

# mFingerprint: Privacy-Preserving User Modeling with Multimodal Mobile Device Footprints

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**Abstract.** The dramatic increase of daily usage of mobile devices generates massive digital footprints of users. Such footprints come from physical sensing such as GPS, WiFi, and Bluetooth, as well as social behavior sensing, e.g., call logs, application usage, etc. Many existing studies apply the mobile device footprints to infer daily activities like sitting/standing and social contexts such as personality traits and emotional states. In this paper, we propose a different approach to explore multimodal mobile footprints and build a novel user modeling framework called mFingerprint that can effectively and uniquely depict users. mFingerprint does not expose raw sensitive information from mobile device, e.g., the exact location, WiFi access points, or apps installed, but computes privacy-preserving statistical features to model the user discriminatively. These descriptive features protect sensitive information, thus can be shared, transmitted, and reused with less privacy concerns. By testing on 22 users' mobile phone data collected over 2 months, we demonstrate the effectiveness of mFingerprint in user modeling and identification. In particular, our conditional entropy footprint statistics can achieve 81% accuracy across all 22 users while evaluating over 10-day intervals.

## 1 Introduction

Mobile devices such as smartphones and tablets have recently become powerful people-centric sensing devices thanks to the increasing varieties of embedded sensors such as GPS, Bluetooth, WiFi, accelerometer, touch, light, and many others. Meanwhile, the devices have also advanced significantly in terms of computational capacity including CPU performance, memory and storage. All of these technical improvements have stimulated the popularity of people-centric mobile applications, ranging from inferring and sharing real-time contexts such as location and activities [3,8] to identifying heterogeneous social behaviors of mobile users [11,6,9,15]. Most of these studies focus on collecting user's phone data to infer and identify physical and social contexts for a particular user at a specific point in time. Additional studies have concentrated on analyzing long-term data from mobile devices to monitor trends and to establish predictive models, such as location prediction [7] and app usage prediction [12].

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In this paper, we take a significantly different view of mobile device data. Instead of focusing on real-time inference of contexts or social behaviors from phone sensors, we explore multimodal mobile usage data to extract simple and effective statistics that can uniquely represent mobile users. As a result, we construct a novel user modeling framework called “mFingerprint” to extract fingerprints that uniquely identify users from mobile device data. Our experiments will show the effectiveness of mFingerprint in modeling users and identifying their uniqueness. In contrast to many user identification studies that try to identify users based on raw sensor data such as touch screen [2] and a few cell tower locations [5], mFingerprint computes privacy-preserving high-level statistical features that do not disclose sensitive information from the phone, such as raw location, browser history, and application names. Therefore, applications can share, transmit, and reuse these descriptive feature vectors to enable new personalized services on mobile devices with less privacy concerns.

**Research Challenges.** It is non-trivial to build a fingerprint based system to identify users based on their daily mobile usage data, due to the following challenges: (1) Mobile devices create heterogeneous logs from various physical sensors such as GPS and accelerometer, and soft application data like app usage and web browser history. How to choose from suitable sources to construct effective mobile fingerprints remains a question. (2) Most mobile data is generated under complex real-life settings without user’s attention or interventions. This usually introduces significant noise that demands robustness in processing. (3) Different from most existing offline data analysis approaches deployed on the server side, our mFingerprint framework focuses on designing energy-efficient algorithms that are able to run on mobile devices directly. (4) Last but not least, mFingerprint must avoid disclosing sensitive mobile data, such as geo locations from GPS, the exact applications installed, and URLs of website visited, to protect user’s privacy.

**Main Contributions.** To address these challenges, this paper presents a novel approach for user modeling and identification based on digital footprints from mobile devices, with the following key contributions: (1) We build mFingerprint, a novel framework to analyze data from mobile devices and model users via digital footprints; (2) mFingerprint generates fingerprints from heterogeneous hardware sensors such as GPS, WiFi, and Bluetooth and soft sensors including app usage logs; (3) By designing a discriminative set of statistical features to capture mobile footprints, mFingerprint is able to effectively identify user’s uniqueness, while preserving user’s privacy.

## 2 Related Work

Recently, user’s digital footprints from mobile device have gained significant attention in various research areas such as mobile computing, data mining and social analysis.

In mobile computing & data mining, several studies are dedicated to building mobile systems to infer context offline or in real-time, such as detecting semantic locations (home and office) from GPS [14], identifying physical activities from accelerometer data [8], estimating user’s environmental contexts such as crowdedness from Bluetooth [13] and noise-level using the microphone [10]. These studies however focus on analyzing only unimodal physical sensors to infer specific types of daily contexts and activ-

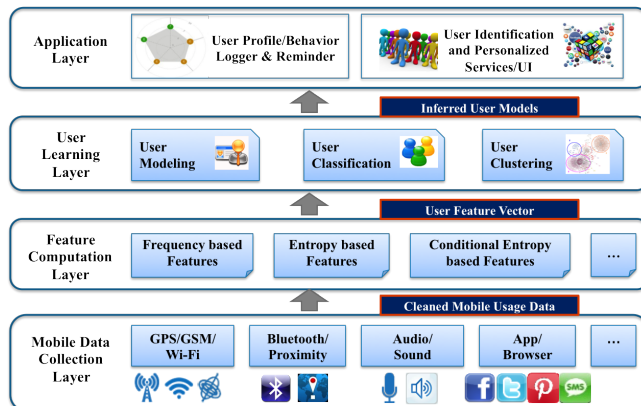


Fig. 1: The mFingerprint framework.

ities. In this paper, we analyze multimodal heterogeneous sensor data including WiFi, GPS, cell tower, Bluetooth collected in non-laboratory settings, compute discriminative statistical features to model mobile users, and identify their uniqueness.

For social and behavioral analysis on mobile data, recent focus is mainly on continuously monitoring user’s daily social contexts, such as inferring emotions from audio [11], detecting mood from communication history and application usage patterns [9], predicting user’s personality using various phone usage data [4][6], and estimating user’s profile and sociability level using Bluetooth crowdedness [15]. mFingerprint framework further extends these studies to analyze multimodal mobile footprints (including both soft usage data and physical sensor data) by extracting discriminative statistical features as a fingerprint to model the user and provide accurate user identification with privacy preservation.

### 3 mFingerprint System Overview

Fig. 1 shows the four layers of the mFingerprint framework. The bottom layer collects various sensor readings using hardware sensors that trace location (e.g., GPS, WiFi, and cell tower), proximity (Bluetooth and microphone). Furthermore, soft sensor data such as application usage and web browser history are also recorded. The second layer of mFingerprint computes a set of privacy-preserving statistical features from these digital footprints. In this paper, we particularly focus on designing frequency and entropy based statistical features to capture mobile device usage patterns. Such features will flow up to the third layer for user learning, which includes building user models via the feature vectors, identifying users via classification methods, and grouping users into meaningful clusters via unsupervised learning. The fourth layer is the application layer where various applications can be established, such as inferring user profile, logging mobile behaviors, and creating personalized services and user interfaces.

## 4 Footprint Feature Computation and User Identification

We focus on designing simple frequency and entropy-based statistical features to create users’ “fingerprints” and evaluate the features’ performance in user identification.

### 4.1 Frequency based Footprint Features

The number of devices and cell towers that are observed by a phone throughout the day provides information about the owner’s environment. For example, a phone in a busy public place will likely observe many wireless devices while a phone in a moving car observes different cell towers over time. Meanwhile, a user’s app usage patterns throughout the day tell us something about his or her daily routine. We thus propose simple frequency-based features that measure how much activity of four different types (Wifi, Cell towers, Bluetooth, and App usage) is observed at different time intervals throughout the day. More specifically, we divide time into  $T$ -minute time periods, and make observations about the phone’s state every  $M$  minutes, with  $M < T$  so that there are multiple observations per time period. In the  $i$ -th observation of time period  $t$ , we record: (1) the number of Wifi devices that are observed ( $W^{t,i}$ ), (2) the number of cell phone towers that the phone is connected to ( $C^{t,i}$ ), (3) the number of bluetooth devices that are seen ( $B^{t,i}$ ), and the number of unique apps that have been used over the last  $m$  minutes ( $A^{t,i}$ ). We then aggregate each of these observation types to produce four features in each time period:

$$F_W^t = \sum_i W^{t,i}, \quad F_C^t = \sum_i C^{t,i}, \quad F_B^t = \sum_i B^{t,i}, \quad \text{and} \quad F_A^t = \sum_i A^{t,i}.$$

A feature incorporating all of these features is simply the vector  $F^t = [F_W^t \ F_C^t \ F_B^t \ F_A^t]$ .

### 4.2 Entropy based Footprint Features

While the simple frequency features above give some insight into the environment of the phone, they ignore important evidence like the distribution of this activity. For example, in some environments a phone may see the same Wifi hotspot repeatedly through the day, while other environments may have an ever-changing set of nearby Wifi networks. To illustrate this, Fig. 2 compares observed frequency versus anonymized IDs

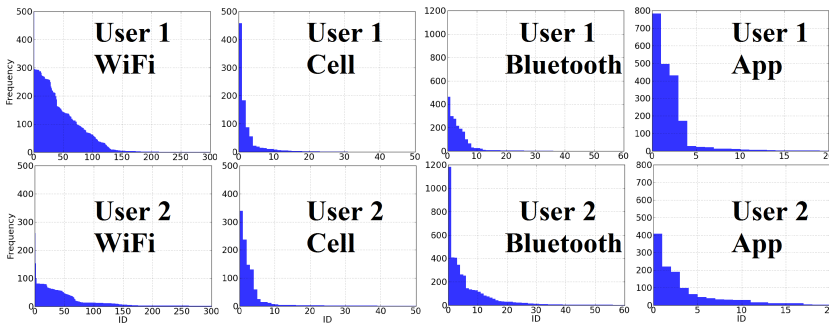


Fig. 2: Mobile device footprints - multimodal data frequency in 10 days. Y-axes are the frequency; X-axes correspond to the ID of Wifi, Cell, Bluetooth, and App, respectively.

for two users across each of the four observation types, for a period of 10 days. We can observe that User 2 is less active in WiFi/cell mobility compared to User 1, but has more Bluetooth encounters and more interests in using diverse apps.

We thus propose using entropy of these distributions as an additional feature of our user fingerprints. The entropy feature summarizes the distribution over device IDs, but in a coarse way such that privacy concerns are minimized. For Wifi, let  $W_j^t$  denote the number of times we observe wifi hotspot  $j$  during time period  $t$ . Then we define the Wifi entropy during time period  $t$  as,

$$E_W^t = - \sum_j \frac{W_j^t}{F_W^t} \log \frac{W_j^t}{F_W^t}.$$

Entropy features for Cell towers, Bluetooth, and Apps ( $E_C^t$ ,  $E_B^t$ , and  $E_A^t$ , respectively), are computed in the same way, and we define a multimodal entropy feature vector  $F^t = [F_W^t \ F_C^t \ F_B^t \ F_A^t]$ , which better represents a user from multiple perspectives.

### 4.3 Conditional Entropy and Frequency based Footprint Features

In our system, we calculate the above entropy and frequency features conditioned on time and location. Intuitively at different times and at different locations, users have different patterns of application usage and surrounding devices (Bluetooth, WiFi, cell, etc.). For example, two users might have similar overall apps usage but one user always uses apps in the mornings, while the other uses them only in the afternoon. Two other users might have similar overall Bluetooth entropies but one might have more surrounding devices at work while the other observes the variety at a coffeeshop. Conditioning on time and space is thus useful to better differentiate users.

**Conditional features on time.** For the frequencies and entropies conditioned on time, we differentiate on time of a day and day of a week respectively. In our current system, we distinguish between three fixed daily time intervals, mornings (0:00 - 8:59), working hours (9:00 - 17:59) and evenings (18:00 - 23:59), and two types of days, weekdays (Mon through Fri) and weekends (Sat and Sun). This gives six time periods over which we compute the conditional and entropy features, respectively. Future work might explore using adaptive time intervals instead.

**Conditional features on location.** We also compute frequency and entropy features conditioned on location. For each user, we filter and cluster their geo-locations in order to identify the top- $k$  significant locations. From data collected at these  $k$  locations, we compute the conditional entropies and frequencies. There are two steps in finding significant locations: *Segmentation* and *Clustering*. In the segmentation step, we find periods of time when the phone appears to be stationary, by looking for time intervals when the IDs of surrounding devices are stable. In particular, we divide the data streams into 10-minute time frames and for each time frame, we record the IDs of the WiFi, Bluetooth and Cell towers. For adjacent time frames, we compute Jaccard similarity of the corresponding sets of IDs,  $J(S_1, S_2) = |S_1 \cap S_2| / |S_1 \cup S_2|$ , where  $S_1$  and  $S_2$  are sets of device IDs. If the similarity is larger than a threshold, we say that the device is stationary during the two time frames. Fig. 3(a) illustrates finding stationary and non-stationary periods according to WiFi readings. Similarly, we perform this on Bluetooth

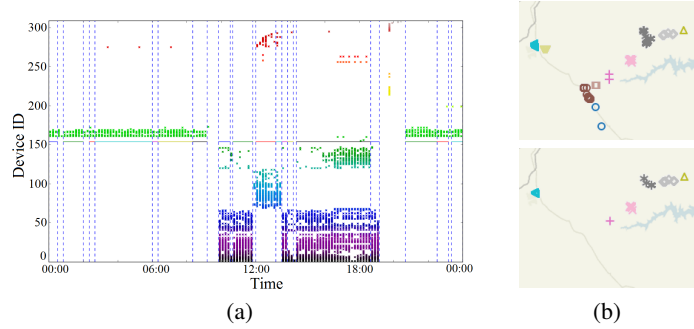


Fig. 3: Time segmentation and location clustering: (a) Finding stationary times using Wifi. (b) Location clustering using all (top) and only stationary (bottom) data.

and Cell readings and take the **union – union or intersection??** of all stationary time periods.

In the clustering step, we apply the DBSCAN clustering algorithm to the stationary segments, in order to identify important locations. Fig. 3(b) shows the clustering results on the same data with or without non-stationary points. We can see that noisy signals (e.g., location points moving along the highways) have been removed by keeping only stationary data, which generates better and fewer clusters. Note that our mFingerprint system computes location based conditional features using anonymized cluster and device IDs, not the original geo-locations, to help preserve privacy.

## 5 Evaluation

We define a user identification problem in order to test whether mFingerprint features can be used to uniquely characterize users. In other words, we want to see whether our simple frequency and entropy statistics can differentiate one user from another. The user identification problem is then a classification problem: *can we build a multi-class classifier trained on user fingerprint features labeled with user IDs, such that it tells which user a certain fingerprint vector belongs to?*

### 5.1 Data collection and experimental settings

To collect data for our evaluation, we deployed an Android app called EasyTrack based on the Funf Open Sensing Framework [1]. This app has a customizable configuration with 17 data types, including WiFi, Bluetooth, cell tower, GPS, call log, app usage etc. We successfully recruited 22 users to install EasyTrack and collected their mobile footprints for 2 months.

We first test the initial user identification performance using different time frame lengths, and determine the optimal time frame. We uniformly sample the instances to make sure that the same number of instances is used to build the classifier for each time frame length. As shown in Fig. 4a, when the length of time frame increases, the

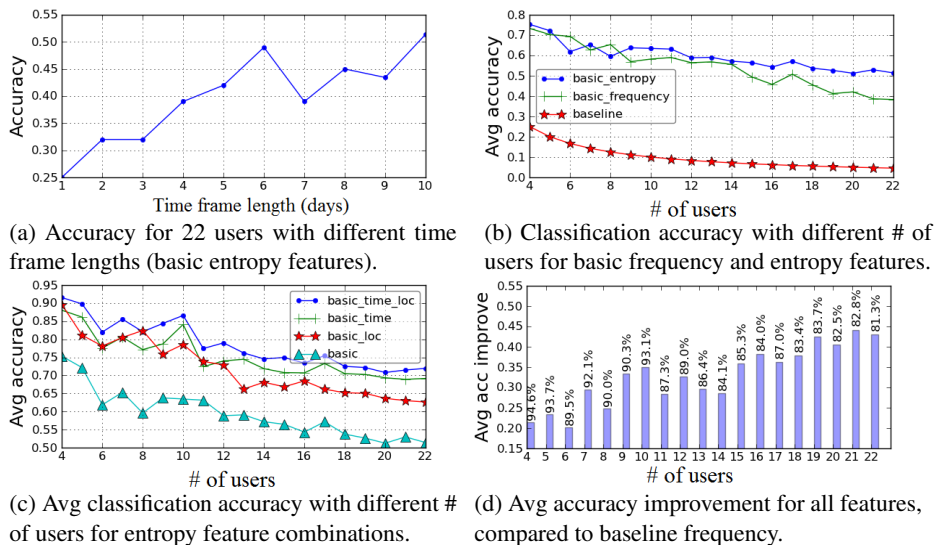


Fig. 4: User identification classification results.

classification accuracy generally improves, despite possible variations caused by weekday/weekend patterns. This suggests that in this range, longer time frames better capture the uniqueness. Since the data collection time span is two months, longer time frames decrease the total number of time periods and thus there are fewer features for training the classifiers. In the following experiments, we fix the time period at 10 days.

With a 10-day time frame, we reach 107 entries in total from 22 users. On average, each user has 4.86 entries. The range is [2, 8] and the standard deviation is 2.2. In total, we have 32 features in mFingerprint. We test combinations of features (multi-modal entropies/frequencies, conditional entropies/frequencies) on multiple classifiers including Naive Bayesian, decision tree, SVM and Multilayer Perceptron. We report the results from the Multilayer Perceptron, which were best. The learning rate is 0.3, momentum is 0.2, the number of hidden layers is set to  $\frac{\#features + \#classes}{2}$  where  $\#features$  is 32 in mFingerprint and  $\#classes$  is 22, which is the number of users. The number of epochs is set to 500. We use 10-fold cross validation for training and testing. We use accuracy as a performance measurement which is defined as  $\frac{\#of\ correct\ predictions}{\#of\ instances}$ .

## 5.2 User Identification Performance

We tested on varying numbers of users from 4 to 22, and observe that as the number of users increases, the average accuracy drops but is still significantly better than random guessing (see Fig. 4b and Fig. 4c). In these experiments, we randomly sample 10 from the  $\binom{22}{n}$  possible combinations (where  $n$  is the number of users being tested), apply 10 fold cross validation on each of the samples, calculate the accuracy and then get the average over the 10 samples. On average, each sample group has 63 instances.

**Performance of standalone frequency and entropy features.** For basic multi-modal frequency and entropy features, each vector has 4 dimensions, corresponding to

WiFi, cell tower, Bluetooth, and apps, respectively. We compare their classification results as shown in Fig. 4b. Both frequency and entropy features outperform the random baseline significantly. Entropies have better performance for large numbers of users compared to frequencies: mean accuracy with entropies drops 22% from 4 users to 22 users, versus a 35% drop using basic frequencies.

**Performance of conditional features.** We also compared various types of conditional features (Fig. 4c). When features including basic multi-modal entropies, location entropies and time entropies are all combined, the performance is the best. Time features perform slightly better than location features and this might be affected by the fact that there are only 2 location-conditioned features but 5 time-conditioned features. With all three kinds of features combined, the accuracy is 71.96% for 22 users while the average accuracy is 91.54% for 4 users and 86.59% for 10 users. Though more features improve accuracy, more computation is required as well, especially for the clustering required by the location conditioning.

**Performance of all features.** Finally, we compute the performance with all mFingerprint features including basic frequencies, entropies as well as conditioned features. Fig. 4d shows its performance improvement against the basic frequency feature results shown in Fig. 4b, with the absolute accuracy marked on the top of each bar: 94.68% for 4 users, 93.14% for 10 users and remains 81.30% for 22 users.

## 6 Conclusion

We presented mFingerprint and showed that its statistics (frequencies and entropies) computed from the device usage data and sensor data that reflect the user’s behavior and social patterns, can be used as a unique fingerprint for user identification while preserving privacy. This serves as the key idea of the proposed mFingerprint framework to collect multimodal mobile data, compute footprint features, build unique user model, and serve on personalized applications. We tested it with a user-identification task and achieve over 81% accuracy even the number of users reaches 22. The mFingerprint feature computation is designed considering both simplicity and energy-efficiency, and thus can be fit into the on-device framework naturally.

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