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MPaaS: Mobility prediction as a service in telecom cloud

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Abstract Mobile applications and services relying on mobility prediction have recently spurred lots of interest. In this paper, we propose mobility prediction based on cellular traces as an infrastructural level service of telecom cloud. Mobility Prediction as a Service (**MPaaS**) embeds mobility mining and forecasting algorithms into a cloud-based *user location tracking* framework. By empowering **MPaaS**, the hosted 3rd-party and value-added services can benefit from online mobility prediction. Particularly we took *Mobility-aware Personalization* and *Predictive Resource Allocation* as key features to elaborate how **MPaaS** drives new fashion of mobile cloud applications. Due to the randomness of human mobility patterns, mobility predicting remains a very challenging task in **MPaaS** research. Our preliminary study observed *collective behavioral patterns* (CBP) in mobility of crowds, and proposed a **CBP**-based mobility predictor. **MPaaS** system equips a hybrid predictor fusing both **CBP**-based scheme and Markov-based predictor to provide telecom cloud with large-scale mobility prediction capacity.

Keywords Mobility prediction · Mobile cloud computing · Telecommunication system · Telecom cloud · Collective behaviors

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1 Introduction

Predicting mobile phone users' locations in next few hours is essential for a wide range of mobile applications, including location-based service (Rao and Minakakis 2003), mobile access control (Klein et al. 2010), mobile multimedia QoS provision (Soh and Kim 2003), as well as the resource management (Roy et al. 2004) for mobile computation (Kumar and Lu 2010) and storage (Studei et al. 2010). Early studies (Kuo et al. 2009) show consumers prefer purchasing these applications through telecom operators as the value-added services (VAS) (De Serres and Hegarty 2001) to complement the basic mobile service subscription; and telecom operators usually host these VAS as 3rd party services (Knightson et al. 2005). In the meanwhile, through long-term evolution (LTE) (Sesia et al. 2009), the traditional communication facilities have been gradually migrated to the telecom cloud[1] (Gouveia et al. 2009; Ericsson Discussion Paper 2012)– a pragmatic type of *mobile cloud computing* (MCC) (Dinh et al. 2011) platforms, due to the economical benefits (Goiri et al. 2012; Mazhelis and Tyrväinen 2012) as well as the controllability of resource, cost, resource and risk (Gutierrez-Garcia and Sim 2012; Hsu et al. 2011; Martens and Teuteberg 2012;

[1]In this paper we use the word "telecom operator cloud" and "telecom cloud" interchangeably.

Yang et al. 2012) carried out by the cloud. Thus it would increase the core competency of a telecom operator to include mobility prediction in cloud. However, until now so few efforts have been done in mobility prediction for the telecom cloud or mobile cloud (Dinh et al. 2011). In this paper, we propose *Mobility Prediction as a Service* (**MPaaS**) – a novel service model (Wikipedia 2012b) of telecom operator cloud which enhances the telecom cloud with mobility prediction capacity.

Mobility prediction can be useful to a wide variety of mobile services. Based on observations from Table 1, the following two types of mobile services have benefited significantly:

- *Personalization* - the service and applications are customized automatically and accordingly to a user's future locations. For instance, iScope photo search engine (Zhu et al. 2009) firstly clusters uploaded photos and makes the index by the trajectory of locations where users took these photos. Once a user takes a new photo or search a photo; iScope matches or retrieves photos by the probable trajectory of her future locations. Generally, *mobility-aware personalization* augments user's experience through suggesting or providing the user with contents, services or other entities placed on her way.
- *Resource Management* - services and applications allocates the resource according to user's future locations. For example, WhereStore (Stuedi et al. 2010) offers a storage cloud with distributed file systems, it stores the data of a user in the servers deployed at her future locations. Similarly, *predictive resource management* improves user experience and accelerates the speed of mobile cloud operations by replacing the remote access to a local access.

In terms of granularity of location prediction, it is largely dependent on particular application domains and its enabling technologies. A mobile device such as a smart phone is usually equipped with a GPS receiver and a WiFi adaptor in addition to the normal cellular interface. Either of these network interfaces could be utilized for getting locations, with GPS providing the finest location information and cellular interface the coarsest. In practice, people usually switch off GPS in order to save battery as GPS consumes much power to operate. In contrast cellular networks can provide reasonable location information while consuming little extra energy for positioning. Therefor this paper assumes that a cellular level of precision is provided. This choice is beneficial to mobile devices that are not equipped with WiFi interfaces and enables location prediction in the usual outdoor environments without the coverage of WiFi APs. Finally, we get motivated to use cellular level locations for mobility prediction by a wide range of MCC services shown in Table 1.

To appropriately support applications, we suggest to equip the functional services of *Mobility-aware Personalization* and *Predictive Resource Management* at the platform layer of telecom opertor cloud. Therefore **MPaaS** should be deployed at infrastructural level. Figure 1 illustrates the architecture of a **MPaaS** empowered telecom cloud where VAS and other services can easily benefit from the platform. Please note **MPaaS** is placed above infrastructural layer partially, since apart from location tracking sensed by cellular network, it relies on the computation power from infrastructural level of cloud as well. In this

Table 1 Mobility prediction in MCC Services

Service and Applications		Features		
Categories	Projects/Studies	Location	Resource	Personal
Storage	Dropbox (Drago et al. 2012), SkyDrive, and GoogleDrive	CELL	Yes	Yes
	STACEE (Neumann et al. 2011)	AP/CELL	Yes	No
	WhereStore (Stuedi et al. 2010)	GPS/AP/CELL	Yes	Yes
	Device Transparency (Strauss et al. 2010)	AP/CELL	Yes	Yes
Offload	MAUI (Cuervo et al. 2010), CloneCloud (Chun et al. 2011)	GPS/AP/CELL	No	Yes
	ThinkAir (Kosta et al. 2012), SmartDiet (Saarinen et al. 2011)	AP/CELL	No	No
Sensing	Integrated Framework (Fakoor et al. 2012)	GPS	No	No
	Jigsaw (Lu et al. 2010)	GPS/AP/CELL	Yes	No
Search & Recommendation	iScope (Zhu et al. 2009)	GPS	Yes	Yes
	CrowdSearch (Yan et al. 2010)	GPS/AP/CELL	No	Yes

Location: the granularity of locations–i.e., AP: the access points of WiFi, CELL: base stations of mobile 2G/3G, and GPS. *Resource*: whether the service allocates resource by predicting users' future locations. *Personal*: whether the service is personalized by predicting users' future locations

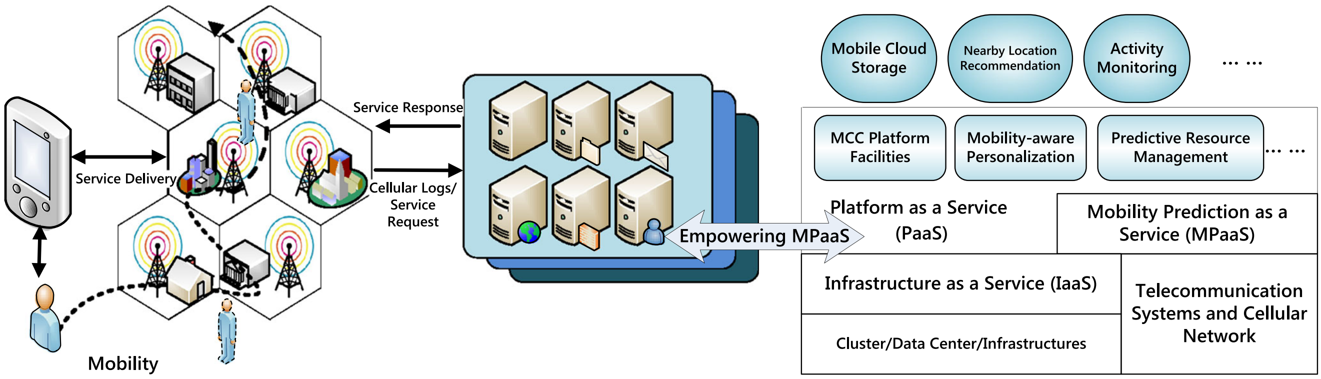


Fig. 1 Architecture of telecom cloud empowered by **MPaaS**

research, **MPaaS** is used to predict the locations of mobile phone users in next 6 hours; and the granularity of location prediction is set at cellular tower level as previous discussion. However it remains challenging to foretell one's locations owing to following two main technical problems:

1. *Continuous tracking of user's location in real-time cellular traces:* a telecom system commonly produces handover logs for more than a million population with tens thousands of cellular towers in every second of its operation. A cellular trace of a user consists a continuous sequence of her handovers. It is thus a big challenge to track each individual's cellular trace from the real-time cellular traces.
2. *Predictability of human mobility:* it is possible to predict user's location by using the schemes based on individual mobility pattern such like Markov-based predictor (Lassabe et al. 2006). However the theoretical analysis (Song et al. 2010) shows that the randomness and individualism of user mobility makes the prediction power of existing predictors based on individual mobility be limited. It is a challenge to investigate the use of other factors or patterns rather than individual's mobility to enhance prediction. In our previous study (Xiong et al. 2012), we uncovered the collective behavioral patterns to improve the predictability of Markov-based predictors.

Thus, our **MPaaS** study mainly focuses on proposing the solutions of above two technical issues. Particularly, we are interested in continuous location tracking strategies to sense and to collect the real-time location information of each individual from big-data of telecom operators. Besides, we have tried our best to extend our previous work (Xiong et al. 2012) in **MPaaS** to resolve the bottleneck of human mobility prediction.

The basic idea about mobility prediction based on *collective behavioral patterns* is summarized as follow: While we agree that the main driver of individual's movement is the regularity of her own mobility, however we also find that the *collective behaviors* affect individual's mobility. Therefore it's logical to recognize and use *collective behaviors* for location prediction. Prior to our efforts in *collective behaviors*, some pioneering work (Gao et al. 2009; Calabrese et al. 2010) had observed or even had measured some social factors affecting individual's mobility. Thus far, the social factors concerned for the most are the social contacts and interactions (Gao et al. 2009). However as a kind of social factors, *collective behaviors* don't rely on the implicit social interactions but much more emphasizes the crowds' behaviors that are occurred "spontaneously". Unfortunately, to the best of our knowledge, few work (Calabrese et al. 2010) has been done to bring the observation and measurement of *collective behaviors* into design of location predictor.

In our previous (Xiong et al. 2012), we characterize the *collective behavioral patterns* (**CBP**) as the association patterns (Han et al. 2007) among the locations of mobile phone users. We observe crowds may stay at the same type of location spontaneously. For example when 90 % users are staying at their own residences, then the rest 10 % are probably located in their residences as well, although these residences are usually in the different locations. We believe such phenomenon is due to the collective behaviors shared by crowds. Thus we adopt the *collective behavioral patterns* to predict one's future location in next hours according to the current locations of other users. Through our predictor design and evaluation, our **CBP**-based scheme achieves 40 %–50 % precision alone. Then we proposed a fusion mechanism to integrate the **CBP**-based predictor with Markov-based predictor (Lassabe et al. 2006). The hybrid predictor achieves a prediction accuracy of 5 %–10 % higher than the Markov-based predictor.

In this work, we mainly focus on the mobility prediction based on telecom cloud. Comparing with those predictors working on personal smartphones (Chon et al. 2011), the telecom cloud tracks the mobility of all users – a large crowds, and approximates to the nature of *collective behavioral pattern* based mobility prediction. Hereby, we summarize the main contributions of this paper as follows:

1. To the best of our knowledge, we are the first to propose mobility prediction as a service (**MPaaS**) of telecom operator cloud, and have given a dapper review of mobility prediction to commonly-seen mobile cloud computing services and mobile computing applications. It shows mobility prediction indeed optimize the resource management of mobile cloud service and provides applications with personalization, all according to users' future locations. Hereby we summarize *mobility-aware personalization* and *predictive resource management* as the goal of **MPaaS** for MCC services and mobile applications.
2. In this work, we try to architect telecom operator cloud with **MPaaS** empowered; particularly user location tracking strategies of **MPaaS** are discussed. Specifically we contribute (**I**) a message-queue-based switch (**MQ-based Switch**) to extract the cellular trace of each individual from the handover logs generated by cellar systems, as well as (**II**) an unsupervised algorithm to track user locations from her continuous cellular trace naturally polluted with ping-pong noise (Katz 2013).
3. We try to adopt *collective behavioral patterns* in mobility predictor design of **MPaaS**. It shows that our **CBP**-based predictor is quite accurate. The experimental result shows the performance of existing approaches based on individual mobility patterns is improved by integrating with our **CBP**-based predictor.

The rest of this paper is organized as follows. Section 2.1 unfolds the discussion of the services and applications listed in Table 1. Section 2.2 briefly overviews the related work in mobility prediction. Section 3 presents the modules and framework of **MPaaS** as well as the formulation of mobility prediction problem within **MPaaS**. Specifically, Section 3.1 presents the Message-Queue-based switch of **MPaaS** for individual cellular trace extraction; Section 3.2 states the algorithmic framework to track locations of each individual within **MPaaS**; and problem statements are discussed in Section 3.3. Section 4 conducts empirical study on *collective behavioral patterns* measurement from cellular traces of crowds. Section 5 discusses our approach to model the *collective behavioral patterns* into location prediction as well as the design of **CBP**-based prediction scheme. A hybrid predictor based on both **CBP**-based and Markov-based schemes is addressed in Section 5. Section 6 reports the experimental results about **MPaaS** prediction performance. Section 7 concludes our work.

2 Related work

In this section, we mainly introduce the related work of mobility prediction in telecom cloud. Particularly, we will present related work in two parts: **I)** mobile cloud computing services and applications enhanced by mobility prediction; and **II)** existing schemes of mobility prediction.

2.1 Mobility-awareness of mobile cloud computing paradigms

Here we elaborate the mobile cloud computing services and mobile applications listed in Table 1. Specifically, we sort them by functionality, and mainly discuss their interactions with the features of resource management as well as service personalization.

2.1.1 Mobile cloud storage

Mobile Cloud Storage (Wikipedia 2012a) seems one of the most popular type of mobile applications in the current market. Basically, it relies on the back-end of cloud facilities to store the contents of users remotely and enables content synchronization among multiple mobile devices. Dropbox (Drago et al. 2012) and WhereStore (Stuedi et al. 2010) optimize the performance of data storage and access by dispatching the storage task of a user to the local replication of storage nearby. Specifically, WhereStore (Stuedi et al. 2010) identifies user locations by the blocks or the subareas of the a city which is more fine-grained than the city-wide granularity used by Dropbox (Drago et al. 2012). However, Dropbox is a wide-use mobile application; while WhereStore is only a prototype tested in the lab. Generally, the Dropbox-liked (Drago et al. 2012) mobile cloud storage applications, such as SkyDrive and GoogleDrive, operates in a "mobile client/server" model. The mobile cloud storage applications based on device transparency (Strauss et al. 2010) are used to synchronize personal digital contents of a user within a private "mobile peer-to-peer" cloud connected by her personal mobile devices. Combing both mobile P2P and C/S model, STACEE (Neumann et al. 2011) improves the quality-of-service (QoS) of a "mobile client/server" storage cloud by scheduling storage tasks to a public "mobile peer-to-peer" cloud based on edge devices. Generally, mobility prediction improves mobile cloud storage by *predictive resource management* (Drago et al. 2012; Stuedi et al. 2010; Neumann et al. 2011). However, mobility prediction also provides mobile cloud storage services like device transparency with *mobility-aware* *personalization*, since device transparency is proposed to arrange the storage of personal contents, and migrates the contents by co-location of devices personally.

2.1.2 Mobile computation offloading

Mobile computation offloading (Kumar et al. 2012) improves computation power or save the energy consumption of mobile phones by offloading the mobile computation tasks to the cloud facilities at the back-ends. Due the limited computation power and communication capacity of a mobile device, the mobile computation offloading programs are usually required to make trade-off between offloading to remote or computing at local. In this case, the location prediction is usually used to make such decision. MAUI (Cuervo et al. 2010), CloneCloud (Chun et al. 2011), ThinkAir (Neumann et al. 2011) and Smart-Diet (Saarinen et al. 2011) generally propose frameworks to yield the energy-cost/ computation-intensive program partitions (Chun et al. 2011; Cuervo et al. 2010) or methods (Kosta et al. 2012; Saarinen et al. 2011) of a mobile application to the virtual machines at cloud side. Rather than augmenting performance by prediction location (Roy et al. 2004), existing research projects mainly made efforts in task and data migration (Chen et al. 2010; Hsu et al. 2011) between virtual machines.

Thus far, mobility prediction has been used to improve mobile data offloading (Siris and Kalyvas 2012). It is confident to expect novel computation offloading paradigms benefiting from mobility prediction, since (Siris and Kalyvas 2012) is obviously capable to improve the QoS of data-intensive cloud computing task (Hsu et al. 2011). More specifically, interested readers are encouraged to see also in the survey (Kumar et al. 2012) of mobile computation offloading.

2.1.3 Cloud-based mobile phone sensing, mobile recommendation and mobile search

Applications of mobile phone sensing (Lane et al. 2010), mobile recommendation (Zheng et al. 2010) and mobile search (Church and Smyth 2008) had been widely studied in pre-cloud era. Mobile cloud provides mobile phone sensing (Lu et al. 2010; Fakoor et al. 2012) with the back-end to analyzing, processing and sharing the sensed data; generally mobile prediction enhances the efficiency of mobile cloud *resource management* which can further improve the mobile phone sensing by sideways, just like mobile storage and mobile computation offloading. Mobile recommendation and search can be sufficiently improved by mobility prediction, especially in terms of *mobility-aware personalization*. Enhanced by mobility prediction, mobile search and recommendation systems provides a user with things, contents and points of interests where are probably nearby to her future locations. For example, iScope (Zhu et al. 2009) clusters photos by the locations where they were taken, and then it indexes the photos and locations by the traveling trajectories of other users in history. When a user submits the search task to iScope, the search engine firstly extracts her next trajectory by mobility prediction and then queries the contents nearby to her future locations. Besides, Crowds-based Search (Shankar et al. 2012) recommends restaurants according to their future popularity; and the popularity is estimated by predicting “Check-In” of mobile users–a type of collective mobility.

Thus far, we have given an introduction to related applications, projects and papers. Interested readers are encouraged to refer to a comprehensive survey of mobile computing services in Dinh et al. (2011).

2.2 Mobility modeling and predicting

A variety of schemes that address the problem of prediction of user location have been studied. In general, they fall into the schemes based on individual’s mobility patterns, the schemes based on social-ties, and hybrid schemes integrating above two.

2.2.1 The schemes based on the individual’s mobility

These schemes take advantage of the temporal and spatial regularities that are exhibited in the individual’s mobility patterns. The prediction schemes based on *markov models*, especially those based on the *higher-order markovian model* (Lassabe et al. 2006) are considered as the state-of-the-art in the practical predictor design (Song et al. 2004), since it takes the probable locations for next movement and the temporal order of movements into account. Besides, some of other schemes foresee user location by detecting periodic patterns in user traces. The predictability of prediction schemes based on individual’s mobility patterns is limited, around 90% in the theoretical upper bound (Song et al. 2010).

2.2.2 The schemes based on social-ties

They postulate that user movement is driven by social-tie, involving the social community identification, and the prediction based on the community attraction to users. However, social-tie is an elementary building block for user mobility, but not the only driver (Cho et al. 2011). As a typical example, CMM (Musolesi and Mascolo 2006) leveraged user friendship to cluster users as communities, and then decided user next location by community attraction.

2.2.3 The schemes integrating the individual's mobility pattern with social-ties

In recent years, many hybrid schemes on predicting user location have been studied. Calabrese et al. (2010) introduced the first realistic predictor fusing the *collective behaviors* and individual mobility patterns for mobile phone users. It employs a prediction scheme based on the periodicity of the individual's mobility pattern, and then uses the collective geographical preferences to refine the prediction result. Comparing with our research, instead of the collective preference, we choose another pointcut i.e., the association properties to model the *collective behaviors*. HCMM (Boldrini and Passarella 2010) was a mixture mobility model that closely resembled CMM. It fused location preference and social attraction together into prediction. Many other pionnering schemes like (Psounis et al. 2007) will not be introduced here.

3 System overview of MPaaS and problem statement of mobility prediction

In this section we present a system overview of **MPaaS**. Figure 2 shows the framework of **MPaaS**. Firstly, it includes a cloud messaging module–**MQ-based Switch** which is used to extract cellular trace of each individual user from the continuous logs of distributed cellular towers. Later, due to the noise caused by ping-pong effects, an unsupervised location identification algorithm–**individual location tracker** is addressed to track a user's locations from the noisy cellular traces. Finally, we formulate the problem of mobility prediction with respects to the proposed **MPaaS** system as well as the characters of cellular-based location trajectories. We will elaborate the design of **mobility predictor** in Section 5.

3.1 Extracting cellular traces with **MQ-based switch**

A cellular trace consists a sequence of time-stamped Cell IDs which the user connects to. We can log the cellular trace of a user straightforwardly by smart phone monitoring (Chon et al. 2011), since the smart phone OS, e.g., Android, notifies the update of the user's location when it triggers a *handoff event* from the source cellular tower to the destination. However, the acquisition of cellular traces through telecommunication system is not a simple stuff. Particularly, the cellular trace of each user is needed for mobility prediction. However, the cellular trace of a user is a sequence of Cell ID with time-stamped; while each cellular tower simply records a list of *connection logs*, each of which contains the user id and the time-stamp of an user connection. Therefore, to record the cellular traces of all users continuously, an efficient distributed information aggregation mechanism is required for large-scale *connection logs* collection.

In **MPaaS**, we propose an asynchronous event aggregation framework with message queues to extract user's cellular trace. Figure 3 illustrates an example of **MQ-based Switch** to extract cellular traces of two users traveling around three cellular towers. Specifically, extraction is in three phases:

1. **Distributed cellular tower logging:** besides, for each cellular tower, a unique message queue **Cell-MQ** is equipped to continuously publish (Eugster et al. 2003) real-time *connection logs* from the cellular tower. For example, in Fig. 3, three cellular towers are illustrated, and each of which continuously publishes its *connection logs* of all connecting users–i.e., user 2 and 30 through its own **Cell-MQs**.

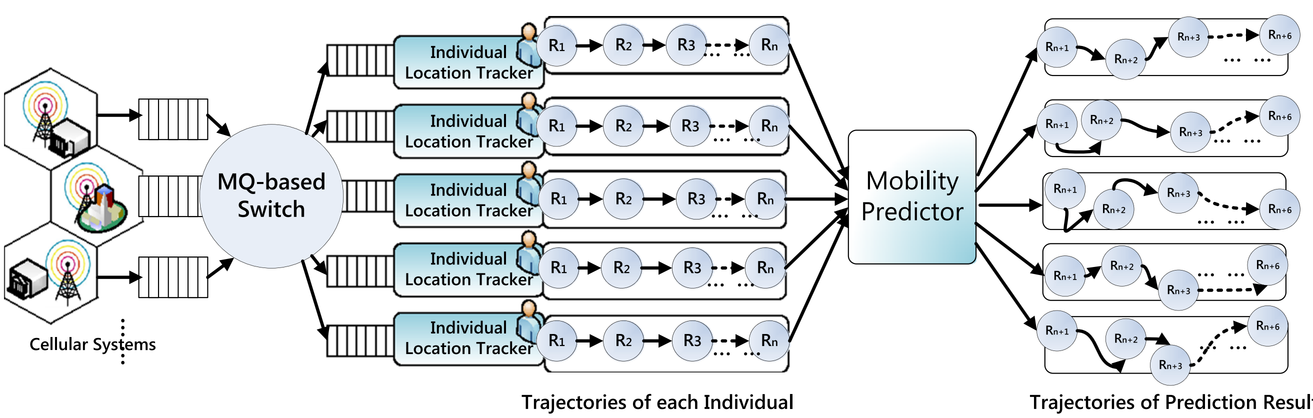


Fig. 2 System overview of **MPaaS**

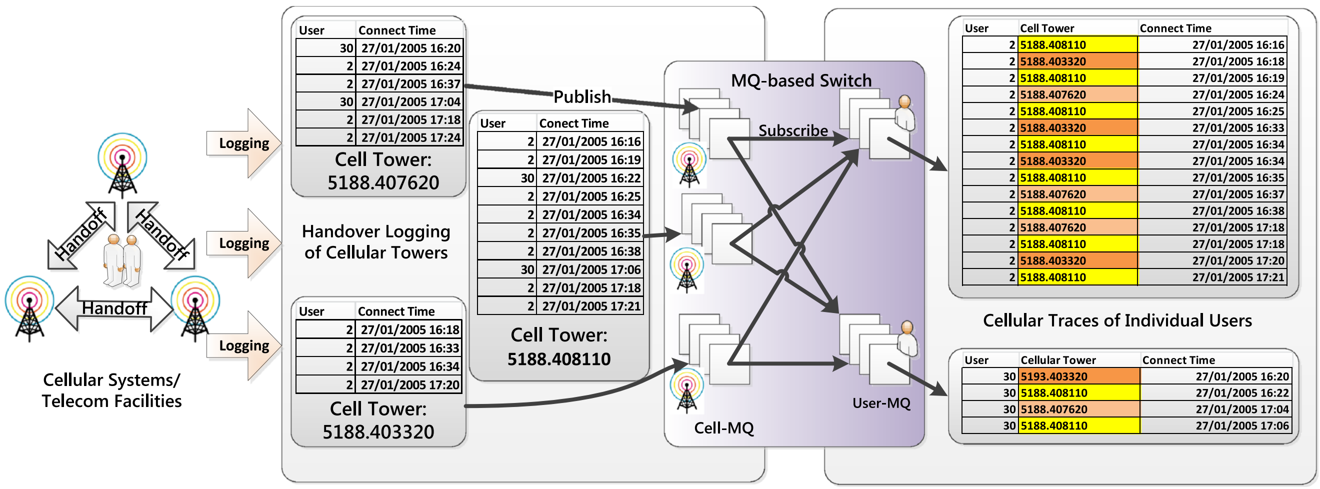


Fig. 3 Cellular trace extraction with **MQ-based switch**

2. **Assorting connection logs by users with MQ-based switch:** oppositely, for each of users, we use a unique message queue (**User-MQ**) to subscribe the *connection logs* from all **Cell-MQ**. The *connection logs* are assorted by Publisher/Subscriber scheme (Eugster et al. 2003) of **MQ-based Switch**. As shown in Fig. 3, each of users (user 2 and user 30) owns a **User-MQ**; and each **User-MQ** subscribes all **Cell-MQs** to collect *connection logs* occurred by the corresponding user. Furthermore, each **User-MQ** collects *connection logs* labeled by their sourcing **Cell-MQ**, i.e.,

$$(user\_id,\ connect\_time) \xrightarrow[Cell\_ID]{\text{Cell-MQ of}} (user\_id, Cell\_ID, connect\_time).$$

3. **Cellular trace extraction from connection logs:** for each of users, **MPaaS** orders her *connection logs* by time-stamp to extract her real cellular trace. The example of Fig. 3 shows each user collects her cellular traces which consists a sequence of Cell ID with time-stamped.

   Based on the aforementioned three steps, **MPaaS** is successfully enabled to extract cellular traces of the large population in the urban-scale cellular network system. Comparing (Zhang et al. 2012) which introduces a generic framework to detect events by matching the inconsistency of contexts in the distributed environment, we adopt similar strategies to aggregate *handoff* events from location change. However, we specifically focus on tracing the trajectories of *handoffs* rather than detecting single event; besides **MPaaS** is more capable, since it uses asynchronous message queues (Eugster et al. 2003; Schmidt et al. 2000).

3.2 Ping-pong noise and individual location tracking

This section presents the typical noise in cellular-based location data and tries to uncover the reasons such noise caused by. Finally, we briefly introduce our data preprocessing stage to reduce the ping-pong noise.

3.2.1 Ping-pong noise

Cellular trace of a user is a sequence of user locations with time stamped and represent the trajectories of users' mobility. The mobile phone would make a log once user handoff to another cellular tower which may have better quality of service (e.g., strength of signal). However, when a user stays in the overlapping coverage of multiple cellular towers without any movement, the mobile phone may frequently handoff among the nearby cell towers even "when radio link still acceptable" (Katz 2013). Figure 4 illustrates a basic scenario that one mobile phone user stays under the coverage of two cellular tower. The frequent handoffs between cell A and B, even the user has no movement at all. These handoffs are considered *unnecessary handoffs*, and the frequent switch with cells of surroundings caused by unnecessary handoffs is named as ping pong effects (Katz 2013).

3.2.2 Individual location tracker

To filter out the noise data, we propose an **Individual Location Tracker** modules to map the coverage of all cells into non-overlapping regions, and identifies each region with *a set of cellular towers covering the region*. For example, in Fig. 4b, the region $\{A, B\}$ is assigned to the location covered by cell tower A and B, but is out the coverage of cell tower C; the region $\{A, B, C\}$ identifies the location covered by

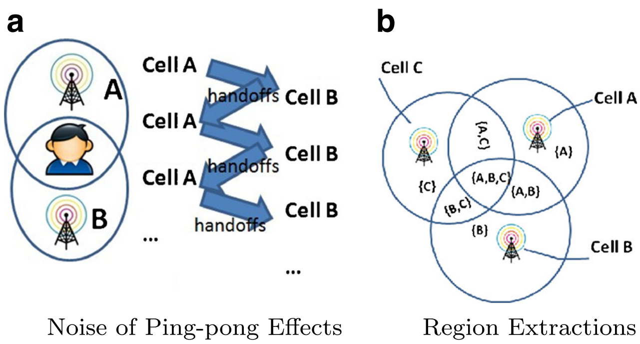


Fig. 4 Example of data noise and regions sliced by cellular towers

cell tower A, B and C; furthermore the region $\{A, B\}$ and $\{A, B, C\}$ has no overlap.

Since the ping-pong noise is mainly caused by unnecessary handoffs, **Individual Location Tracker** will firstly detect the cellular subtraces of unnecessary handoffs, and then it extracts the corresponding sequence (*SEQ*) of unnecessary handoffs. For example, in Fig. 5, *SEQ'*–the sequence of unnecessary handoffs was extracted from the whole cellular trace of user 2. *SEQ'* represents handoffs among cellular towers of *A, B* and *C* in specific order–i.e., $A \to B \to A \to B \to A \to C \to B \to A \to B \to A$, and lasts for 10 minutes totally. Since user's *region* is labeled as a set of cellular towers, then *region* must be a subset of or equal to *CELL* ($region \subseteq CELL$), where *CELL* is the full set of cellular towers–e.g., $CELL = \{A, B, C\}$ in *SEQ'*. Thus, in *SEQ'*, user 2 must be located at one of following region: $\{A\}, \{B\}, \{C\}, \{A, B\}, \{A, C\}, \{B, C\}$ and $\{A, B, C\}$.

Later on, **Individual Location Tracker** provides an unsupervised region-identification algorithm based on

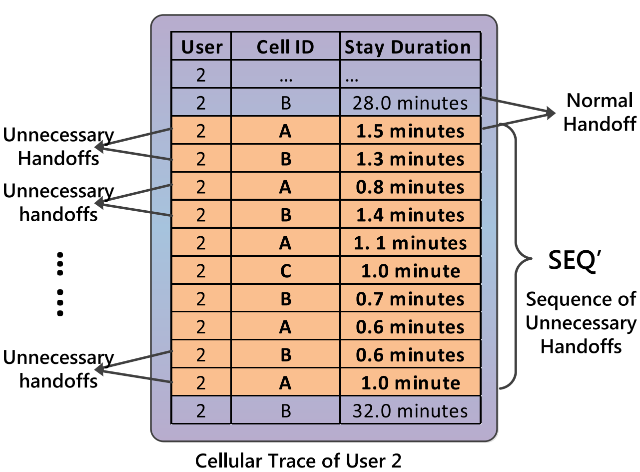


Fig. 5 The example sequence of unnecessary handoffs *SEQ'*

multiple-reference area measurement (Liu et al. 2010) to identify the user's region from her sequence. Given a sequence (*SEQ*), as shown in Eq. 1, we select the most probable $R \subseteq CELL$ from the super set ($\mathbb{R}^+$) of *CELL*,

$$\begin{aligned} region &= \underset{R\in\mathbb{R}^+}{\operatorname{argmin}}\ KLD(SEQ||R) \\ &= \underset{R\in\mathbb{R}^+}{\operatorname{argmin}} \sum_{cell\in CELL} \left| P(cell|SEQ) * ln\frac{P(cell|SEQ)}{Q(cell|R)} \right| \end{aligned} \tag{1}$$

where, taking *SEQ'* as an example, $\mathbb{R}^+$ identifies the super set of $CELL = \{A, B, C\}$–i.e.,

$\mathbb{R}^+ = \{\{A\}, \{B\}, \{C\}, \{A,B\}, \{A,C\}, \{B,C\}, \{A,B,C\}\}$.

For each possible region $R \in \mathbb{R}^+$ and $R \subseteq CELL$, Eq. 1 estimates the Kullback Leibler Divergence of the probability distribution on full set *CELL* of cellular towers between the sequence – $P(cell|SEQ), \forall cell \in CELL$ and the region – $Q(cell|R), \forall cell \in CELL$. The probability distributions are estimated as Eq. 2. *P(cell—SEQ)* counts the frequency that the user connected to cellular tower *cell* during the whole sequence *SEQ*. *Q(cell—R)* estimates the probability that user connects to cellular tower *c* when she stays at region *R*.

$$\begin{aligned} P(cell|SEQ) &= \frac{\text{total time connect to } cell \text{ in } SEQ}{\text{total time of } SEQ} \\ Q(cell|R) &= \begin{cases} 1/|R| & cell \in R \\ 1/(10 * |R|) & cell \notin R \end{cases} \end{aligned} \tag{2}$$

Ideally, when an user stays at region *R*, the user should has equally possibility to connect to cellular tower $\forall cell \in R$. It is reasonable to assume that *Q(cell—R)* falls to an uniform distribution of *R*, i.e., $\forall cell \in R$, $Q(cell|R) = |R|^{-1}$. However, due to the interference, it is still possible to connect to a cellular tower *cell'* out of region *R*, i.e.,$\forall cell' \notin R$, even though probability of connecting to *cell'* approximates to zero. Hereby we set $Q(cell'|R) = (10 * |R|)^{-1}$ for normalization.

In our aforementioned example, we assumed the duration between two consequence handoffs is equivalent, $P(A|SEQ') = 5/10 = 0.5$, $P(B|SEQ') = 4/10 = 0.4$ and $P(C|SEQ') = 1/10 = 0.1$. Table 2 presents the examples of $KLD(SEQ'||R)$ estimation, and it shows the region $\{A, B\}$ should be selected as the most probable region for *SEQ'*. It is too seldom in *SEQ'* to handoff to cellular tower *C*, then we can consider the handoff to *C* is due to the interference of cellular towers. Therefore, the region $\{A, B\}$ is more probable than $\{A, B, C\}$ here.

We say our algorithm here is unsupervised, because we don't have the exact regions in ground-truth. However,

Table 2 Examples of $KLD(SEQ'||R)$ estimation

R	Q(A|R)	Q(B|R)	Q(C|R)	KLD
{A}	1.0	0.1	0.1	0.901
{B}	0.1	1.0	0.1	1.171
{C}	0.1	0.1	1.0	1.589
{A,B}	0.5	0.5	0.05	0.159
{A,C}	0.5	0.05	0.5	0.993
{B,C}	0.05	0.5	0.5	1.401
{A,B,C}	0.33	0.33	0.33	0.396

the use of region is necessary to determine the real location from noisy and frequent handoffs. Moreover, our identification of the region is credible, since the design of algorithm follows the generic criteria of localizability (Liu et al. 2010) in the multiple-reference localization cases. Finally, in Reality Mining dataset, we totally discovered 34546 regions from the cellular traces of 32579 cell towers. In our research, the locations for inputs and output of our predictors are regions.

3.3 Problem statement of location prediction

Through individual location tracking of **MPaaS**, the cellular trace of each user is converted into a sequence of regions with time stamped. We pick up the longest stay region for each hour i.e., the region where user spent the longest time for every hour slot, and then thread these regions into a sequence. Such sequence represents the trajectory of user's mobility.

Definition 1 A user's trajectory is a sequence of regions that user spend the longest time for each time slot, i.e.,

$$t : r_1 \rightarrow r_2 \rightarrow \cdots \rightarrow r_n$$

where r_i identifies the longest stay region in i_{th} time slot.

Since one of our research goals is to exploit associations or exactly, the *collective behavioral patterns* to predict user locations, our problem formulation naturally relies on the locations and trajectories for a set of users rather than individual's location.

Problem 1 Given a set of users $U = \{u_1, u_2, \ldots, u_n\}$ and the set of trajectories for these users $T = \{t^1, t^2 \ldots t^n\}$ where $t^i = r_1^i \rightarrow r_2^i \cdots \rightarrow r_m^i$ (r_m^i denotes u_i's location in the m_{th} time slot); predict $r_{m+\tau}^k$, i.e., the region of user u_k being about to stay at the future time τ where $1 \leq k \leq n$ and $\tau \in$ **N+**.

Particularly, as the definition of problem, **MPaaS** is motivated to predict locations for each user of large crowds. Because **MPaaS** collects and holds the mobility data from large population of mobile users. Sometimes it is saying *"Stronger ability and more responsibilities"*. Rather than predicting the locations of each user by her individual's mobility, **MPaaS** should find a way to *predict the locations of crowds by the mobility of whole crowds*. Thus, it becomes our great research opportunity and challenge to investigate the mobility patterns of crowds to *correlate the locations among different users*.

In the latter part of this paper, by exploiting the association properties of mobile phone user's locations, we propose a predictor to forecast one user's locations from other users' locations for next 6 hours (i.e., $\tau \in (0, 6]$).

Table 3 Statistics of MIT reality mining dataset

Item	Description	Item	Description
Starting time	Jan/2004	Ending time	Jul/2005
# of users	106	# of faculties	11
# of cell towers	32,579	# of areas	1,027
# of GSM trace	2,667,895	Avg. # of trace	46.7
# of mobile calls	112,508	Avg. # of call	≈ 4
Logical location	lac.cell	Physical location	no

4 Measuring collective behavioral patterns in human mobility

In this section, we aim at validating the existence of *collective behavioral patterns* (**CBP**) and measuring the effects of **CBP** to human mobility. The final goal of this empirical study is to investigate if it is possible to infer one user's location from the locations of other users. To achieve the goal, we try to discover the *association patterns and rules* in user's locations of mobility.

4.1 Empirical study setup

This empirical study was made on MIT Reality Mining dataset (Pentlandb et al. 2009). Table 3 addresses a brief overview to MIT Reality Mining dataset. Due to the limited of dataset, for example many users are inactive sometimes, we simply pick up 15 active users[2] from all 106 users as well as their cell logs dating from 01-Nov-2004 to 29-Dec-2004. All cell logs are converted into the sequences of regions.

The association patterns that we attempt discover are based on the locations of users. Therefore each of the items is a user specified region, i.e., the tuple $\langle r_a, u_i \rangle$ which represents the user u_i staying in region r_a. We have found 1868

[2]The user #4, #8, #12, #23, #6, #69, #102, #37, #9, #26, #25, #27, #35, #73 and #53 are involved for empirical study.

tuples for these 15 users. Therefore the transaction (Han et al. 2007), i.e., locations of users in the same time slot, is specified as a set of tuples. More specifically, in this empirical study, each transaction is a set of 15 tuples.

Following above specifications, an association rule becomes the inference from left-hand set (**LHS**) of the tuples to right-hand set (**RHS**) of the tuples, for example:

$$\{\langle u_i, r_a\rangle, \langle u_j, r_b\rangle, \langle u_k, r_c\rangle\} \Rightarrow \{\langle u_l, r_d\rangle, \langle u_m, r_e\rangle\}$$

where u_i, u_j and u_k identify users and r_a, r_b and r_c are regions.

4.2 Observations

We formulate our association analysis (Han et al. 2007) result as the two main observations:

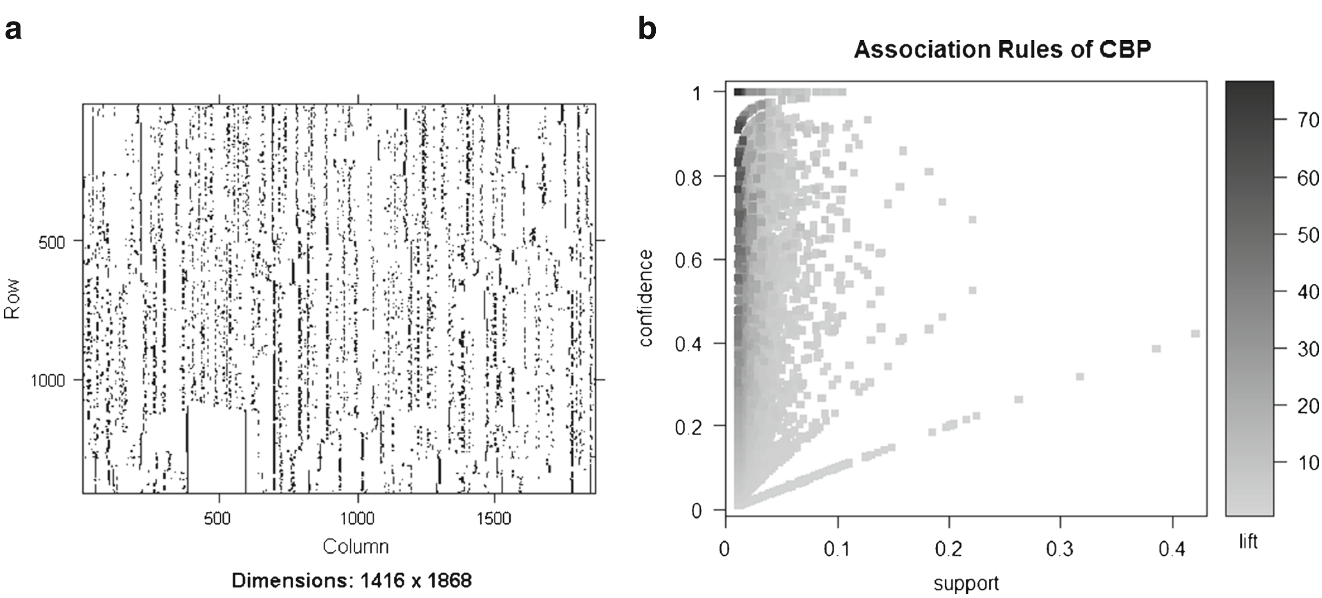
1. **Locations of mobile phone users are associated.** Since 1868 user specified locations have been found (tuples) in the selected dataset, then we simply map each transaction into a vector of 1868 dimensions. The transactions throughout 59 days (1416 hours) are formed into a 1416 × 1868 matrix as the Fig. 6a illustrated. Each pair of parallel segments indicates that these two user specified locations are associated; for instance when the user u_a stays at region r_i, the u_b always appears in the region r_j. Then we discover that most of these locations are in two types: (1) office, including MIT Media lab (cell tower 5119.408110 and 5119.403320) as well as their own working sites, and (2) their own residences. Finally we remark that the locations of users are associated by collective behaviors of crowds–i.e., going to work place in working time and staying at home in the time to rest.
2. **Association rules of CBP are supportless but confident.** We totally discovered 98853 association rules in selected transactions with support threshold of 1 % and the confidence threshold of 10 %. It is obvious that the most of rules are supportless, and only 79 rules are with the confidence larger than 10 %. That means each of rules only exists in a limited number of transactions. However many rules are still confident. Inside of these 98853 rules, there are 82906 association rules with the confidence higher than 50 %; and the confidence of 64621 rules is above 80 %. Therefore, the association rules only exist in some part of users' locations, but it is confident to infer a user's location from others' locations when the rule matches.

4.3 Discussion and threats to validity

From the observation 1 and 2 above, we can make a conclusion that the *collective behavioral patterns* (**CBP**) and *association rules* of **CBP** are confident in inferring a user's locations from others in the meanwhile.

However, this empirical study significantly suffers several threats to validity. Specifically, we select some of them:

1. ***Threats to External Validity:*** Reality dataset (Pentlandb et al. 2009) totally collects cellular traces of 106 faculties and students in MIT campus; and we pick 15 of



Matrix Form of Transaction

Association Rules of CBPs

Fig. 6 Empirical study

them to conduct this empirical study. It is reasonable to doubt that our observations are dataset-dependent, due to its less samples and limited participators. However, we believe our conclusion is still validated in making a generalization, since our observations coincides with our commonsense in ground truth.

2. ***Threats to Internal Validity:*** As shown in Section 3.3, our problem is defined to predict the user's locations based on the cellular traces collected by telecom cloud; while Reality dataset was collected by mobile phones. Specifically the mobile phone is capable to collect more comprehensive cellular traces, since it is complicated for telecom cloud to detect handoff events and track cellular traces from large-scale distributed cellular systems but a mobile phone collects its cellular traces simply by logging all its cellular connections. Thus, above empirical observations might not be relevant to our study of **MPaaS**. However, we have equipped **MPaaS** with **MQ-Switch**. Therefore, we are confident to assume the cellular traces collected by mobile phones are equivalent with those extracted by **MQ-Switch** of telecom cloud.

Driven by our conclusion, we have developed a location prediction model that considers the locations of all users, and predict their locations from the locations of other users for next 6 hours. We will explain our algorithm in details the next section.

5 Location prediction by collective behavioral patterns

In this section, we present the mechanism to predict user's location by adopting *collective behavioral patterns*. Furthermore, we integrate our **CBP**-based scheme with a Markov-based predictor (Lassabe et al. 2006) into a hybrid prediction scheme regarding to both individual's mobility patterns and *collective behavioral patterns* associated with crowds. **MPaaS** indeed uses this hybrid scheme to make prediction for telecom cloud users.

Although we have empirically observed the association rules of **CBP**, we still found that it is not appropriate to directly apply the association mining approaches and rule-based inference to location prediction, for many reasons. The main causes are: ***a)*** The association rules are not capable to infer a series of locations for one user in next 6 hours, since the **LHS** and **RHS** of a rule here reflect the locations of users in the meanwhile; ***b)*** Rules may have conflicts, e.g., $\{a, b\} \Rightarrow c$ and $\{a, b\} \Rightarrow d$, but the resolution way is not clear.

Hereby, we proposes a Bayesian framework to predict user's locations from crowds to overcome above limits; and **MPaaS** combines such Bayesian framework with a commonly-seen Markov-based predictor into a hybrid prediction scheme. Please make note that the inputs of **CBP**-based, Markov-based and the hybrid predictors are the trajectories pre-processed as Section 3.2.

5.1 CBP-based bayesian predictor of MPaaS

In this section, we attempt at presenting the design of Bayesian scheme to predict one user's future locations from the current locations of other users.

The predictor has two main components– candidate set generator and the probabilistic inference engine. (1) The candidate set generator yields a set of possible regions nearby user's *current location* first. (2) Then our predictor uses probabilistic inference engine to pick up the most probable location from the candidate set as the prediction result for the next hour. (3) Since we assume the user would move to the location of prediction result in time, we assign user's current location with the prediction result, finally repeat step (1), (2) and (3) five more times for 6 hour prediction. Algorithm 1 addresses the skeleton of this predictor. The result of algorithm is an ordered list with 6 locations representing the locations for next 6 hours.

Algorithm 1 Skeleton of the Bayesian Predictor

```
slot ← 0
current_location ←user's current location
next_location ←NULL
C ← ∅
/*initiate the candidate set with an empty set*/
repeat
    C ← gen(current_location)
    /*generate candidate set from current location*/
    next_location ← infer(C, slot)
    /*forecast user's location by given time slot*/
    list.add(next_location)
    /*add to the result list*/
    current_location ← next_location
    /*user is assumed to move to the next_location*/
    slot ← slot + 1 /*move to next hour*/
until slot=6
/*finish the prediction for six hour*/
return list
```

5.1.1 Candidate set generation

The Bayesian predictor picks up the most probable location from a candidate set of regions as the forecast result. Therefore, the generation of candidate set should have user's current spatial/temporal situation concerned. According to the Definition 1 in Section 3, **MPaaS** has pre-processed data and extracted the previous trajectories of all users. Then we recover the topology of regions based on these trajectories. First, **MPaaS** collects all possible neighbors of user's current locations in topology. Besides, user may still stay in the current location for future. Therefore the candidate set indeed is the collection of user's current location and its neighbors.

5.1.2 Probabilistic inference engine

Given the current locations of other users, i.e., the tuples $\langle u_1, r_1\rangle \ldots \langle u_n, r_m\rangle$, the corresponding set of candidate locations C and the τ^{th} hour in future, this model is enabled to find out the most probable location:

$$\textbf{select}\ r \in C\ \textbf{max}\ P(\langle u, r\rangle | \langle u_1, r_1\rangle \ldots \langle u_n, r_m\rangle, \tau) \quad (3)$$

where u and r are the target user and the location (region) for prediction. $P(\langle u, r\rangle | \langle u_1, r_1\rangle \ldots \langle u_n, r_m\rangle, \tau)$ identifies the conditional probability of user u staying at region r in future τ with the current locations of other users–i.e., $\langle u_1, r_1\rangle \ldots \langle u_n, r_m\rangle$ given.

$$\begin{aligned} &P_{bayes}(\langle u, r\rangle | \langle u_1, r_1\rangle..\langle u_i, r_j\rangle..\langle u_n, r_m\rangle, \tau) \\ &= \frac{P(\langle u, r\rangle) \times \prod_{i=1}^{n}\prod_{j=1}^{m}(P(\langle u_i, r_j\rangle, \tau | \langle u, r\rangle))}{P(\langle u_1, r_1\rangle..\langle u_i, r_j\rangle..\langle u_n, r_m\rangle)} \end{aligned} \quad (4)$$

Suppose the locations between each of user pairs are weakly dependent, hereby it is reasonable to formulate the conditional probability in Eq. 3 with Naive Bayes modeling as Eq. 4.

$$P(\langle u, r\rangle) = \frac{\#records\ of \langle u, r\rangle}{\#all\ records\ of\ user\ u} \quad (5)$$

identifies the probability user r stay in region r.

$$\begin{aligned} &P(\langle u_i, r_j\rangle, \tau | \langle u, r\rangle) \\ &= \frac{\#records\ of\ \langle u_i, r_j\rangle\ in\ the\ \tau^{th}\ hour\ before\ \langle u, r\rangle}{\#\ records\ of\ \langle u, r\rangle} \end{aligned} \quad (6)$$

is the probability that user u_i staying at r_j in the τ^{th} hour before user u staying in region r. Both probabilities are formulated in Eqs. 5 and 6 with simple accumulation and statistics. If the acquired record don't exist–i.e.,$\#records = 0$, our predictor assigns $\epsilon = 0.000001$ as the value of these two probabilities in calculation. Furthermore, **MPaaS** simplifies the Bayesian probability calculation as to estimate likelihood formulated in Eq. 7 which is proportional to the Bayesian probability.

$$\begin{aligned} &P_{bayes}(\langle u, r\rangle | \langle u_1, r_1\rangle..\langle u_i, r_j\rangle..\langle u_n, r_m\rangle, \tau) \\ &\propto \frac{P(\langle u, r\rangle) \times \prod_{i=1}^{n}\prod_{j=1}^{m}(P(\langle u_i, r_j\rangle, \tau | \langle u, r\rangle))}{\prod_{i=1}^{n}\prod_{j=1}^{m} P(\langle u_i, r_j\rangle)} \\ &= Likelihood(\langle u, r\rangle | \langle u_1, r_1\rangle..\langle u_i, r_j\rangle..\langle u_n, r_m\rangle, \tau) \end{aligned} \quad (7)$$

Finally the normalized likelihood shown in Eq. 8 is employed as the approximation of conditional probability $P(\langle u, r\rangle | \langle u_1, r_1\rangle..\langle u_n, r_m\rangle, \tau)$. As supplementary, for each user u, **MPaaS** considers the region r that maximizes the normalized likelihood as the solution of Eq. 3.

$$\begin{aligned} &P(\langle u, r\rangle | \langle u_1, r_1\rangle..\langle u_n, r_m\rangle, \tau) \approx \\ &\frac{Likelihood(\langle u, r\rangle | \langle u_1, r_1\rangle..\langle u_n, r_m\rangle, \tau)}{\sum_{r_k \in C} Likelihood(\langle u, r_k\rangle | \langle u_1, r_1\rangle..\langle u_n, r_m\rangle, \tau)} \end{aligned} \quad (8)$$

5.2 **MPaaS** Predictor Integration

The **CBP**-based predictor is not designed to handle the main factor of human mobility–i.e., the individual's mobility pattern. Therefore **MPaaS** integrates the **CBP**-based scheme with a Markov-based predictor regarding to the individual's mobility patterns. The architecture of the hybrid predictor is illustrated in Fig. 7. In this section, we mainly address the design issues of the markov-based predictor and the fusion process to combine the results of two predictors.

*5.2.1 Markov-based predictor of **MPaaS***

The location/trajectory predictors based on Markov chain model treat user mobility as sequences of locations, and take the individual's mobility patterns including the probability of transition between locations and the order of transitions into account. The implementation of our Markov-based location prediction scheme is derived from Begleiter et al. (2004) the state of the art of VMM-based sequence predictor.

For each user, **MPaaS** trains a 6th-order markov chain to learn its mobility, and makes the prediction by Partial Match (PPM) mechanism. This Markov-based predictor relies on the candidate set generation in Section 5.1.1 also, and selects the most probable region from the candidate set C as the prediction result. The evaluation result Section 6 will show our Markov-based predictor delivers a sound prediction power, and it is a high quality baseline for performance comparison.

5.2.2 Prediction result fusion

The fusion process will be activated, when the prediction results of **CBP**-based and Markov-based schemes are different. Here **MPaaS** resolves the conflict through re-estimating the probability of each candidate region by using Evidence Theory (Shafer 1976). The re-estimation is based on the joint mass (combination) calculation from the probability distributions of candidate regions given by above two predictors.

Thus, we consider the fusion process as the combination of evidences from both predictors based on Dempster's rule. In the framework of DS-Theory, mass functions are needed to give every possible set of results a degree of belief–i.e.,

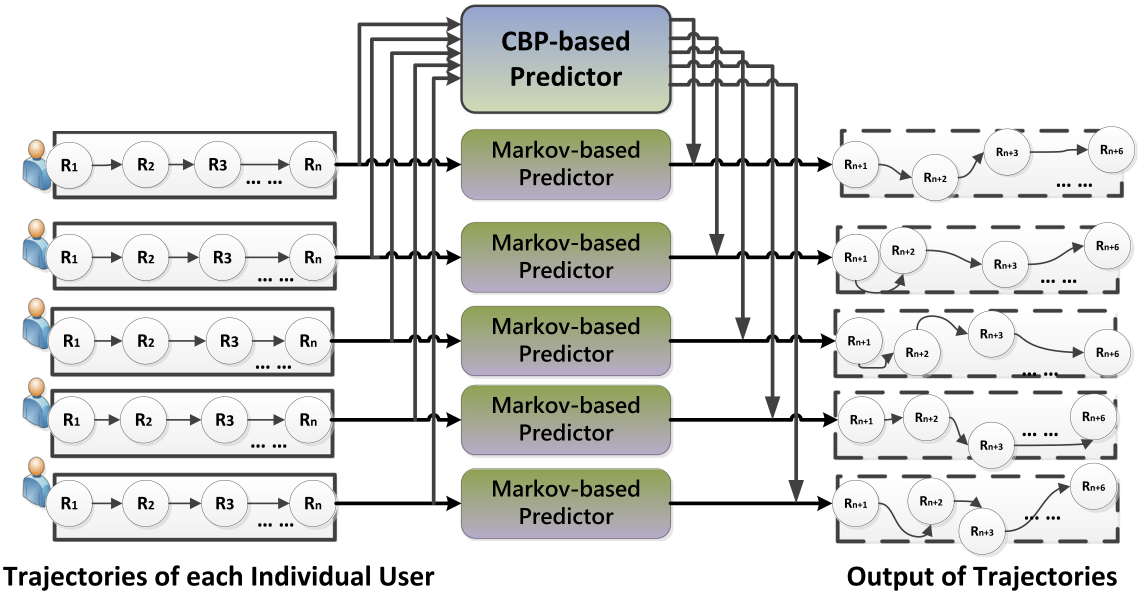


Fig. 7 Architecture of the Hybrid Predictor in **MPaaS**

$2^C \mapsto [0, 1]$, where C is the candidate set of regions and 2^C is the power set of C. The masses for **CBP**-based predictor m_c and the masses for Markov-based scheme m_m are formulated in Eq. 9. $P_{CBP}(r)$ identifies the probability of region r for **CBP**-based prediction, and it is the same to P_{markov} for Markov-based predictor. Since the prediction result in our framework is a single region, so the masses of empty set and the set of multiple regions must be zero.

$$m_c(A) = \begin{cases} 0 & |A| \neq 1 \\ P_{CBP}(r) & A = \{r\} \end{cases} \quad A \in 2^C$$
$$m_m(A) = \begin{cases} 0 & |A| \neq 1 \\ P_{markov}(r) & A = \{r\} \end{cases} \quad A \in 2^C \tag{9}$$

The fused probability from two predictors is formulated as the evidence combination as in Eq. 10, where A *and* $B \subseteq 2^C$. According to the definition of masses in Eq. 9, we can see the fused probability is actually proportional to the joint probability of **CBP** and Markov.

$$\begin{aligned} P_{fused}(r) &= (m_c(\{r\}) \oplus m_m(\{r\})) \\ &= \frac{\sum_{A \cap B = \{r\}} m_c(A) m_m(B)}{1 - \sum_{A \cap B \neq \emptyset} m_c(A) m_m(B)} \end{aligned} \tag{10}$$

Therefore, we can simply view the fusion result as the region r which can maximize the joint probability from both **CBP** and Markov.

Thus far, we have introduces the design and the implementation of three predictors – **CBP**-based scheme, Markov-based scheme and the hybrid predictor of **MPaaS**. The evaluation result presented in next section will further show the forecasting power of **CBP**-based scheme and proves the capability of *collective behavioral patterns* to augment Markov-based approach; and the hybrid predictor of **MPaaS** outperforms the rest all. Finally, we would be glad if interested users could contribute the other design of prediction scheme regarding to the *collective behavioral patterns*.

6 Evaluation and result

In this section, we show the evaluation results of our predictors on MIT Reality dateset, and conduct a series of experiments to evaluate the prediction power of the **CBP**-based approach and its enhancement to Markov-based predictor. As was discussed in Section 4.3, the evaluation result of proposed predictors on MIT Reality dataset sounds equivalent to their performance on the realistic **MPaaS** deployment.

In particular, we would like to answer: 1) whether **CBP**-based approach has ability to predict; and 2) in what degree

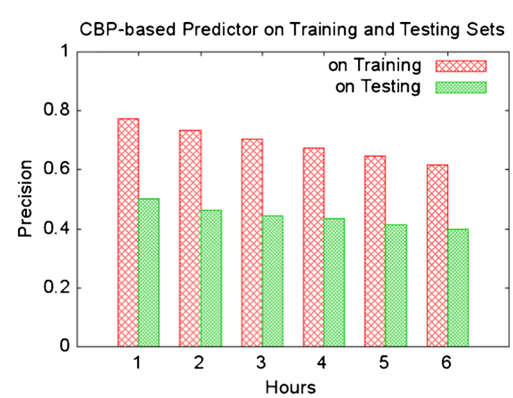


Fig. 8 Aggregated result: **CBP**-based scheme

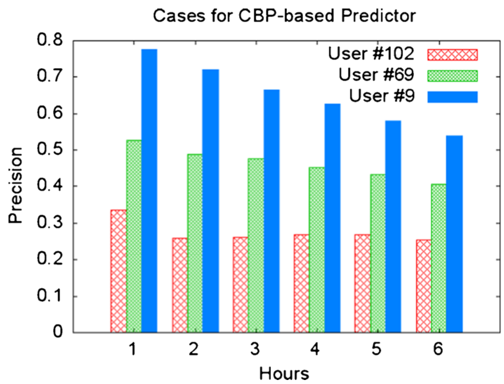


Fig. 9 Cases of three users: **CBP**-based scheme

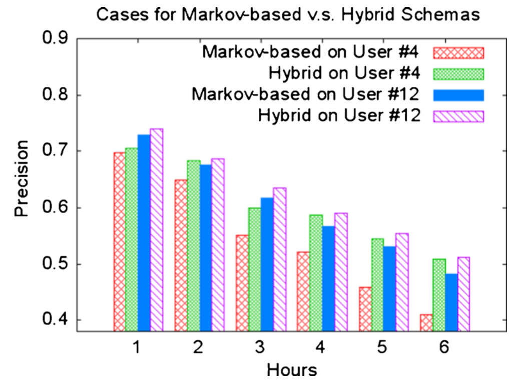


Fig. 11 Cases of two users: markov-based v.s. hybrid schemes

the **CBP**-based scheme can enhance the Markov-based predictor. Hereby, we start-up two sets of experiments, the first is the standalone evaluation of **CPB**-based scheme, and another is performance comparison between Markov-based scheme and the hybrid predictor. In this paper, we present the aggregated results of these experiments as well as the case study of few users.

Figure 8 illustrates the precision of **CBP**-based predictor running on the both training set and testing training. The precision on training set is decreasing from 77 % to 62 % for the prediction of 6 hours. It shows **CBP**-based scheme conforms regularity of location prediction but is not overfitting. The precision on testing averagely declines from 50 % to 40 % in the prediction of 6 hours. Thus we believe **CBP**-based scheme delivers sound quality of performance. Furthermore, the standalone performance of **CBP**-based scheme for three users is addressed in Fig. 9. These three cases are chosen as the worst (user #102), the average (user #69) and the best (user #9) cases of the standalone evaluation. It is reasonable to conclude that at least **CBP**-based scheme is capable to achieve around 30 % precision, however to the best case, the scheme reaches more than 70 % accuracy in the first hour prediction and decreases to the precision of 60 % in the sixth hour prediction.

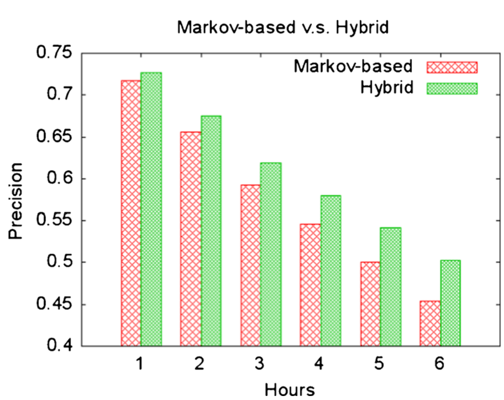


Fig. 10 Aggregated result: markov-based v.s. hybrid schemes

Figure 10 illustrates the aggregated performance comparison between Markov-based predictor (baseline) and hybrid scheme. In average, our baseline–Markov-based scheme delivers precision of 72 % to 45 % for the first to sixth hour prediction. It shows our hybrid scheme outperforms Markov-based predictor averagely 1 % in the first hour and around 5 % in the sixth hour. The improvement of hybrid scheme gradually raises for one to six hours. Besides the performance comparison between user #4 and user #12 is presented in Fig. 11. The improvement on user #4 case goes from 1 % to 10 % for 6 hours; while the enhancement on user #12 cases remains no more than 3 % for all hours. The improvement of both cases are gradually increased by the hours for prediction, it is the same as what we have observed in aggregated comparison. We consider it is due to that **CBP**-based scheme is able to correct the cumulative error in the sequence-liked prediction.

Reviewing above result and observation, it is reasonable to conclude that: 1) *collective behavioral patterns* can be used to predict mobile phone user's prediction, although they are not the main driver of human mobility, 2) our **CBP**-based scheme is accurate and finally 3) *collective behavioral patterns* and our **CBP**-based scheme can be adopted to augment the performance of Markov-based predictor or other predicting approaches. Thus, **MPaaS** of cause adopts the hybrid scheme, a predictor that fuses, and outperforms the both of **CBP**-based as well as Markov-based schemes, to predict the mobility of crowds.

7 Conclusion

Mobility prediction has received substantive attention in recent years, yet it still remains to be addressed, particularly when it comes to mobile phone user mobility in urban environment. We are first to discuss mobility prediction in the context of mobile cloud, and we think telecom operator cloud should take the responsibility of mobility prediction through a dapper analysis in both technologies and consuming markets. Thus, we propose **MPaaS**–a novel mobile cloud computing paradigms based on telecom cloud. We have discussed the design and implement issues of **MPaaS**, especially we elaborate the tracking framework to identify locations of each individual user in massive crowds. And we have carefully designed the framework to make it efficient in processing the noisy handoff logs generated by the large-scare distributed cellular towers.

Besides, in our previous work, we had proposed *collective behavioral patterns*, the association patterns among multiple users' locations at the same moment, had provided a new perspective to leverage social aspects into user movement forecast. Moreover, we had designed and implemented a Bayesian prediction scheme based on the *collective behavioral patterns* which had been validated to improve the performance of Markov-based predictor. In this paper, **MPaaS** adopts the **CBP**-based scheme to predict the mobility of crowds, and hosts 3rd party applications as well as other MCC services with the prediction results.

However, as we had concluded in Xiong et al. (2012), **CBP**-based scheme could be further improved; and we are still working in designing new prediction schemes adopting *collective behavioral patterns*. Besides, we will also evaluate the scalability and performance of **MPaaS** on a realistic telecom deployment with full workloads.

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