# All Your Location are Belong to Us: Breaking Mobile Social Networks for Automated User Location Tracking

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# All Your Location are Belong to Us: Breaking Mobile Social Networks for Automated User Location Tracking

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***Abstract*—Many popular location-based social networks (LBSNs) support built-in location-based social discovery with hundreds of millions of users around the world. While user (near) realtime geographical information is essential to enable location-based social discovery in LBSNs, the importance of user location privacy has also been recognized by leading real-world LBSNs. To protect user's exact geographical location from being exposed, a number of location protection approaches have been adopted by the industry so that only relative location information are publicly disclosed. These techniques are assumed to be secure and are exercised on the daily base. In this paper, we question the safety of these location-obfuscation techniques used by existing LBSNs. We show, for the first time, through real world attacks that they can all be easily destroyed by an attacker with the capability of no more than a regular LBSN user. In particular, by manipulating location information fed to LBSN client app, an ill-intended regular user can easily deduce the exact location information by running LBSN apps as location oracle and performing a series of attacking strategies. We develop an automated user location tracking system and test it on the most popular LBSNs including Wechat, Skout and Momo. We demonstrate its effectiveness and efficiency via a 3 week real-world experiment with 30 volunteers. Our evaluation results show that we could geo-locate a target with high accuracy and can readily recover users' Top 5 locations. We also propose to use grid reference system and location classification to mitigate the attacks. Our work shows that the current industrial best practices on user location privacy protection are completely broken, and it is critical to address this immediate threat.**

## I. Introduction

Mobile social networks have gained tremendous momentum since recent years due to both the wide proliferation of mobile devices such as smartphones and tablets as well as the ubiquitous availability of network services. Millions of users are enabled to access and interact with each other over online social networks via their mobile devices. Moreover, the positioning technologies such as GPS, and wireless localization techniques for mobile devices have made both the generation and sharing of real-time user location updates readily available. This, in turn, leads to the extreme popularity of location-based social networks (LBSNs) such as Facebook Places, Google Latitude, PCube, Foursquare, Wechat, Momo, Badoo, Grindr, Blendr, and Tapmee, which boost up to hundreds of millions of users. As one of the most popular LBSNs in China, Wechat achieved more than 300 million registered user accounts in only two years, and is used in over 200 countries [1]. Another LBSN app Momo has 30 million users, 2.2 million of whom use the app on a daily base [2], [3]. Skout, a very popular dating app in North America, draws 1.5 million new users a month who check into the app an average of nine times a day [4].

In contrast to traditional LBSNs such as Foursquare, which allow users to check-in at locations and share the information with friends within vicinity, the newer ones put tremendous focuses on location-based social discovery as the latest trend. Location-based social discovery explicitly enables on-the-spot connection establishments among users based on their physical proximity. Examples of such LBSNs include Google Latitude, PCube, Wechat, Momo and Skout. While services like Google Latitude and PCube allow their users to control with whom they want to share the location information, popular ones like Wechat, Momo and Skout allow location-based social discovery solely based on users' physical proximity.

Along with the popularity of location-based social discovery is the increasing danger of user privacy breaches due to location information exposure. Recent studies have shown that four spatiotemporal points are sufficient to uniquely identify the individuals in an anonymized mobility data set [5], [6] and little outside or social network information is needed to re-identify a targeted individual or even discover real identities of users [5], [7], [8]. Furthermore, users' location traces can leak much information about the individuals' habits, interests, activities, and relationships as pointed out in [9]. And loss of location privacy can expose users to unwanted advertisement and location-based spams/scams, cause social reputation or economic damage, and make them victims of blackmail or even physical violence.

Recognizing the danger of user location privacy leakage due to the use of mobile device in general, various research efforts have been devoted to location privacy. Most of them focus on developing the general location privacy protection mechanisms for location-based services (LBSs) that allow users to make use of LBSs while limiting the amount of disclosed sensitive information [10], [11], [12], [13], [14], [15], [16], [17]. Example techniques include anonymous service uses, cloaking based technique[15], mixzone or silent period[12], [16]. Mechanisms are also proposed to enable proximity testing without revealing the mobile users' real location information [18], [19] for privacy preserving distributed social discovery.

User location privacy in real-world LBSN apps, however, has not received enough attention. Current industrial practices are yet to be scrutinized for their (in)adequacy, and users are usually kept in the dark for the potential risks they face. Different from directly access (e.g., iAround, SayHi) or authorized access type LBSNs (e.g., Google Latitude and PCube), some popular apps including Wechat, Momo, and Skout hide the exact location of mobile users by only sharing the relative distances among the users, limiting the localization accuracy to a certain range or restricting the display coverage to a particular area.

These location obfuscation techniques are expected to enable location-based social discovery, while at the same time protect users' location privacy. And millions of users are made to believe so and thus fail to be conscious about the potential risk of leaking their location information when using the services. This could be potentially more dangerous than the former case of exact location exposure as in Banjo, etc., should these hiding techniques fail, because in the former case users are explicitly aware of the risk and can thus either proactively avoid it by logging off the service when necessary or voluntarily take it.

In this paper, we ask and answer two fundamental questions regarding user privacy in the most popular LBSNs protected by the-state-of-art location hiding techniques. First, is it possible to make an involuntary localization of a random LBSN user by exploiting the public available information only? That is, without hacking into the services and using only the client side information that publicly available through the unmodified app of LBSNs, could we accurately localize a random online user of no priori knowledge? Second, could we freely track a particular user within a reasonably short time period? By investigating three most popular LBSN apps (Wechat, Momo and Skout), our answers to these two questions are more than a simple "yes". Our research findings show that: 1) An attacker could perform a range-free, involuntary user localization with high localization accuracy; 2) Furthermore, it can successfully establish very accurate user location traces.

We implement FreeTrack, an automated user location tracking system for mobile social networks, which could automatically track Wechat, Skout and Momo even without users' awareness. To demonstrate the effectiveness of FreeTrack, we perform a three-week real-world attack towards 30 volunteers from United States, China and Japan. By comparing the collected users' real trace with the inferred trace, it is found that the mean tracking error of FreeTrack is 51m for 74 Wechat tests, 25m for 119 Momo tests, and 130m for 156 Skout tests. What's more, users' Top 5 locations could be easily identified by the attacker. According to the existing works, more than 50% of the individuals could be uniquely identified if given top 2 locations[5]. Hence, the newly identified attacks pose a serious threat towards the locations privacy of hundreds of millions of LBSN users.

The rest of paper is organized as follows: Section II is the classification of LBSNs. Section III describes our attack methodology, which is followed by Section IV describing the implementation of the attack. Section V presents the evaluation results. In Section VI, the mitigation approaches are discussed and Section VII summarizes the related work. Finally, Section VIII concludes the paper.

## II. LBSN: The State-of-the-Art

### A. Classification of LBSNs

With the wide use of mobile devices, and the increasing attention on mobile social networking, location-based social networks (LBSN) focusing on the small local social network derived from a user's geographical location become increasingly popular. In addition to the conventional location-based user check-in apps (e.g., Foursquare), more LBSN apps are exploiting the users' geographical information to achieve distance-based social discovery and location sharing. Based on how real-world LBSNs share the location information among their users in order to allow location-based social discovery, they can be classified into two main categories: I) LBSNs with Exact Location Sharing and II) LBSNs with Indirect Location Sharing. Table I is a summary from our survey of 20 popular real-world LBSNs.

Category I has two subtypes. The Subtype I is *Open Access Location Sharing*. These LBSNs present the exact locations of their users without any restriction. Take Banjo as an example. By clicking "Places" tab, the users are allowed to see people of the same city, the exact location of which are explicitly displayed on a map. Similar applications include SayHi, I-Am, iAround. The Subtype II is *User Authorized Location Sharing*. For this type of LBSNs, users can have the control to choose with whom they share their exact location information. For example, in Google Latitude or PCube, a user can define the set of other users (or friends) who are allowed to see his position on the map. In general, when the users choose this kind of apps, they should have a clear idea about the potential location privacy risk and be willing to share their location information with other LBSN users or only share their location with their trusted friends.

In Category II, the exact geographic information is hidden or obfuscated by a series of location privacy protection techniques. Different from Category I which reveals users' exact locations, in Category II LBSNs, users are assured that their exact location information are never shared for the purpose of privacy protection. To achieve this goal, LBSN service providers adopt the following location obfuscating techniques.
**I. Relative Distance Only**: This has been a very common location hiding technique adopted by many popular LBSNs, including Wechat, Skout, and Momo. Users in this case can

| | Distance | Accuracy Limit | Coverage Limit | Number of Users (millions) | Platform or region | SDK | Category |
|---|---|---|---|---|---|---|---|
| Wechat | Y | 100m | 1km (shanghai) | 300 millions | iOS/Android/WP | Google | II |
| Skout | Y | 0.5mile | N/A | 5 millions | iOS/Android/WP | Google | II |
| Momo | Y | 10m | N/A | 30 millions | iOS/Android/WP | Baidu | II |
| Whoshere | Y | 100m | N/A | 5 millions in 2012 | iOS/Android | Google | II |
| MiTalk | Y | 100m | 0.6km (shanghai) | 20 millions | iOS/Android | Baidu | II |
| Weibo | Y | 100m | 1600m | 500 millions | iOS/Android/WP | Google | II |
| SayHi | Y | 10m | 1000km | 500 thousands | iOS/Android | Google | I/II |
| iAround | Y | 10m | N/A | 10 millions | iOS/Android | Baidu | I/II |
| Duimian | Y | 100m | N/A | 500 thousands | iOS/Android | Google | II |
| Doudou Friend | Y | 10m | N/A | 1 million | iOS/Android | Amap | II |
| $U+$ | Y | 10m | N/A | 10 millions | iOS/Android | Baidu | II |
| Topface | Y | 100m | N/A | 50 million | iOS/Android | Google | II |
| Niupai | Y | 10m | N/A | 61 thousands | iOS/Android | Google | II |
| LOVOO | Y | 100m | 27.8km (shanghai) | | iOS/Android | Google | II |
| KKtalk | Y | 10m | N/A | 320 thousands | iOS/Android | Google | II |
| Meet24 | Y | 0.5mile | N/A | | iOS/Android | Google | II |
| Anywhered | Y | 10m | N/A | 750 thousands | Android | Baidu | II |
| I Part | Y | 10m | 1000m | 8 millions | iOS/Android | Google | II |
| Path | N | N/A | N/A | 10 millions | iOS/Android | Google | I |
| TweetCaster | N | N/A | N/A | 10 millions | iOS/Android/WP | Google | I |
| Google Latitude | N | N/A | N/A | 10 millions | iOS/Android/WP | Google | I |
| eHarmony | N | N/A | N/A | 5 millions | iOS/Android | Google | I |
| SinglesAroundMe | N | N/A | N/A | 1 million | iOS/Android | Google | I |

TABLE I: Location based friend discovery apps

only see others' geographic distances instead of location coordinates. From the user's point of view, revealing the distances rather than coordinates could hide the exact location but still allow the potential near strangers (or potential friends) to discover the presence of this user.

**II. Setting the Minimum Accuracy Limit**: Setting a safe localization accuracy limit is a traditional location obfuscation technique [20]. Most of the LBSN apps predefine a certain minimum accuracy limit for geo-localization to further protect the users' exact location. For example, Skout defines localization accuracy to 1 mile, which means that the users will be located with an accuracy no better than 1 mile. Similarly, Wechat and Momo set 100m and 10m as their localization accuracy limits.

**III. Setting the Localization Coverage Limits**: To prevent malicious users from abusing the geo-localization, an additional functionality, Localization Coverage limit is provided to restrict the users' localization capability to a specific region or under the maximum number of displayed users. For example, Wechat only displays the relative distance of users, the number of which is less than a predefined threshold (e.g., 800m in wechat for a high user density region).

In addition to above mentioned location hiding techniques, there are other factors which contribute to the localization errors, which will be presented as follows.

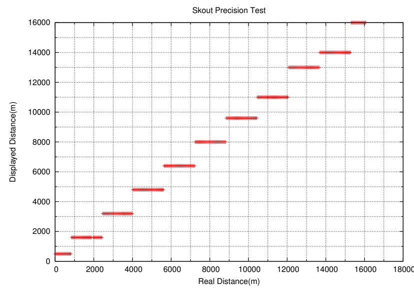
### *B. Location Update in LBSNs*

In general, the localization accuracy of smartphone relies on which kind of location data sources it used. The location data sources (also called as location providers) include: GPS, WiFi, and Cell ID (cell tower), which could achieve the localization accuracy of 10m, 80m and 600m, respectively, as shown in the existing works [21]. However, the location accuracy of location providers will not be immediately translated into the location accuracy of LBSN apps, which is caused by different location updating strategies of LBSN apps. In practice, it's up to the app developers themselves to decide which location source to trust and it is always a trade-off between waiting time, precision and energy consumption[22], [23]. To have a better understanding on the updating strategy of LBSN apps, we perform the following accuracy testing experiments.

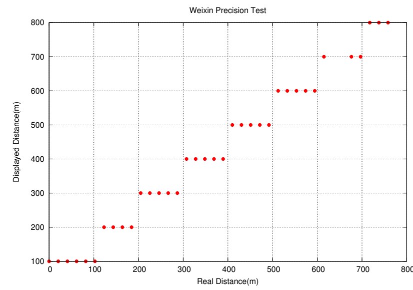
In our experiments, we choose GPS localization in which it could achieve the highest localization accuracy. We mainly perform the accuracy testing on three apps: Wechat, Skout and Momo. To perform the experiments, we pre-define a reference point both in the physical world and the virtual machine. In the apps, this reference point will be a virtual user located in this position. Then, we enlarge the physical distance between our mobile device and the reference point and record the relative distance displayed on apps. We compare the physical distance and the distance shown in apps and obtain the accuracy testing results, which are depicted in Fig 1.

Since Momo's localization accuracy limit is set to 10m, we choose a test point for every 2m. From Fig 1a, we could confirm 10m as the localization accuracy limit. Such a distance will be rounded for every 5m. For example, the distance in momo will display 0 if the physical locations of two users are less than 5m away. In Skout, the localization accuracy bound is 800m or 0.5mile. In the experiment, we evaluate the localization accuracy for every 50m. From Fig 1b, it is observed that Skout's minimum coverage is around 800m, which is 0.5 mile. Also, the distance will be rounded for half a mile and the distance will be increased for every 1.6km or 1mile. In Wechat, the coverage bound could be $x$m, where $x$


(a) Momo precision test




(b) Skout precision test




(c) Wechat precision test

Fig. 1: Updating Strategy Evaluation Results

can be up to 10km in sparsely populated area and generally 1000m in densely populated places. In the experiment, we set the reference point for every 20 meters. From Fig 1c, it is observed that Wechat has no round-offs in its distance and the boundary is quite clear between every 100m.

### *C. User Location Privacy in LBSNs*

From above discussions, we could conclude that, in general, the locations reported in LBSN apps honestly reflect mobile users' real locations, though users' exact locations are hidden or obfuscated by various location hiding techniques. For example, Momo only adopts the strategy of showing the relative distances (strategy I). Skout only shows the distance and, at the same time, enforces the minimum localization limit (strategy I & II). As a comparison, Wechat adopt all of location hiding strategies I, II, III.

In this paper, we argue that, relying on the above mentioned location privacy hiding techniques may introduce a more dangerous location privacy leaking issues. Due to trust on these location hiding/obfuscating techniques, LBSN users are more willing to share the PROTECTED location information with the potential adversary, which could recover users' exact location or even traces by using the methodology proposed in this paper. Without full knowledge of its potential risk, LBSN users may face the serious location privacy leaking issue, while the adversary could gain a significant advantage during the attack process since the victim even has no idea about its risks. From the attacker's point of view, he aims to make an involuntary geo-localization or even tracking towards a specific victim. In the next section, we will present our attack methodology in details.

## III. Attack Methodology

In this section, we will introduce our attacker model, as well as the attack methodology in details.

### *A. Attacker Model*

In this study, we consider a capability-restricted attacker aiming at geo-locating an LBSN user, who does not need to have a priori social association with him, i.e., an in-app friend. The attacker's capability is restricted in sense that I) It only has the access right no more than a normal user of a given LBSN service, which means that he can only access the publicly available information provided by the LBSN app. II) It is not allowed to hack the LBSN service by interfering its internal operations, that is, we do not consider an attacker that can compromise the LBSN servers and thus can directly access the user location information as a consequence. In summary, our attacker is a very weak one which can't gain any additional information from the LBSN services other than what is entitled to a regular service user. Specifically, the attacker will try to infer a user's location information based only on the relative distance information displayed by the LBSN apps. Note that, to obtain the relative distance, it is even not necessary for the attacker to be friend of the victim. Instead, it will automatically display the relative distance of nearby users in most of considered Category II apps. For Momo, the attacker can obtain the distance by searching the victim via Momo ID and in Skout, the distance between the victim user and the attacker can always be displayed as long as the attacker has sent a regular message (a greeting for instance) to the victim before. We are concerned that if the LBSN under examination can't resist even such a weak attacker, the user's location privacy is obviously in a great danger as any user can be an attacker.

We further distinguish two different types of attackers, i.e., a Casual Localization Attacker and a Determined Tracking Attacker. A Casual Localization Attacker reviews the profiles of nearby users when logging in to a LBSN app as a regular user, randomly picking up a tracking target and then try to geo-localize the target. A Determined Tracking Attacker may start with a known User ID (ID) and/or User Number as its chosen attacking target and perform the tracking towards a specific victim for a certain duration. The goal of the tracking attacker is revealing users' Top N locations (e.g., his home or office)[8]. Note that, a tracking attacker may start with a target person in mind and exploit certain side-channel information of the target to help obtain the corresponding UID or user number. For example, user photos shared among various social network sites can be used to establish the linkage for the same user, which in turn can lead to the acquisition of UID/ User number information in a particular LBSN. Social engineering approaches like this have been widely studied in the literature and is not a focus of this paper[24]. We assume that a determined tracking attacker will be able to start with a chosen UID or user number he wants to locate.

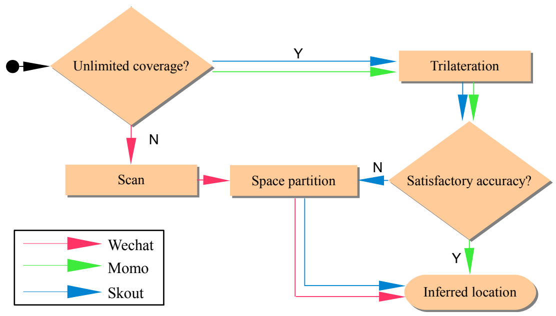


Fig. 2: The Attack Flow

### B. *Methodology Overview*

The security of the state-of-the-art privacy protection techniques are based on the assumption that the location cannot be faked. Under this assumption, the exact location of the mobile users could be hidden/obfuscated by the above mentioned three strategies. Therefore, the intuition behind our attack is that, if the attacker could freely generate the fake anchor points with new locations, LBSN apps will be a distance oracle, which will always return the relative distance with these anchor points to the attacker. By exploiting the returned information, the attacker could launch different localization algorithms to geo-locate the victim and even break the accuracy limit.

As shown in Fig 2, the attacking procedure could be illustrated as follows. When the attacker determines a particular victim, it could generate three fake anchor locations and obtain the relative distance to the victim. With 3 anchor locations and their corresponding distances, it could trigger the Iterative Trilateration based Localization Algorithm and obtain the first inferred location, which will be set to the new anchor point. With this inferred location as well as two other anchor points, the attacker could launch a new round of attack. This process will be repeated until the distance between the new inferred location and the victim reaches the localization accuracy limit. After that, the attacker could trigger space partition attack, which further improves the accuracy until the distance reaches the predefined accuracy threshold. For those apps with the coverage limit, the attacker could scan the possible locations until the victim is shown in the "nearby list" of the attacker. Then, it could take advantage of space partition attack to make an accurate localization. In the following sub-sections, we will introduce each basic algorithm one by one.

### C. *Iterative Trilateration based Localization Algorithm: Skout and Momo*

Our localization approach is based on the traditional Trilateration Position Problem. In our long distance tracking, we start from 3 randomly generated positions, which serve as the first three anchor points. In Section IV-A, we will introduce how to generate the fake locations on Android. The triggered Trilateration algorithm will return back the first localization results. To minimize its distance from the target, the least squares solution could be used to solve this problem as suggested in [25]. We iteratively perform the trilateration localization and generate the next reference point from the previous round localization results. We denote $P$ as the List of reference points sorted by the relative distance to the target point from smaller to larger. Without loss of the generality, the first three items of $P$ are represented by $p_1, p_2$ and $p_3$. We further define function $dist(a, b)$ to measure the distance between the point $a$ and $b$, as well as function $Lsp(a, b, c)$ to return the least square estimation of the localization target based on three reference points $(a, b, c)$. We summarize our iterative trilateration localization algorithm in Algorithm 1. In FreeTrack, the least square solution is implemented by calling GNU Octave's "bfgsmin" method inside the "optim" package. The connection of Octave and the attacking kit is established by the open source project Java Octave.

**Algorithm 1:** The Iterative Trilateration based Localization Algorithm

**Data**: List $P = \emptyset$, in which the elements are sorted by their distance to targeted node
**Result**: $p_0 = (x_0, y_0, z_0)$ the location of the target

Generate 3 random reference points and put them into $P$;
**while** $|dist(p_1, p_3)| > threshold$ **do**
  $p_1, p_2, p_3 \leftarrow$ first 3 elements of $P$;
  $t \leftarrow Lsp(p_1, p_2, p_3)$;
  Insert $t$ into $P$;
**end**
Output $p_1$;

**A Real-world Attack Example**: Due to no display distance boundary, Momo and Skout users could always obtain their distances with their friends even in the global scale. Fig 3 shows a real-world attack example launched from China towards a user in Bufflo, NY. Our initial 3 anchor points are randomly set at Beijing, Shanghai and Chengdu. The numbers in the graph represent the positions inferred in the order. Postions 2 – 5 are intermediate results and each one is closer to the target. It takes 5 rounds to finish this attack.

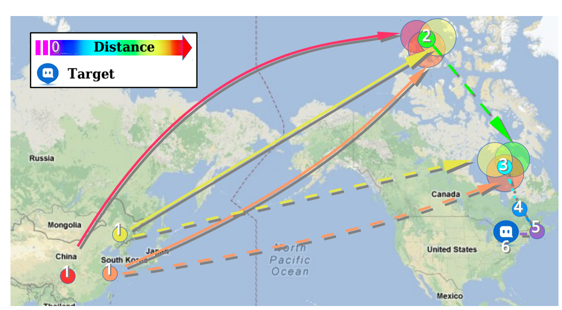


Fig. 3: Trilateration on Global Scale

*D. Breaking Minimum Distance Limit via Space Partition Attack: Skout and Wechat*

Another best practice measure to provide location privacy protection for users is to limit the relative distance to a certain accuracy, (e.g., 800 m in Skout or 100 m for Wechat). In this section, we propose a space partition attack algorithm to further enhance the localization accuracy and thus breaking the minimum distance limit. The basic idea of space partition attack is similar to space partition algorithm, which is defined as the process of dividing a space (usually a Euclidean space) into two or more non-overlapping regions and thus locating any point in the space to exactly one of the regions. The basic idea of space partition attack is illustrated in Fig 4.

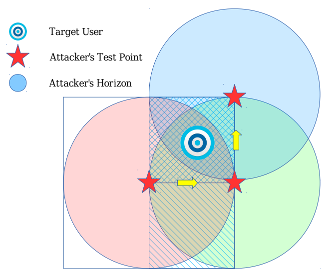



Fig. 4: Illustration of Space Partition Attack

For the simplicity of problem presentation, we consider the minimum distance limit as the box rather than the circle. Given the minimum distance limit $R$, the edge length of the box is set to $2R$. The space partition attack could be illustrated as follows. For each round checking, the potential area of length $r$ is partitioned into two regions. Then, we will check if it is within one region. If yes, it is derived that the user is in this half. Otherwise, the user is located in another half. We could repeat this partition for multiple rounds until the expected detecting accuracy is achieved. The whole algorithm is summarized in Algorithm 2.

*E. Breaking Localization Coverage Bound with Scan and Space Partition: Wechat*

Some apps such as Wechat set a certain coverage limit. For such kind of apps, the first step of launching an attack is to enable the FreeTrack to see the attacking target shown in the "Nearby" list of this app. To achieve this, if knowing the possible visiting areas of the target, we could *SCAN* the areas to discover the presence of the users. After that, FreeTrack could launch the Space Partition attack similar to the second stages of other apps.

The scan strategy is to query over a particular area at a particular distance $d$ until the user is presented inside the "Nearby" list. Take Wechat as an example, in a high user density area (e.g., Lujiazui Area of Shanghai), to cover an area of 28km$^2$ with the distance $d$ = 1km, it only needs to query 28 times at the worst case. It is noted that, the coverage limit of Wechat varies with the user density of this region. In an area of low user density (e.g, Buffalo), the coverage bound could be as far as 10km. Therefore, it only takes 5 queries to cover the whole downtown area. Upon discovering a user, we could use Space Partition attack as indicated in last section.

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**Algorithm 2:** Space Partition Attack Algorithm

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**Data**: An estimated point $p_0 = (c_X, c_Y)$ and its range from target point $T$, given in form $dist(p_0, T) \leq R$.
**Result**: $T'$, the final estimation for $T$

$dim = X$;
$\delta_X = R$;
$\delta_Y = R$;
**while** $\delta_X \geq threshold$ *or* $\delta_Y \geq threshold$ **do**
  Shift $p_0$ in $dim$ dimension by $R$ to $p'$;
  **if** *Distance reading from app* $\leq R$ **then**
    $c_{dim}$=$c_{dim} + \delta_{dim}/2$;
  **end**
  **else**
    $c_{dim}$=$c_{dim} - \delta_{dim}/2$;
  **end**
  $\delta_{dim} = \delta_{dim}/2$;
  $dim = \{X, Y\}/dim$;
  $p_0 = (c_X, c_Y)$;
**end**
Output $p_0$;

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**Performance Enhancement by Using Social Popularity Index:** To further improve the performance of the launched attack, we could use the social popularity index to accelerate the attack. This strategy comes from a simple observation that, the possibility of a node staying at different locations is far from uniform, and it is very likely that a user stays at the location that is most popular at that time. The social popularity is a spatial-temporal concept. Intuitively, it is more likely for a user to be at the restaurant at 6 pm in the afternoon rather than at office. However, this statement may not hold at 10 am in the morning. In our implementations, we measure the social popularity of different locations by collecting their user population information at different time slots. Then, based on the number of users, we could assign a higher priority to those areas with the higher user population.

In addition to the above described methodology, there are still implementation challenges, including: how to generate the fake locations in smartphone which allows the above methodology to work and how to fetch the relative distance after setting a fake location in smartphones. More importantly, all of these should be performed in an automated way. We'll introduce the implementation details in the next section.

## IV. Implementation of FreeTrack

Besides the algorithms introduced in previous section, the implementation of FreeTrack will require other 2 key modules: the location spoofing module and the location reading module. Mainly, our FreeTrack is implemented in Clojure[26] in order to cope with MonkeyRunner[27] to control Android virtual machines and send commands. We also implement a LocationFaker app that receives HTTP request from FreeTrack and set the location in Android. To address problems we encounter during location faking and result reading, we make multiple tweaks in the Android framework as well.

### A. Generating Fake Anchor Locations on Android

To launch the proposed attack, we need to allow the FreeTrack to freely generate the anchor location points, which are used to obtain the relative distances of the victim users. Android SDK ships with QEMU based virtual machine that allows setting location via Telnet, but the virtual machine is too slow for real-world automated tracking. Thus, we set our Android system on real Android X86 images[28] running on VirtualBox[29]. It is important to point out that, since almost all of the LBSN apps cover all of the platforms (please refer to Table I for our survey), including IOS/Android/WP, spoofing the android device's locations could allow the attacker to obtain the relative distances with LBSN users on IOS/WP, and thus launch the attack towards the users on all of platforms.

There are several ways to spoof Android device's locations, including: using mock location, or intercepting network traffic. We do not consider some existing apps such as Developer Shell [30] and FakeGPS [31] because they are either unstable due to potential bugs or cannot allow us to set the location arbitrarily, which motivates us to implement our location spoofing component, LocationFaker. LocationFaker is implemented as a system service which eliminates the possibility that Android system may kill the activities to release resources. Also, it has embedded Jetty[32] as a web server to provide stateless http-based interface to set locations and act as a fake location server when we redirect the network traffic.

In general, most of the LBSN apps on Android either use built-in Android API (Wechat or Skout) or third-party SDKs (e.g., Momo using Baidu Location SDK), which lead to different spoofing strategies. For built-in Android API, we adopt *Fake Location Provider based location spoofing*. However, according to the official document[33], Baidu Location SDK does not function well on virtual machines. For this case, we achieve location spoofing by using *Network Redirection*. In the follows, we will introduce both of approaches in details.

*1) Location Spoofing with Fake Location Provider:* Android apps mostly acquire locations via one or more location providers (e.g., "gps" and "network") retrieved from the *location* system service. Android allows users to freely add location providers under certain circumstances such as debugging or providing locations from other devices, eg. Bluetooth. By enabling "Allow mock location" option in developer options and adopting the API "addTestProvider", it is possible to add a user-written location provider. Interestingly, we could set the provider's name to "gps" to make it indistinguishable from the real gps, and thus fool the system and make it believe that they are receiving locations from the real GPS chip. Our fake location provider is running on its thread, feeding location information every $700ms$.

Another challenge of spoofing the location on Android is that the provided location should satisfy a certain accuracy. If failing to achieve, some apps may fail to accept it. For example, in Wechat, it is observed that the system will return error messages if FreeTrack tries to send the locations to Developer Shell. We verified it by checking it manually on Google Map and it is found that the accuracy is only 90,000m. To address this issue, we decompiled the Android system framework with ApkTool[34] and modified the constructor of "android.location.Location" by coercing "mHasAccuracy" to "true" and enforcing "getAccuracy" to always return 70m. In this way, apps will always retrieve consistently accurate value under different circumstances and the location faking component starts to work as expected.

*2) Location Spoofing with Network Redirection:* For those LBSN apps which do not adopt Android built-in APIs for location retrieval, we introduce another approach based on Network Redirection. In this section, we use Momo as an example to show how it works. Basically, Momo uses Baidu Location SDK to obtain the user location. We start from analyzing the network traffic with Wireshark[35] and Tcpdump[36]. It is observed that the API first posts the coordinates and supplemental information, which is obtained from the device, to http://loc.map.baidu.com/sdk.php. The server returns a plaintext JSON object carrying location information as follows:

```
{"content":{"addr":{"detail":""},
            "bldg":"","floor":"",
            "point":{"y":"","x":""},
            "radius":""},
 "result":{"error":,"time":""}}
```

By comparing the failed request against successful one, it is found that the key fields are the $x$ and $y$ coordinates in "point", "radius", the error code and the timestamp. The error code 161 indicates a *successful* query and the $y$ and $x$ carry the computed coordinates of the latitude and longitude. We utilize Iptables[37] in our implementation to build a NAT that redirects all the requests originally sent to Baidu location server back to our embedded Jetty web server running by LocationFaker. LocationFaker will then construct a similar JSON object carrying fake locations to trick Baidu Location SDK to accept the received location as the real location.

### B. Fetching the Location Readings

Location fetching module is the last component of FreeTrack. The basic strategy of FreeTrack is actually running the client and simulating the user's inputs to retrieve distance readings. To simulate user inputs, we adopt the MonkeyRunner library bundled with the Android SDK. With MonkeyRunner scripts provided in Jython, it simulates user inputs in apps to allow us automatically to perform various tests on apps. We integrate the API with our attacking framework to allow user defined inputs. We simulate consecutive operations in forms of touch, drag, scroll, input numbers, shell command and key press to mimic a user's behavior to the apps to trigger a location information update and scroll down the list to read out all items.

To read the distance from the apps, we choose to modify the framework to dump the text in stead of choosing OCR since the former one is more reliable and accurate especially in virtual machines. To dump the text, we modified the "android.widget.TextView" to dump text to log messages whenever "setText" method call is made. FreeTrack then retrieves text from the Adb logcat buffer and reads specific app's output by filtering log level, grepping by PID and tags then matching particular regular expression pattern.

## V. Real-world Attack Evaluations

To evaluate the effectiveness of FreeTrack, we implement the real-world experiments by recruiting 30 volunteers for the 3 kinds of LBSN apps: Wechat, Skout and Momo. We evaluate the *Localization Accuracy* of FreeTrack by comparing the distance between the user's *Real Locations* and *Inferred Locations*, and *Localization Efficiency* of FreeTrack by measuring the latency of launching an attack for different apps. In the experiments of real-world tracking, we evaluate the effectiveness of FreeTrack by measuring how many top locations could be recovered by using 3-week track.

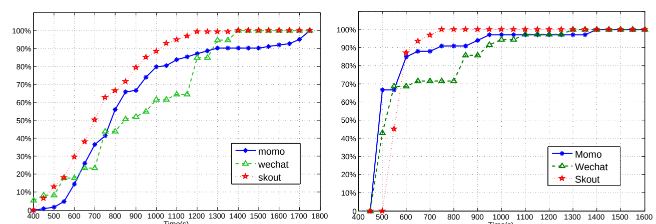
### A. Localization Accuracy and Efficiency

To well evaluate the localization accuracy, we set that the attack is triggered as soon as the user reports his real location obtained from location providers (e.g., GPS, wifi, or cell ID). The attack and real location reporting is set to the synchronous mode because we need to make sure that users' mobility will not impact the localization accuracy. To achieve this, we deploy a web server in which users with HTML5-capable browsers could retrieve their locations directly from location providers of their smart phones, and then submit their real location, user information to the server. The server will immediately launch an attack toward this user by using his user information. The server will maintain a task queue and each idle node will be assigned with a task and schedule an attack, the results of which will be reported to the server and compared with the exact location. Members of our groups regularly submit their locations to the server. We've collected in total of more than 350 location reports and attack results. The testing regions include United States, China and Japan.

*1) Localization Accuracy:* The evaluation on localization accuracy is shown in Fig 5. From Fig 5, it is observed that the majority of the results achieve a very high localization accuracy. For Momo, nearly $60\%$ of the attacks can geo-locate a user at the accuracy of less than 20m and only less than $10\%$ of the localization accuracy is more than 60m. In general, it could achieve an average localization accuracy of 25.8233m for 119 evaluations. For Skout, though the minimum localization limit is 800m, most of the localization could achieve the accuracy of less than 60m while over $70\%$ of the localization is less than 120m. The average localization accuracy could reach 129.3674m for 156 tests, which well demonstrates the effectiveness of the Space Partition algorithm. For Wechat, whose minimum localization limit is 100m, FreeTrack is able to geo-locate $50\%$ of users in less than $40$m. The average accuracy is $51.0888$m for 74 tests. Note that, there are different factors which contribute to the localization errors. For example, localization errors may come from different way to fetch location from HTML geo API, choosing inconsistent location providers, various location calculation algorithm or location cache.

*2) Localization Speed:* We also evaluate the efficiency of FreeTrack by measuring the execution time of an individual attack and the results are shown in Fig 6a and Fig 6b, which correspond to the case of randomly setting first 3 anchor points and social popularity enhanced attacking approach.

From the Fig 6a, it is shown that over $80\%$ of the attacks for all 3 apps could be finished within $1200s$. It is important to point out that most of the time is spent on waiting for the app server's response. Take Wechat as an example. Each query should wait $40s$ to ensure that the user's location is fetched due to network latency and for Momo, the number increases to $55s$ while for Skout, it spends on $20s$ on queuing per query. In the evaluation, Momo has a faster localization speed as the iterative trilateration converges faster than space partition and thus requires less query time. From Fig 6b, it is shown that, after adding some side information such as social popularity index in Wechat or setting the initialization point in the approximate area (e.g., Shanghai) for Momo or Skout, the localization performance could be enhanced for $1.5$ times.

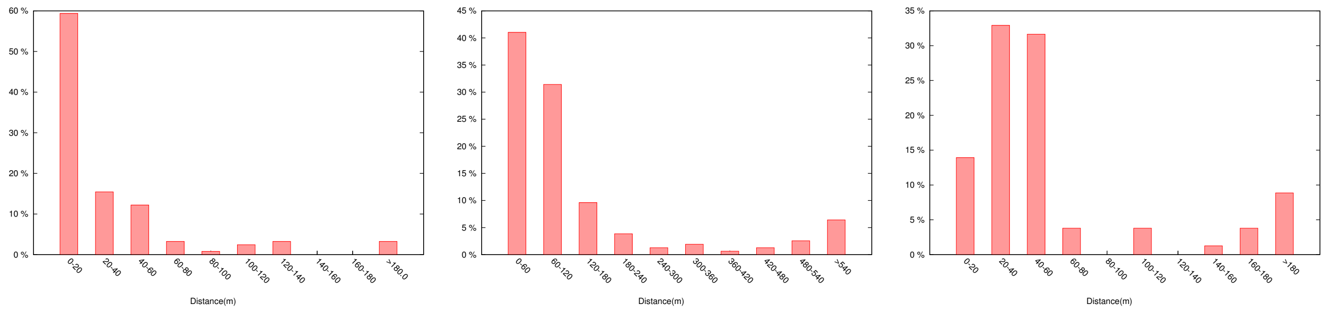



(a) Localization inference time on different apps (b) Improved localization inference time on different apps

Fig. 6: Localization Efficiency of the Original and Enhanced Scheme

### B. Real-world Tracking: Tracking Accuracy and Top Location Coverage

In this section, we evaluate the effectiveness of FreeTrack in real-world tracking. The basic goal of this experiment is to compare the inferred mobility traces of the mobile users with their real mobility trace to measure how much location information the attacker could obtain by tracking the users in a certain duration. In this phase, we recruit 30 volunteers from China, Japan and United States to participate in our three-week real-world experiments. Due to no display coverage limit, the tracked Skout and Momo volunteers are scattered in these three countries. For Wechat, due to the coverage limit, FreeTrack covers a region of the size of 3km$*$5km in Shanghai and




(a) Momo's Localization Accuracy

(b) Skout's Localization Accuracy

(c) Wechat's Localization Accuracy

Fig. 5: Evaluation on Localization Accuracy

20km∗20km in Buffalo. In these three weeks, the volunteers use the LBSN apps in the same way as other typical LBSN users. To obtain the ground truth data (or user's real mobility traces), we develop an app based on Baidu Location API, which runs as a service in the background, recording their locations every half an hour and submits the traces to the server. In the server side, we run 3 Momo FreeTrack instances, 7 Wechat nodes and 3 Skout nodes to track Momo, Wechat and Skout users, respectively. We continuously track them for 3 weeks and collect 3395 inferred points in total. Fig 7 shows the tracking results of 3 users in one day. Note that, the plotted red, yellow, and blue lines represent users' real mobility traces, while the red, yellow, and blue bubbles indicate the locations inferred by FreeTrack.

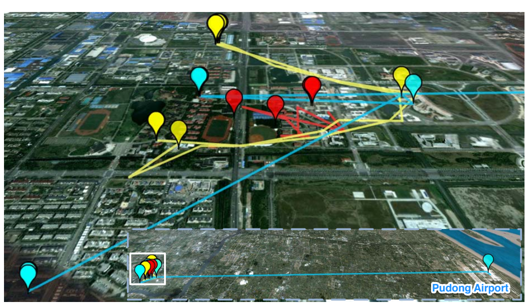



Fig. 7: Three Real-world Traces and Inferred Locations

*1) Tracking Accuracy:* In real-world tracking, synchronization of user real trace reporting and our tracking is almost infeasible due to unexpected user usage pattern as well as the randomness of the delay between victim's location updating and our tracking. Therefore, we also evaluate the tracking accuracy in the asynchronous mode. In particular, the user's real-world trace is periodically updated (e.g., 30 mins), and the tracking on users is also periodically launched (40 mins). In this case, we define the *Tracking Accuracy* as the distance of the inferred location and its closest counterpart of the reported user traces (ground truth data) in time domain. In general, tracking accuracy provides the upper bound of the localization error.

The evaluation of tracking accuracy is shown in Fig 8. The experiment results demonstrate that the asynchronous tracking can also achieve a very high level of accuracy. As shown in Fig 8a, more than $80\%$ of tracking results on Momo can geo-locate the victims in 40m, more than $90\%$ of tracking results on Skout can break the distance limit of $800m$ to geo-locate the victims to $0-20$m and $80-100$m, and over half of the tracking on Wechat users can be located to the accuracy of less than 60m.

The factors which may potentially affect the tracking accuracy includes: the location providers (GPS, Wifi, or Cell ID), which have different localization accuracy of less than 10m, tens of meters, and several hundred meters, respectively; cache policy, which defines how long the user's location is buffered at the server side. We've investigated the cache policy of Wechat by comparing the results from China and US, which have different user populations and thus different cache time. The results are indicated in Fig 9. In China, as one of the most popular LBSN apps, Wechat has a huge population of users, which makes the users' locations buffered at the server side for a shorter duration, making user tracking more difficult to perform in China. Instead, it is much easier to track a Wechat user in United States due to less number of users and a much longer time of users' location cache.

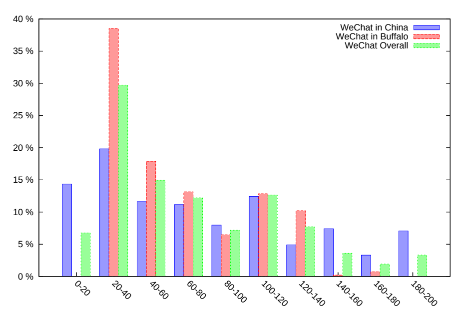
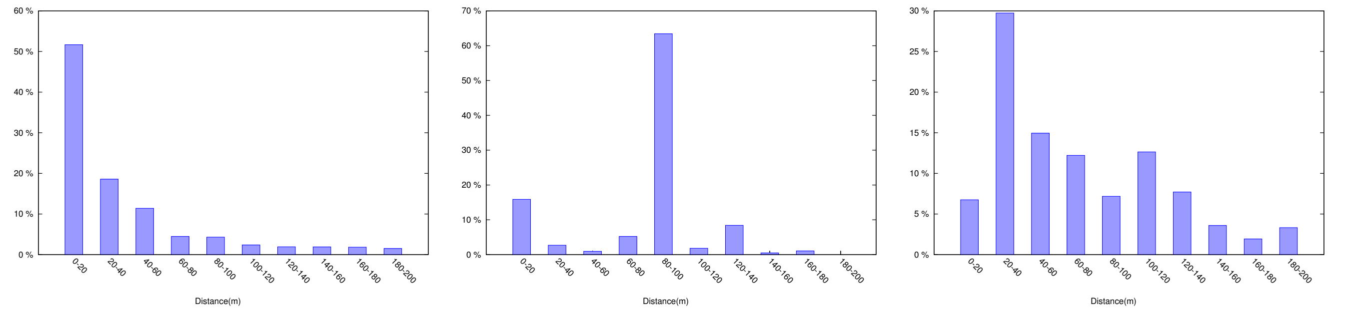



Fig. 9: Wechat Accuracy Comparison

## C. The Coverage Rate of Top N Location

According to [8], "Top N" locations refer to the locations that are most correlated to users' identities. For example, "top 2" locations likely correspond to home and work locations, the "top 3" to home, work, and shopping/school locations. In




(a) Tracking Accuracy of Momo (b) Tracking Accuracy of Skout (c) Tracking Accuracy of WeChat

Fig. 8: Evaluation Results on Tracking Accuracy

the section, we investigate how much location information the attacker could gain from launching FreeTrack by introducing the concept of Top N location Coverage Rate, which is defined as follows. Given $\mathbb{G}$ as the set of reported traces (ground truth data) and $\mathbb{I}$ as the set of inferred traces, we define $Top_N()$ as the function that returns $N$ most visited locations from a specific trace and thus define Top $N$ Location Coverage rate as

$$TNR = \frac{|Top_N(\mathbb{G}) \cap Top_N(\mathbb{I})|}{N},$$

which refers to the percentage of locations that belongs to both of Top $N$ locations in reported mobility traces and inferred mobility traces.

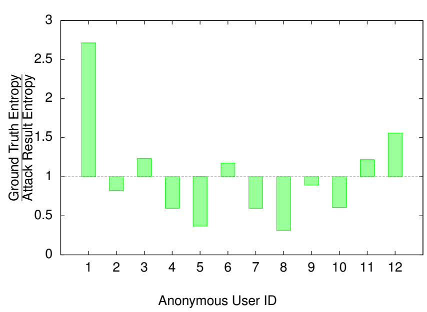



Fig. 10: Ground Truth vs. Attack Result in Entropy

**Impact of Usage Pattern:** Interestingly, our experiment results show that the inferred Top N locations of users do not exactly match to their real Top N locations. For example, for some users, the inferred Top 1 location may be the Top 2, or 3 location in their real traces just as shown in Table II that Top 2 location coverage sometimes is less than Top 3 coverage. In our experiments, it is found that only $65\%$ volunteers' top $1$ locations exactly match with their top $1$ locations in ground truth trace. This can be explained by investigating the difference between every user's real traces and his usage pattern. We adopt the definition of location entropy[16], which is defined as:

$$H(x) = -\sum_{x \in Loc} p_x \log p_x \tag{1}$$

where *Loc* is the location set consisting of the locations that a user visited, $p_x$ is the probability that the user is at the location $x$. From this definition, it is observed that the bigger the location entropy is, the more diversified the user's locations are. Here, we measure both of the ground truth trace location entropy $H_1$ and the inferred location entropy $H_2$. $H_1$ indicates how many places the users visited, while $H_2$ shows how many places the users use the app. Therefore, the metric $H_1/H_2$ shows the usage pattern, which is shown in Fig 10. In Fig 10, we randomly sample 12 volunteers' ground truth location to tracking location rate. Fig 10 shows that the ground truth trace location entropy $H_1$ is not always close to the inferred location entropy $H_2$. For example, a user spends most of his time at his home and office which makes the value $H_1$ very small, but he may always uses the LBSN app in different places which will induce a large $H_2$ and a small $H_1/H_2$ rate. Similarly, if a user travels to many places which leads to a large $H_1$, but he mainly uses at his home so that his $H_2$ is very small (i.e., close to 0) and the rate will be large. Therefore, from the attacker point of view, Top $N$ locations should be regarded of the same importance, which motivates us to use unordered Top $N$ locations in our evaluation.

**Evaluation Results:** Without loss of the generality, we set $N = 5$ and evaluate the top location coverage rate for three weeks, which is shown in Table II. From Table II, it is observed that Momo shows the best coverage rate. After three weeks tracking, we can obtain all the volunteers' top $1$ locations and about $70\%$ volunteers' top $2$ locations. For Wechat, we could successfully infer $71.4\%$ $21.4\%$, $28.5\%$ of top $1, 2, 3$ locations after $3$ week tracking. For Skout, $60.0\%$, $40.0\%$, $80.0\%$ volunteers's top $1, 2, 3$ locations could be successfully recovered. Our evaluation results also show that the temporal factor plays an important role in Top $N$ location recovery. In particular, the Top $N$ location coverage rate will significantly increase along with more tracking days. In general, FreeTack shows a high Top $5$ location coverage rate.

## VI. Attacks Mitigation

In this section, we aim to propose some suggestions to limit the attacking capability of the attackers. We hope that the following discussion would raise location privacy awareness of the LBSN developers and would also inspire other researchers to find more advanced protection techniques.

| top location | one week | | | two weeks | | | three weeks | | |
|---|---|---|---|---|---|---|---|---|---|
| | Momo | Wechat | Skout | Momo | Wechat | Skout | Momo | Wechat | Skout |
| 1 | 92.3% | 50.0% | 20.0% | 100.0% | 57.1% | 60.0% | 100.0% | 71.4% | 60.0% |
| 2 | 46.1% | 21.4% | 0.0% | 46.1% | 21.4% | 40.0% | 69.2% | 21.4% | 40.0% |
| 3 | 30.7% | 21.4% | 20.0% | 46.1% | 28.5% | 60.0% | 38.4% | 28.5% | 80.0% |
| 4 | 23.0% | 35.7% | 20.0% | 30.7% | 35.7% | 40.0% | 38.4% | 35.7% | 40.0% |
| 5 | 23.0% | 21.4% | 0.0% | 15.3% | 21.4% | 40.0% | 15.3% | 14.2% | 40.0% |

TABLE II: Top 5 Location Coverage Result for 3 Weeks

### *A. Prevention of Using LBSN as Location Oracle*

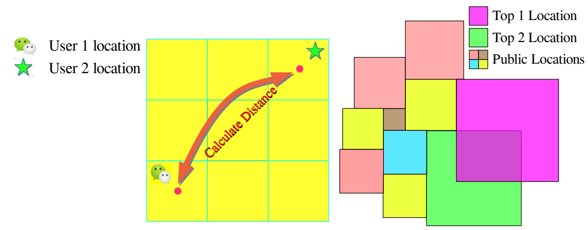
Firstly, the feasibility of considered attack roots in the fact that these app servers retrieve location without requiring effective location proofs. One potential countermeasure for the considered attack is adding some location proof modules to ensure the authenticity of the locations. The typical location proof techniques include using the deployed trusted infrastructures (e.g., cell tower or Wi-Fi access points) [38] or using environmental signals as the location tags [19], [18], [39]. However, they either require the presence of trusted infrastructure or are only effective in a small-scale (e.g., less than 100m) due to the spatial diversity of wireless signals. As a result, the existing location proof techniques are only feasible in a small-scale region and less practical in our scenario.

To limit the attacker's capability, the service provider could compare users' location changes with their mobility patterns or behavior patterns to identify the potential anomalous users (e.g, changing the locations too frequently or making too many queries within a short period). For example, from our experiment, it is observed that Wechat has put a limit on the number of queries issued at a certain duration (depending on the workload of the server) and the misbehaving account will be blocked for a specific period, which significantly slows down attacking process. Our real-world experiments show that, though the attacker may use multiple accounts to speed up the attack, a more stringent limit on the number of queries will increase the difficulty of launching the attacks since the attack should be finished between two consequent location updating events of the target.

### *B. A User Controllable Privacy Enhancement Framework*

In this subsection, we present a user controllable privacy enhancement framework. Our basic idea is that we could use a global grid reference system to generate the relative distance, providing obfuscation functionalities to mobile users. Even though some advanced obfuscation techniques including enlarging the radius of cloaking region or shifting the location by randomly generated distance and rotation angle can be implemented at the client side [40], the major limitation for client-based obfuscation technique is that different users may have different privacy protection levels and acceptable utility levels (the measurement error of relative distance). However, the relative distance error is determined by the geo-location error of both parties, which may exceed the acceptable utility level of any single party.

**Distance Obfuscation with Grid Reference System:** In this work, we propose a distance obfuscation based on grid




(a) Basic Grid Reference System (b) Classified Grid Reference System

Fig. 11: The Grid Reference System

reference system, which aims to prevent the attacker from using LBSN as the location oracle to obtain the accurate location information. As shown in Fig 11a, the server maintains a grid reference system, where the location of a mobile user can be expressed as the center of the grid cell that the user is located in. Therefore, the relative distance of two users is expressed by the distance of two grid cells defined as the minimum path connecting these two cells. The benefit of using grid reference system to express the relative distance of two users is that it obfuscates the real location of mobile users with the center of the cell and the attacker cannot obtain extra information of the target if the generated fake anchors are located at the same cell. Similar to other obfuscation techniques, grid reference system will also decrease user utility. Considering the relative distance is the main metric of LBSN, we define the metric of privacy as:

$$Privacy = Dist(Loc_R, Loc_O),$$

where $Loc_R$ and $Loc_O$ refer to the real and obfuscated location of the mobile user, respectively, and function $Dist()$ returns the distance of two locations in Grid reference system. By given a specific anchor node at location $Loc_A$, we further define the utility metric as

$$Utility = 1 - \frac{|DDist(Loc_R, Loc_A) - DDist(Loc_O, Loc_A)|}{Dist_{max}},$$

where function $DDist()$ returns the displayed distance in LBSN apps, $Dist_{max}$ represents the maximum distance that the user could tolerate. It is obvious that, when the displayed distance between the real location and anchor point $DDist(Loc_R, Loc_A)$ equals displayed distance between the obfuscated location and anchor point $DDist(Loc_O, Loc_A)$, the utility achieves the maximum value 1. When $DDist(Loc_O, Loc_A)$ is much larger or smaller than $DDist(Loc_R, Loc_A)$ (their gap should not be larger than

$Dist_{max}$), the utility is close to 0. By assigning different values to the size of the cells, we could achieve different location privacy protection level as well as different utilities. We evaluate the effectiveness of location privacy protection and its impact on the utility by applying grid reference system to the data set collected from our real world experiments (ground truth data and inferred location data). Fig 12 shows the privacy gain and the utility under different settings of cell size. It is observed that the increase of privacy gain will lead to the decrease of the utility, and vice versa. We will discuss how to achieve the tradeoff of privacy and utility next.

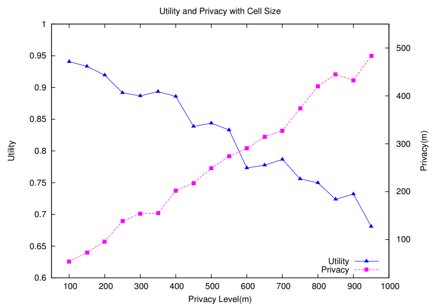



Fig. 12: Relationship of Utility/Privacy with Cell Size

**Achieving Privacy and Utility Trade-off via Classification of Users' Locations:** In the previous section, we have shown that the obfuscation techniques will bring the decrease of the utility. To achieve the tradeoff between the privacy and utility, we introduce a novel user controllable location privacy protection scheme. The proposed scheme is motivated from the observation that the user has different location privacy protection preference for different locations. For example, a mobile user cares more about their Top 2 location privacy (e.g., home, work place) while care less about the location privacy issue when he is at public regions (e.g., cafe or bars), which makes him have different privacy protection requirements. Therefore, in a user controllable location privacy protection solution, the mobile users could classify the locations into several categories, which correspond to different privacy protection requirements as well as different obfuscation parameters. During the subsequent LBSN usage process, users record their location profiles that are ranked with their visiting frequency and could be dynamically updated along with users' usage. With such a location profile with different ranking, the most frequently visited locations are given more privacy protection and thus suffer from a lower utility while the less frequently visited locations could enjoy more utility with less privacy protection as indicated in Fig 11b. To implement our idea, we transform the original grid reference system of the uniform cell size to the non-uniform grid reference system, in which top locations cover a larger area while public regions cover a smaller area. Note that the proposed location classification concept could also be applied to other existing obfuscation techniques [40]. To evaluate the proposed solution, we compare the uniform grid reference system with non-uniform grid reference system based on the data set collected from our real-world experiments. In the uniform grid reference system, we tune the cell size from 200m to 1000m, which correspond to the privacy level from 50 to 400. In the non-uniform grid reference system, we fix the cell size of top locations to 1000m to provide highest privacy protection level while tune the cell size of normal location from 200m to 1000m. It is observed that the non-uniform grid reference system based on location classification has a significant advantage in privacy/utility trade-off over the uniform grid reference system as shown in Fig 13.

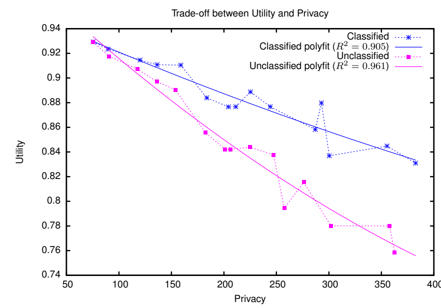



Fig. 13: Comparison of Utility/Privacy Trade-offs

We notice that Momo and Wechat provide an option to manually remove their locations from the public. However, with no idea about the potential risks brought by LBSN apps, few people do choose this option. This further signifies the importance of making the public more aware of the potential risk, which is one of major motivations of this paper.

## VII. Related Work

Location Privacy Protection in location-based services is a long-standing topic and has received a lot of attentions in the last decades. The most popular approach to achieve location privacy in LBS is utilizing the obfuscation techniques to coarse the spatial or temporal granularity of the users' real locations [41], [42]. A different approach to hide the users' location is based on mix zones. Mix zones are defined as the regions where users keep silent while changing their pseudonyms together[12]. The third approach is to protect location privacy by adding dummy requests, which are issued by fake location and indistinguishable from real requests [15]. A recent work [14] proposes a game-theoretic framework that enables a designer to find the optimal LPPM for a given location-based service, ensuring a satisfactory service quality for the user. As shown in the paper that, it is possible to apply various obfuscation techniques to enhance the location privacy of LBSN. Different from the location privacy issues considered in previous works, providing the relative distance is the key functionality of LBSN apps while the obfuscation will inevitably reduce the utility of LBSNs. Therefore, how to achieve the tradeoff between the location privacy and the utility is of the highest priority. The proposed users' location classification based approach could help to reduce the impact of obfuscation techniques on users' utility, and thus can be a compliment to various obfuscation techniques.

There are many other works which study how to infer the victim's trajectory and further re-identify his other private information [43], [8], [7], [5]. This work is different from the existing work in that we propose an novel attack approach, which could be exploited by anyone to perform an involuntary tracking towards any specific target. The collected tracking traces could be used for user re-identification.

There are some research efforts targeting at secure friend discovery in mobile social networks[44], [45], [46]. These works consider testing equalility between attributes in profiles and setting threshold on number of matching pairs, which is different from our considered problem.

We also notice that there are some smart-phone privacy leaking work, most of which focus on various types of mobile malware on various platforms of iOS, Android and Symbian[47], [48], [49]. Our work is different from existing works in that the proposed attack is actually based on one of system design drawbacks. To the best of our knowledge, our work is the first one to investigate the location privacy leaking issue from LBSN apps.

## VIII. Conclusion

LBSN is becoming extremely popular recently. However, most LBSN users are unaware of the location privacy leaking issue. We target at 3 most popular LBSN apps and develop a novel automatic tracking system, which could achieve range-free, accurate, and involuntary tracking towards the target by only using the public information. Our real-world attack experiments show that the attack could achieve high localization accuracy and the attacker could recover the users' top 5 locations with high possibility and hence, in addition to the malware, inappropriate location privacy protection techniques of LBSNs pose a more serious threat in practice. We've discussed various mechanisms to mitigate such threats and analysed the privacy and utility trade-off. As the first work of its kind, our study is expected to urge LBSN service providers to revisit their location privacy protection techniques and call for more attentions from the public to have the full knowledge of the potential risks brought by LBSN apps. Our mitigation suggestions will provide a guideline for future revisions of these LBSN apps.

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