MOBILITY PREDICTION IN TELECOM CLOUD USING MOBILE CALLS

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ABSTRACT

The proliferation of the telecom cloud has fostered increasing attention on location-based applications and services. Due to the randomness and fuzziness of human mobility, it still remains open to predict user mobility. In this article, we investigate the large-scale user mobility traces that are collected by a telecom operator. We find that mobile call patterns are highly correlated with the co-location patterns at the same cell tower at the same time. We extract such social connections from cellular call records stored in the telecom cloud, and further propose a mobility prediction system that can run as an infrastructure-level service in telecom cloud platforms. We implement the mobility pattern discovery into a cloud-based location tracking service that can make online mobility prediction for value-added telecom services. Finally, we conduct a couple of case studies on mobility-aware personalization and predictive resource allocation to elaborate how the proposed system drives a new mode of mobile cloud applications.

INTRODUCTION

Growing convergence among mobile devices, wireless communication, and cloud computing sparked the development and deployment of location-based mobile social services. Predicting mobile user location in the next few hours is essential to various telecom applications, involving mobile access control, mobile multimedia quality of service (QoS) provision, and resource management for mobile computation and storage. Previous studies show that consumers prefer purchasing such kinds of applications through telecom operators as value-added services to complement their basic mobile subscriptions [1]. Due to the inherent limitations of mobile device computation capability, battery, and storage, many conventional services have evolved into mobile cloud-based telecom services (e.g., [2]), among which location prediction at the cell tower level in the telecom cloud is fundamental.

A variety of mobility prediction systems have been proposed (e.g., human community-based mobility [3] and inter-call mobility [4]). These systems draw several principal conclusions. One is that real-world mobile traces might not be available for public access due to privacy and security concerns. Another is that every user exhibits a certain kind of mobility patterns. For instance, some users periodically visit several locations (e.g., home, markets and offices). Users, however, comply with the mobility patterns in a very loose manner. Finally, social networks are a significant driver to user movement. Social relationships are closely correlated with user mobility patterns. A user pair possibly makes movements for face-to-face communication according to their social relationships and their distance [5]. By identifying and tracking such movements, we can predict the user location.

This article investigates the relationship between telecom call patterns and their mobility behaviors afterward. It leverages the large-scale and continuous telecom calls to study user mobility in the upcoming one to six hours. These traces involve more than one million telecom data extracted from a telecom operator. We conclude that the effectiveness of future telecom services and applications can be significantly boosted with the new system. In summary, the main contributions of this article are threefold.

1) This article finds that the call patterns between two users are highly correlated with the time interval between two consecutive user encounters in two cases: there is a telecom call between two consecutive encounters (case 1), and there is no telecom call in between (case 2). On average, the time interval between consecutive encounters in case 1 is 1/4 times that of case 2. Consequently, it introduces the social interplay concept to reveal social relationships embedded in telecom calls. It can be defined as a convolution between entropy characterized call strengths and the probability distribution of two users co-locating in the same telecom cell.

2) This article proposes a cloud system of mobility prediction, the first (to the best of our knowledge) to forecast user mobility based on telecom calls. The system consists of processing

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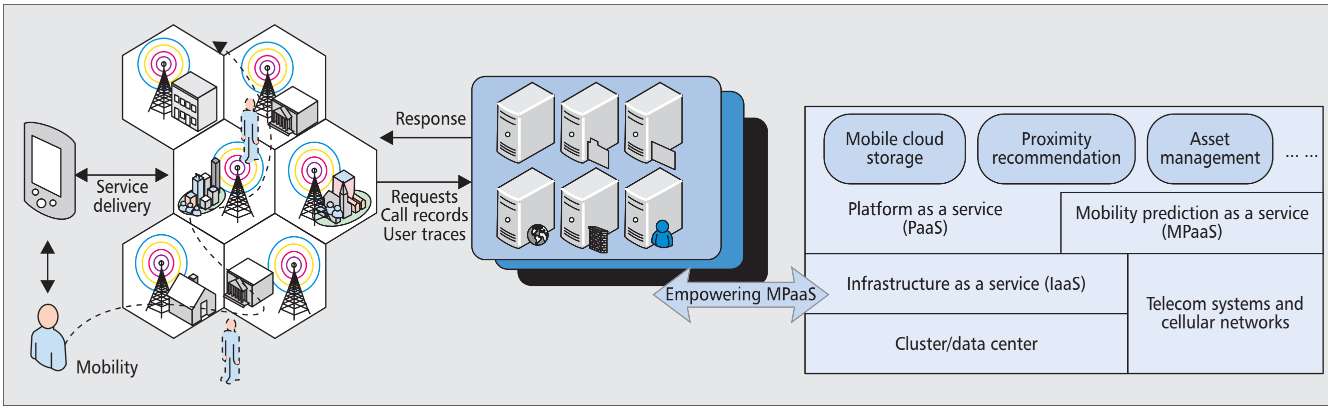

Figure 1. *Telecom cloud architecture empowered by cloud-based mobility prediction.*

mobile call logs and user traces, call pattern recognition, and prediction modules based on user periodic patterns and social patterns.

3) The proposed system is capable of tackling symbolically represented locations of cell towers. This abates the complexity of detecting cell tower topology and transforming code names of cell towers to computable coordinates.

The rest of this article is organized as follows. We give an overview of the mobility prediction in the telecom industry. We introduce the design of the proposed system in detail. We report on our preliminary results. We conclude the work.

Mobility Prediction Overview in the Telecom Cloud

Location is one of most important pieces of user contextual information. Via billions of GPS-enabled mobile phones, location data is permeating holistic telecom spaces and fostering various location-based services. Mobility prediction provides these services a means to further customize user experience. It is usually deployed at the infrastructural layer of the telecom operator's cloud. Figure 1 shows the telecom cloud architecture that encompasses the cloud-based mobility prediction (CMP), where third-party services can easily access the capability from the cloud. CMP also shares the computation and communication capabilities in telecom infrastructure for location information: aggregating, cleansing, preprocessing, and prediction.

Currently, most mobile devices are equipped with modules of GPS, WiFi, and near field communication in addition to conventional cellular interfaces. GPS is widely used to provide fine-grained location information. However, GPS falls short in indoor environments due to fast power attenuation and severe signal multipath. Furthermore, GPS is in need of significant cell phone traffic that is not free of charge. For these value-added services to flourish, telecom operators turn to cellular networks for less fine-grained location information. In this article, we focus on cell-level location forecast using telecom calls and cell tower transition data.

In the following sections, we mainly introduce previous efforts of mobility prediction in the telecom cloud. CMP is powering social interaction, mobile sensing, targeted advertising, geofencing, and many other services. Table 1 summarizes two typical types of mobile cloud services: resource orchestration and personalization.

Mobile cloud storage is one of the most popular mobile applications in the current market. Generally, it relies on the back-end of cloud facilities to remotely store users' contents, and enables content synchronization among multiple mobile devices. Dropbox and WhereStore [6] optimize the performance of data storage and access by dispatching the storage task of a user to a local replication. To be specific, WhereStore identifies user location by the blocks or the subareas of a city. This is more fine-grained than the city-wide granularity used by Dropbox. CPM improves mobile cloud storage by predictive resource management and device transparency with mobility-aware personalization. Due to the limited computation and communication capacities of mobile devices, mobile computation offloading programs usually make trade-offs between remote offloading and local computing. To make such decisions, CMP is leveraged. ClondCloud [7] and ThinkAir [8] propose frameworks for splitting computation-intensive mobile applications into many computing units at the cloud side, respectively. As for mobile sensing and mobile search, they were widely studied in the pre-cloud era. Many mobile sensing applications aim to build cloud services to collect and process captured data from mobile phones to enhance promising applications such as real-time advertisement and large-scale environment surveillance [9]. Mobile cloud environments provide mobile sensing with back-end analysis, processing and sharing the sensed data. With the knowledge of a user's future locations, mobile sensing can be more efficient than what is used today. By harnessing personal and spatial relations, the work in [10] proposes an analytical model according to differential equations for malware propagation in mobile devices. It consists of propagation detection in local infected areas and remote social networks.

Note that various systems addressing the prediction problem of user location have been studied. In general, they fall into three types of systems: systems based on individual mobility, those based on social relationships, and systems

NextMe involves two prediction engines based on the user behavior periodicity and social relationships. To aggregate the prediction results, it presents a self-adjust learner that involves two steps: top-L selection of cell towers and prediction aggregation.

Services and applications		Features		
Categories	**Projects/studies**	**Location**	**Resource orchestration**	**Personalization**
Storage	Dropbox*	Cell	Yes	Yes
	WhereStore [6]	GPS/AP/Cell	Yes	No
Offloading	CloneCloud [7]	GPS/AP/Cell	No	Yes
	ThinkAir [8]	AP/Cell	No	Yes
Sensing	Mobile sensing [9]	GPS	No	No
*https://www.dropbox.com				

Table 1. *Mobility prediction in mobile cloud computing services. Location: the granularity of location — AP, the access points of WiFi; cell (base stations of telecom 2G/3G), and GPS. Resource orchestration: whether the service allocates or recycles a resource after getting predicted user location information. Personalization: whether the service is tailored to users according to their future location in the forthcoming hours.*

based on both. The first type of systems takes advantage of the temporal and spatial regularities that are exhibited in individuals' mobility patterns. They employ machine learning techniques for pattern discovery. The second type of system postulates that user movement is driven by social relationships, involving social community identification and prediction based on a community's attractiveness to users. As a typical example, HCMM [3] exploits user friendship to cluster users as communities, and then decides on the user's next location using community attraction. In recent years, many hybrid systems have been proposed that take user pattern regularities and social friendships into account (e.g., [5]).

Mobility Prediction in Telecom Cloud Using Mobile Calls

Motivation

To motivate our study, we investigate the relationship between telecom calls and user mobility patterns for face-to-face communication. We define two kinds of events between two users. These events are a *cellular call event*, a directed call from one to another, and a *co-cell event*, two users visiting the same cell tower at the same time. We select telecom data from a telecom operator because of its real-time and large-scale community. The dataset consists of 983,477 cellular calls and 1,632,000 hours of human behavior information such as user location and co-location information. We extract the cell transition data, user traces, mobile call logs, and map logs into the study.

Given a pair of users, we introduce two concepts: *inter-contact time* and *inter-call-contact time*, illustrated in Fig. 2a. The first concept is the time interval between two consecutive co-cell events, where it does not matter whether mobile calls happen or not. The latter concept refers to the time interval between two consecutive co-cell events during which these two users have at least one phone call with each other. The inter-call-contact time is a special type of inter-contact time. It means that phone calls happen between two consecutive co-cell events. Note that the inter-contact time of users having reciprocal calls does not mean inter-call-contact time. It is the inter-contact time between user pairs that have reciprocal phone calls, whereas the inter-call-contact time identifies the time duration from their call to contacting a user pair.

Figure 2b shows the cumulative distribution functions (CDFs) of the inter-call time, inter-call-contact time, and inter-contact time among users that have called each other. The inter-call-contact time is averaged as 1/4 that of the inter-contact time. Around 90 percent of the inter-call-contact time occurs in two days, while the same amount of inter-contact time lasts eight days. This phenomenon explains the fact that people may meet after cellular calls. This is because cellular calls drive call pairs to meet afterward.

As shown in the comparison between the lines of inter-contact time and inter-contact time of users having reciprocal calls, users with reciprocal calls would meet more frequently than users without bilateral calls. This denotes that the social interplay considerably affects user mobility afterward for reciprocal users.

NextMe: A Cloud-Based Mobility Prediction System

In this section, we introduce the proposed system that predicts user location for the forthcoming one to six hours from telecom calls and cellular traces at the cell tower level. We overview the system and then report on its design in detail.

Overview — *NextMe* consists of two sub-goals: how many cell towers users will go and which cell towers they will reach. Figure 3 illustrates the architecture of the NextMe system involving several separate components: data preprocessing, call pattern recognition, periodicity-based module, social-based interplay module, and a

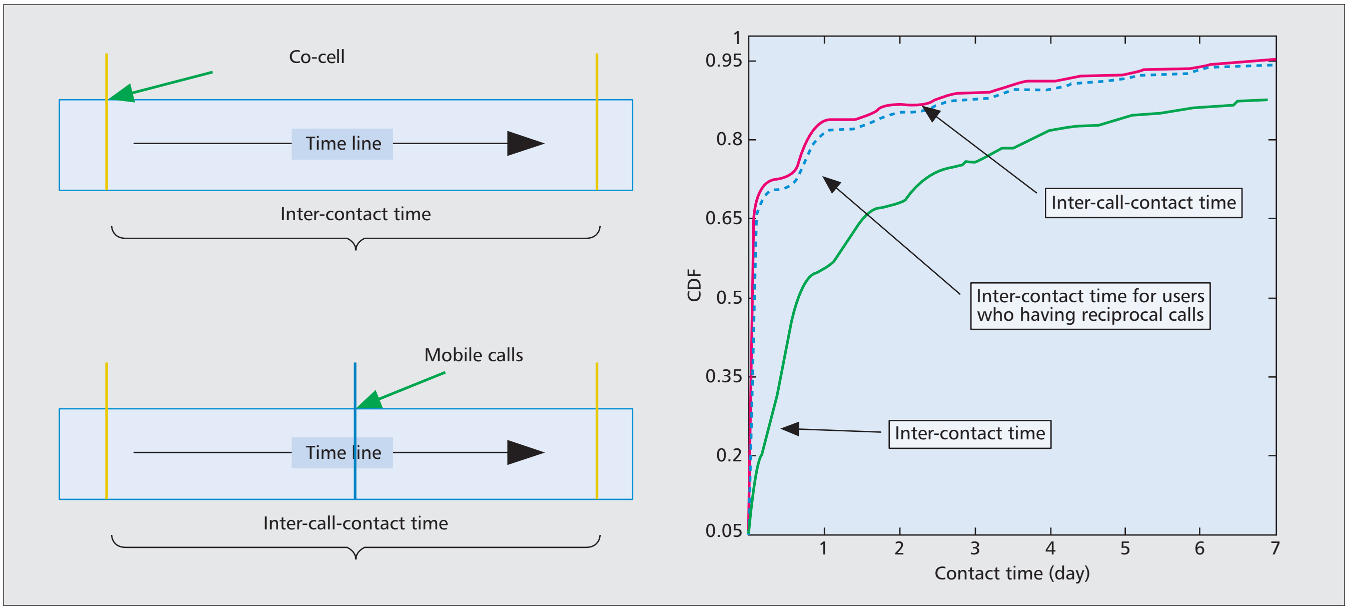

Figure 2. *a) The concepts of inter-contact time and inter-call-contact time; b) the CDFs of inter-contact time and inter-call-contact time.*

self-adjust learner. NextMe uses the first component to handle user mobility regularity originating from spatial and temporal perspectives. It employs the second component to cope with the non-periodic mobility behaviors caused by social interplay. Then NextMe leverages an adaptive self-learner to aggregate the outputs of two predictors.

1) Data preprocessing: There are lots of data noise in a cell tower. Cell towers frequently transit with nearby cells due to cell oscillations. Such oscillations are more evident when a user stays in the overlapping coverage of multiple cellular towers. Figure 4 illustrates an example of unnecessary handoffs, from which we identify that cells A, B, and C are mutually overlapped. We provide an unsupervised region identification algorithm based on multiple-reference area measurement to identify user region according to cell tower sequences.

2) Periodicity module: This module foretells a user location by exploiting the temporal and spatial features of user mobility behaviors. Because the locations of cell towers are represented by symbols, not GPS coordinates, any arithmetic and logical operations over them are invalid. To this end, we design and implement a module for periodicity detector, Perio, which exploits the Kullback-Leibler divergence (KLD) as the metric to discover the behavior periodicity. We select KLD as it is a well-known distance measure between two probability sequences. To be specific, Perio involves three sub-steps: detecting the periods in user movement traces, identifying the periodic movement behaviors, and forecasting user movements. In the first step, it captures the locations that are frequently visited by users as reference locations. Through reference locations, Perio obtains the periods using a hybrid method of auto-correlation and Fourier transform. In the second step, Perio presents a probabilistic model to characterize the periodic behaviors. By clustering, periodic behaviors are statistically generated from movement sequences. Finally, Perio makes a prediction based on the detected periods.

3) Social interplay module: Based on the mobile calls and digital traces of users, the social interplay predictor forecasts user location from the social network perspective. To be specific, it first identifies the user pairs that have social relationships. Then it computes the entropy-based social interplay and makes recommendations accordingly.

4) A self-adjust learner: NextMe involves two prediction engines based on user behavior periodicity and social relationships. To aggregate the prediction results, it presents a self-adjust learner that involves two steps: top-L selection of cell towers and prediction aggregation.

In step one, NextMe generates two lists of cell towers from modules of periodicity and social interplay for the prediction interval. In step two, NextMe makes the prediction by aggregating the prediction using a boosting technique. By aggregating all the elements in these two lists, we easily get the top-L recommendations for the t interval. For the $t + 1$ interval, we aim to boost the influence of the predictor that correctly predicts at the t moment, and decrease the influence of the predictor that wrongly predicts. Therefore, we introduce two aggregation parameters in the proposed self-adjust learner. We assume that a factor correctly predicts the user location for the time being, and has a large probability of determining user location the next time. This means that for this interval, the prediction mechanism makes a correct prediction. In the forthcoming interval, this mechanism inclines to correctly predict the user location again.

Call Pattern Recognition — This component aims to identify when the social interplay-based predictor works. In this article, the social-interplay-based predictor is triggered by mobile calls. We hereby propose the concepts of critical call patterns and critical calls. Then we present a mechanism of critical call patterns that can detect the

By scanning the telecom calls and GSM traces, NextMe works in an online manner. As we do not know the next co-location time and region, we may get false positive errors. To avoid such errors, we introduce the confidence level for fault tolerance.

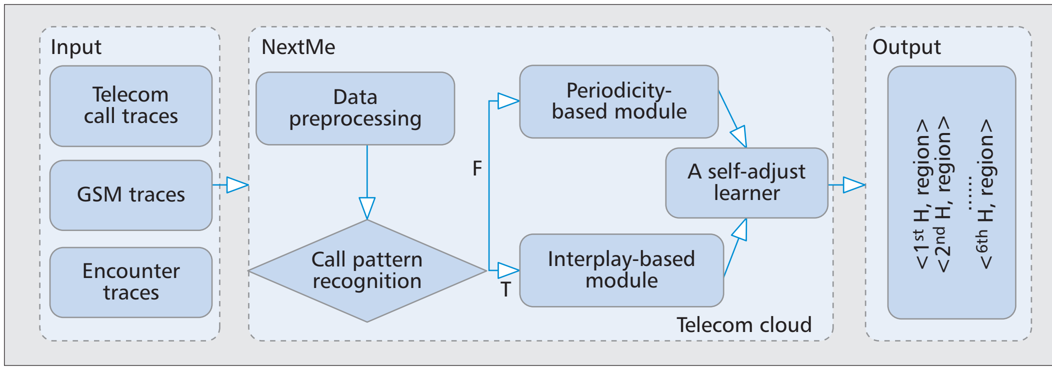

Figure 3. *The design of the proposed mobility prediction scheme in the telecom cloud.*

moment the call pairs will socialize their activities. The mechanism employs a real-time monitoring technique for call patterns that independently analyzes the call sequences and automatically detects the critical call patterns when user behaviors begin to be driven by social factors.

Given a call pair, a critical call pattern refers to specific cellular call pattern sequences that would lead to their co-region with a high probability; the critical call denotes the last mobile call in the sequence. This kind of call pattern satisfies two requirements: the call frequency of the call pair is bigger than a threshold, and the interval between the last two cellular calls is shorter than another threshold. These two thresholds are specified in previous empirical studies.

At runtime, NextMe recognizes critical call patterns from a couple of perspectives. First, it will check the co-location history of the given call pair. Then it checks the number of cellular calls and the interval between the last two cellular calls. According to the thresholds given beforehand, NextMe easily identifies the critical call patterns as well as critical calls. By scanning the telecom calls and GSM traces, NextMe works in an online manner. As we do not know the next co-location time and region, we may get false positive errors. To avoid such errors, we introduce the confidence level for fault tolerance.

Social-Interplay-Based Predictor — We would like to examine how much and when the social interplay can affect user mobility according to historical call records. Given a call pair, we model the social interplay as the link in a static and weighted co-location graph $G(\eta, e)$, where η is the total number of users, and e represents the edges between co-location users. We create such a graph for each user's call records by aggregating the entire sequence of contacts between a pair of users. Each user i is a node of the graph, and the edge $e_{i,j}$ denotes nodes i and j having co-location. The key to establishing a meaningful social graph is the metric used to aggregate contacts, which determines whether two nodes have a social connection. In our study, we use entropy-based call strengths. The main reason we use this metric is to comprise many regular social relationships according to historical call records and co-location logs.

To be specific, we compute the link weight (i.e., the degree of social interplay) in two parts: call strengths and call relative entropy. The first part denotes the call frequency and call duration of call pairs, whereas the second part is to characterize the asymmetry degree of call pairs. When the call strengths of both sides for a call pair become significantly different, the entropy will decrease. Given two users u_a and u_b, the call strength from u_a to u_b, $\lambda u_a,u_b$, is defined as the average call duration per week from u_a to u_b. Then the call relative entropy between u_a and u_b, $\xi u_a,u_b$ is given as

$$\xi u_a,u_b = -p\log_{10}(p) - (1-p)\log_{10}(1-p) \quad (1)$$

where $p = \lambda u_a,u_b/(\lambda u_a,u_b + \lambda u_a,u_b)$. The call entropy characterizes the degree of the call strength between u_a and u_b. Thus, the social interplay from u_a to u_b, $\sigma u_a,u_b$, is defined as

$$\sigma u_a,u_b = \lambda u_a,u_b * \xi u_a,u_b \quad (2)$$

Thus far, we have deduced the influence of social interplay for call pairs. In order to revoke the social-interplay-based predictor, we revisit the call patterns. NextMe will perform a call pattern monitoring algorithm for each call pair, which aims to answer three questions: 1) when will the call pair co-locate? 2) to where will the call pair co-locate? and 3) for how long will the pair co-locate?

When will the call pair co-locate? NextMe puts forward an algorithm that determines the critical calls in a real-time manner. The algorithm first detects the critical call patterns for call pairs, and then identifies the critical calls in the corresponding patterns. Once it gets a critical call, NextMe will immediately revoke the social-interplay-based predictor. However, this kind of action generates many prediction errors. For example, some users call frequently and follow certain call patterns, but they occasionally meet. To filter such errors, we account for the inter-call-contact time of call pairs.

In general, given a call pair, we derive the distribution for their inter-call-contact time. We collect the call sequences and validate their distribution by many continuous and discrete distributions, and find that the Poisson distribution is the best distribution that fits the data. NextMe leverages parameter estimation to get the mean and variance of the inter-call-contact time. Then NextMe obtains the probability density function.

Especially, NextMe aggregates the inter-call-contact time of a given call pair from the telecom dataset. Then it obtains the Poisson distribution of the inter-call-contact time using the Poisson parameter estimation technique. According to the derived Poisson distribution, NextMe determines the possible intervals at which the call pair would encounter. It further runs the algorithm to detect the critical call patterns and critical calls. With knowledge of the inter-call-contact time of call pairs, NextMe not only dramatically improves the prediction accuracy of the social-interplay-based predictor, but also significantly reduces the detection overheads. In addition, NextMe considers a temporal constraint that user mobility is subject to the current time; that is, the next visit to a place relies on the current time.

To where will the call pair co-locate? NextMe predicts the regions to which the call pair may co-locate, as users usually prefer to co-locate in nearby regions. Hence, the proposed system incorporates the region preference into the prediction results. It builds two indices for all co-locate records. One is the hour index, which resorts to a certain hour in a day. The other is the region index by occurring regions. From these two indices, we can easily get the co-locate probability of every region.

For how long will the pair co-locate? NextMe is targeted to forecast a user location in the forthcoming one to six hours. Hence, after prediction for the first hour, it needs to estimate the co-locate duration.

NextMe takes advantage of two sources to estimate the duration: the average time of the user pair co-location and the location inference. The former source is computed from the call logs as the ratio of the total co-locate time of a user pair to their co-locate times. In contrast, the latter source is from GSM traces and reveals the user location most of the time. User location is associated with cell tower addresses and sample time in GSM traces. By continuously sampling user location in GSM traces, we infer the duration of a user staying at a cell tower.

Preliminary Results

In this section, we carry out a set of experiments to validate the proposed system. In particular, we would like to examine:

1. The overall performance of the proposed system
2. How much the social interplay affects the prediction accuracy of the proposed system

We select a periodicity-based predictor, with Perio as the baseline, which adopts KLD as the distance measurement for user behavior traces. We select a telecom operator's logs as the raw dataset, which collects 983,477 cellular calls, 1,632,000 hours of human behavior information such as user location and co-location information, and 2,666,897 GSM traces. The operator developed a log software about class schedule so that every subscription is encouraged to try. Note that human behavior traces contain cell transition information, user phone status, user location at the cell tower level, and phone types. In the experiments, human behavior traces are the ground truth.

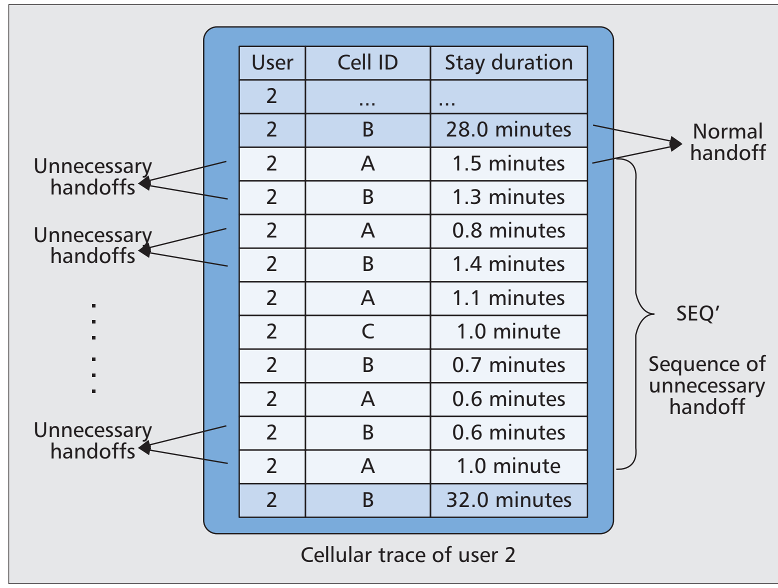

Figure 4. *An example of unnecessary handoffs.*

We use the aggregated prediction accuracy as the metric. The aggregated prediction accuracy is computed as the average accuracy of all predicted users for every prediction span. We extract 100 user call pairs from telecom log traces, and examine the prediction accuracy. Every user has 60 contacts on average and 240 calls during the past year. These users are classified into two classes, active users and passive users. Active users are people who have frequent contacts with other people, while passive users are not.

Figure 5 illustrates the overall performance of the proposed scheme, where the x-axis is the forthcoming hour, and the y-axis is the prediction accuracy. With the value of x varying from 1 to 6, the values of y for both NextMe and Perio schemes decrease. Compared to the Perio scheme, NextMe exhibits a slow downward trend. Meanwhile, NextMe achieves higher prediction accuracy than Perio in all prediction intervals. This indicates that the proposed system performs better than Perio in terms of prediction accuracy and accuracy downward trend.

We have also extracted all user call pairs to validate the degree to which social interplay promotes face-to-face meetings. We regard every call pair as a new user. This indicates that the prediction accuracy is the average accuracy for two users in a call pair. Figure 5b gives the results for the call pair (74, 94). As expected, NextMe outperforms Perio regarding the prediction accuracy. Its improvement ranges from 3 to 14 percent, and its average improvement is 9.1 percent. By counting on all user call pairs, we find that the contribution of social interplay is upper-bounded by about 12 percent for the telecom dataset.

Conclusion

In this article, we have achieved two findings from large-scale telecom traces: telecom call patterns are highly correlated with co-locate patterns, and call patterns affect short-term user

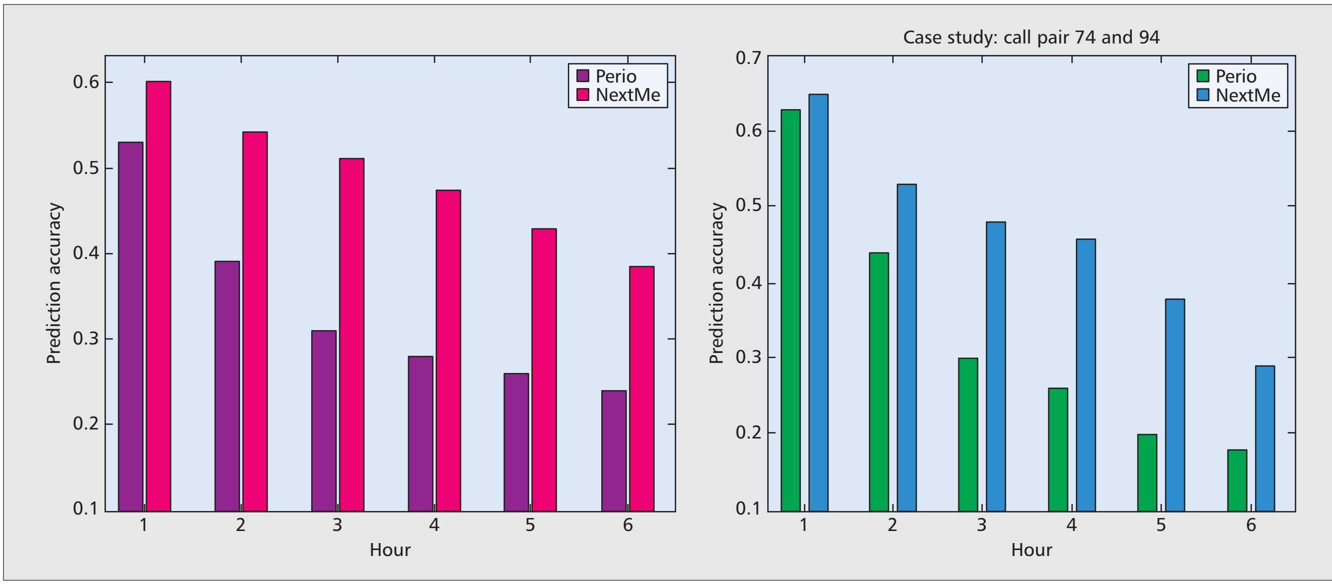

Figure 5. *The overall performance of Perio and NextMe schemes.*

mobility. We have introduced social interplay to capture such social relationships among mobile call pairs, and further proposed a system called NextMe for predicting user location at the cell tower level in the forthcoming several hours. We implemented the proposed system as a cloud-based service in the telecom cloud.

NextMe, however, could be further improved. We will account for other types of telecom communication records between users (e.g., short messages and emails). We plan to validate the proposed system in a wider spectrum of user mobile traces. We will also investigate user mobility patterns before and after the calls for a short time, and then incorporate the data into the current design. Finally, we expect to deliver a public service running in the telecom cloud that can deduce user presence with time-stamped cell tower coordinates, and spur value-added location-based telecom services.

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