 0$); *prediction failure* means that the model generates S_i but the probability for the actual duration of stay is zero ($f_c = 0$ and $\int_0^\infty S_i(t)dt > 0$); *none-prediction* means that the model generates no probability distribution ($\int_0^\infty S_i(t)dt = 0$). The prediction failure is a more critical error than non-prediction, since prediction failure is a false-positive case, whereas the non-prediction can be compensated by the fallback mechanism. Despite similarly predictable cases (i.e., about 68%), the location-independent model derives about 15% higher prediction failures than the location-dependent model, as illustrated in Figure 3. In other words, the upper bound of both models is similar, but the location-independent model derives more false-positive cases. This result indicates that the location-dependent model is more robust than the location-independent model for temporal prediction.

The ratio of predictable cases decreases as the model uses more contexts. The high-order models generate significantly fewer predictable cases: the order-2 model shows about 56% of predictable cases, and the order-3 model shows only about 35%. This indicates that the sequence of visited locations or arrival times excessively filter out the information required for predicting stay-duration. In contrast to high-order models, the time-aided and return probability-aided schemes show robust predictability: about 60% of predictable cases and 20% of prediction failure, which is 9% fewer predictable cases and 8% higher prediction failure compared to Markov, as illustrated in Figure 3.

Next, we evaluate the actual provision probability in predictable cases. We present some metrics as relative ratios to the result from $\mathbb{M}$ instead of absolute values, since absolute value is dependent on personal mobility patterns and the Markov predictor is the simplest method. Figure 4 describes the information in CDF form using a relative ratio.

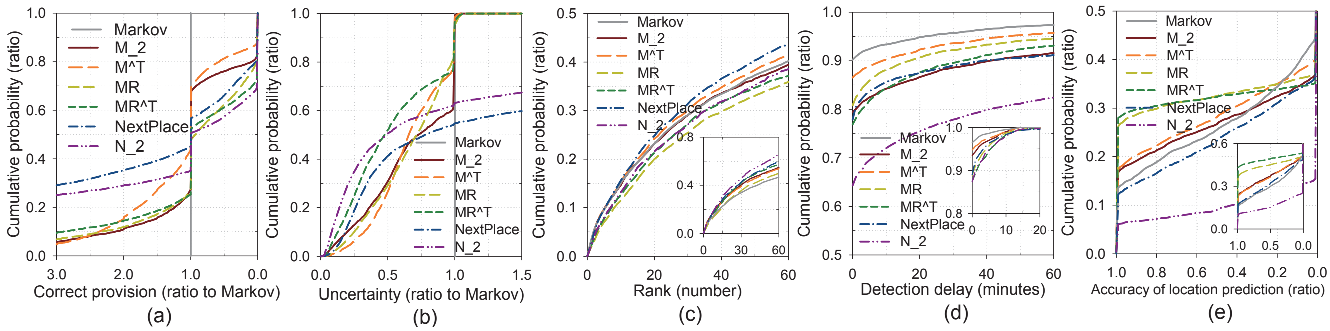


Figure 5. Performance of location-dependent and location-independent models. The inset in (c)-(e) presents the result without prediction failure.

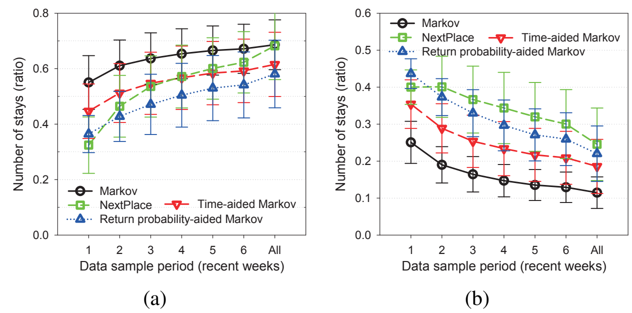


Figure 6. Ratio of (a) predictable cases and (b) prediction failure according to amount of input data.

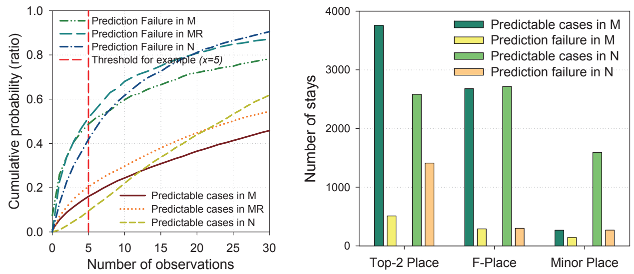
In Figure 4, the $x = 1$ line indicates that the result is equal to the result from $\mathbb{M}$. The left-most curve in CDF indicates better performance in all metrics. Note that we exclude the non-prediction in evaluating the predicted result.

Figure 5 presents the performance of the mobility models with feature-aided schemes. The result shows that the $O(1)$ model outperforms high-order models in terms of f_c, rank, delay, and f_a. In high-order models, the cost of prediction failure is exorbitant, although such models provide low uncertainty, low rank, and high f_a in predictable cases, as illustrated in Figure 5(c-e). The uncertainty of $\mathbb{M}$ and $\mathbb{N}$ are similar, but $\mathbb{N}$ derives larger location failures, longer delay, and lower f_a than $\mathbb{M}$. The rank of $\mathbb{N}$ is better than $\mathbb{M}$, but it does not outweigh the drawback of the location-independent model. Consequently, this result reveals that (1) temporal behavior is dependent on current location; and (2) the longer sequence of past context is inadequate to extract meaningful patterns for temporal prediction. For example, people tend to stay for different durations in offices and restaurants, although they visit both places at the same arrival time. The duration of stay at home is not strongly correlated to previous locations (e.g., office or cafeteria).

Compared to $\mathbb{M}$, cases $\mathbb{M}^T$ and $\mathbb{MR}$ effectively filtered out redundant information for the prediction of temporal behavior. Both models reduced uncertainty in 79% of cases, with 8% greater prediction failure. $\mathbb{M}^T$ outperforms other mobility models in terms of f_c, and $\mathbb{MR}$ shows clearly higher f_a than other models, as illustrated in Figure 5(a) and (e). The simultaneous use of both time-aided and return-probability-aided schemes is not effective: $\mathbb{MR}^T$ shows 28% prediction failure, which is 8% worse than for $\mathbb{M}^T$ and $\mathbb{MR}$. $\mathbb{MR}^T$ clearly shows low uncertainty, but the advatanges in rank, delay, and f_a are trivial. Thus, the efficiency of $\mathbb{MR}^T$ is not acceptable, due to the high level of false-positive cases. Consequently, the use of time-aided or return-probability-aided scheme is effective to increase the accuracy of mobility prediction. Both schemes reduced uncertainty in 79% of cases, yet they still provide higher or equal f_c in 59% of cases, and better f_a, as illustrated in Figure 5. The time-aided scheme is robust and the return-probability-aided scheme is efficient for location prediction.

We are also interested in measuring how much information is needed to accurately predict mobility. To answer this question, we restrict the amount of input data to recent days. Figure 6 presents predictability according to the data period, ranging from 1 week to 6 weeks. Intuitively, all models provide more predictable cases and reduced prediction failure as the amount of data increases. The difference between predictable cases in $\mathbb{M}$ and $\mathbb{M}^T$ shows a relatively consistent difference (from 10% for 1 week to 7% in all periods), while the difference between $\mathbb{M}$ and $\mathbb{MR}$ decreases as the data sampling period increases (from 19% for 1 week to 9% in all periods). In addition, the predictable case of $\mathbb{N}$ rapidly increases as the data period increases. This result indicates that the location-dependent model requires less information than the location-independent model to achieve optimal prediction results. Due to space limitations, we do not show the performance of provision probability with different amounts of input data, but $\mathbb{M}^T$ and $\mathbb{MR}$ still show better f_c, uncertainty, rank, and f_a results than $\mathbb{M}$ in predictable cases although the amount of data is small. This result indicates that both schemes still have the advantage when using small amounts of data, but the use of the temporal periodicity requires larger amount of data than the use of arrival time.

Finally, we explore features related to prediction failure: false-positive cases. To compensate for the cost of prediction failure, we previously reported the adaptive sensing policy in resource allocation problem [8], but here we present the feature of user contexts. We analyzed the correlation



(a) (b)

Figure 7. Amount of predictable cases and prediction failure according to (a) number of samples and (b) place types. A minor place is a place that a user visited less than four times.

between prediction failure and various features, including arrival time, stay duration, type of day, and collection period. We found that the number of previously observed data and place type are useful to reduce false-positive cases. With a small observation, the mobility model has higher prediction failure than predictable cases, as illustrated in Figure 7(a). When the threshold was set to 5 observations, prediction failure declined by 42-53%, with a corresponding 9-20% reduction in predictable cases. The optimal threshold is dependent on the application.

Figure 7(b) shows that the model generates different predictability depending on the place types. For top-2 places (usually home and workplace), the location-dependent model correctly predicts 88% of cases, while the location-independent model generates 2.8 times higher prediction failures. However, the location-independent model correctly predicts about 1,600 cases of stay-duration in minor places, which were missed in the Markov model due to the small number of visits. In other words, the stay-duration in minor places is strongly correlated to arrival time, but the stay-duration in the top-2 places is dependent on the place. For example, people tend to spend similar durations in minor places at 6 p.m. However, the time spent at home at 6 p.m. is entirely different from the duration in other places at 6 p.m. This result reveals that the application can adaptively use mobility models depending on the target domain of places.

VI. Conclusion

In this paper, we evaluate several mobility models for temporal prediction using high-granularity mobility data. We conducted empirical analysis on a variant of mobility model using fine-grained mobility data collected over a two-month period. We set forth the accuracy and cost of several mobility models. Our study produced several important findings. First, a high degree of spatio-temporal regularity is found in a few places with high visit frequency. Second, the location-dependent model is better than the location-independent model for the prediction of temporal behavior. However, the sequence of previously visited locations is inadequate to extract the information necessary for predicting stay-duration. Third, the time-aided and return-probability-aided schemes are effective to extract meaningful patterns for mobility prediction. Both features correctly remove redundant information, yet still provide better performance in predictable cases. Finally, the number of observations and the place type are correlated with the false-positive predictions. The application can adaptively use both features, depending on the target domain. Consequently, our results have important implications for the development of mobility prediction-related applications.

Our current work is based on a small dataset, obtained from 10 graduate students whose life patterns are rather irregular. To collect large-scale mobility data for individuals of various jobs and ages, we have deployed our mobility monitoring system on the Android market and solicited data donations from people around the world. With donated mobility data, our future work will address large-scale data analysis to explore important features of human mobility.

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