Are You Really Hidden? Predicting Current City from Profile and Social Relationship

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Abstract

Privacy has become a major concern in Online Social Networks (OSNs) due to threats such as advertising spam, online stalking and identity theft. Although many users hide or do not fill out their private attributes in OSNs, prior studies point out that the hidden attributes may be inferred from some other public information. Thus, users’ private information could still be at stake to be exposed. Hitherto, little work helps users to assess the exposure probability/risk that the hidden attributes can be correctly predicted, let alone provides them with pointed countermeasures. In this article, we focus our study on the exposure risk assessment by a particular privacy-sensitive attribute - current city - in Facebook. Specifically, we first design a novel current city prediction approach that discloses users’ hidden ‘current city’ from their self-exposed information. Based on 371,913 Facebook users’ data, we verify that our proposed prediction approach can predict users’ current city more accurately than state-of-the-art approaches. Furthermore, we inspect the prediction results and model the current city exposure probability via some measurable characteristics of the self-exposed information. Finally, we construct an exposure estimator to assess the current city exposure risk for individual users, given their self-exposed information. Several case studies are presented to illustrate how to use our proposed estimator for privacy protection.

Keywords: Online Social Network, Location Prediction, Privacy Exposure Estimation

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1. Introduction

During the last decade, Online Social Networks (OSNs) have successfully attracted billions of people who share a huge amount of personal information through the Internet, such as their background, preferences and social connections. Owing to the increase of potential violations such as advertising spam, online stalking and identity theft [15], in recent years, more and more users have concerns about their privacy in OSNs and become reluctant to publish all their personal information [10]. Consequently, users may not fill out their privacy-sensitive attributes (e.g., location, age, or phone number), or they hide this information from strangers and only allow their friends to view such information [7].

While hiding the privacy-sensitive attributes, users usually expose some other information that appears to be less sensitive to them. It has been reported that Facebook users publicly reveal four attributes on average, and 63% of them uncover their friends list [13]. Due to the correlations among various attributes, some of the self-exposed information may indicate the invisible privacy-sensitive attributes to some extent [6, 29]. Hence, it is questionable whether the privacy-sensitive attributes that a user intends to hide are really hidden.

This work, using location information as a representative case, aims to assess what is the risk that a user’s invisible information could be disclosed. There are several reasons that lead us to conduct this study based on location information. First, among various kinds of information, location is usually one of the privacy-sensitive attributes for most users [4]. In real-life OSNs, we notice that users are quite careful to not reveal their location information: 16% of users in Twitter reveal home city [23] and 0.6% of Facebook users publish home address [3]. Second, location information is a commercially valuable attribute which might even be misused by unscrupulous businesses to bombard a user with unsolicited marketing [12]. In addition, location information leakage may lead to a spectrum of intrusive inferences such as inferring a user’s political view or personal preference [12, 17]. Therefore,
protecting the hidden location information for a user becomes rather critical. In particular, as Facebook is the most popular OSN [35], we concentrate on the attribute of current city in Facebook and investigate the following issues:

1) **Is the private current city that a user expects to hide really hidden? In other words, if a user hides his current city but exposes some other information, can we predict a user’s current city by using his self-exposed information?**

2) **Can we help individual users to understand the actual risk (probability) that their private current city could be correctly predicted based on their self-exposed information? Furthermore, can we provide some countermeasures to increase the security of the hidden current city?**

To address these issues, we first propose a current city prediction approach to predict users’ hidden current city. Although many location prediction approaches have been developed for Twitter [5][8][21][32] and Foursquare [29][30], they cannot be appropriately implemented on Facebook because of the different properties (e.g., obtainable information) in these OSNs. For Facebook, Backstrom et al. predict users’ locations based on their friends’ locations [3]. In addition to friends’ locations, users’ profile attributes, such as hometown, school and workplace, may also indicate their current city to some extent [6]. In order to achieve high prediction accuracy in Facebook, we devise a novel current city prediction approach by extracting location indications from integrated self-exposed information including profile attributes and friends list.

Second, based on the proposed prediction approach, we construct a current city exposure estimator to estimate the exposure probability that a user’s invisible current city may be correctly inferred via his self-exposed information. The exposure estimator can also provide a user with some countermeasures to keep his hidden current city hidden. To the best of our knowledge, this is the first work that estimates the exposure probability of a user’s invisible attribute by his self-exposed information.

It is a non-trivial task to construct either the current city prediction approach or the exposure estimator. We encounter the following challenges:
1) How to extract and integrate different location indications from a user’s multiple self-exposed information? Since the proposed prediction approach explores location indications from both profile attributes and friends list, two subproblems are considered. (i) A user probably reveals multiple attributes (e.g., hometown, workplace) which may indicate different locations; besides, a certain attribute might indicate several locations. For example, a user working in Google suggests that the user could probably live in any city where Google sets up an office, e.g., California, Beijing or Paris. (ii) The friends of a user, probably residing in different cities, may be close to or far away from the user. These strong or weak geographic relations may influence the significance of the friends’ location indications. Thus, it is challenging to appropriately combine these various location indications into an integrated model, so as to determine the probabilities of locations where the user may live.

2) How to predict a user’s current city when we obtain the probabilities of the user being at various locations? By overcoming challenge 1, we can obtain a probability vector which indicates the probabilities that a user resides at certain locations. With this probability vector, a straightforward prediction approach could select the location with the highest probability as the user’s current city. However, this might not be the best option when concerning the locations’ geographic relations. Assume the probability vector suggests that a user $u$ has 40%, 35% and 25% probability of residing in Beijing, Paris and Evry respectively. Then, $u$ is more likely to live in the area around Paris and Evry than Beijing, because Paris and Evry are only 30km apart but they are thousands of kilometers away from Beijing. Hence, a location selection method should be carefully designed for a current city prediction approach.

3) How to estimate the exposure risk of a user’s hidden current city? To help a user understand the exposure risk of his hidden current city, a straightforward method would be to provide a predicted location; thus the user can decide whether his current city can be predicted correctly (risky) or incorrectly (secure). However, this method may not meet users’ expectations. A user, whose location is correctly predicted, may expect being able to know which of his self-exposed information primarily leads to the leakage of his
private current city and how to increase its security. A user, whose hidden location is not predicted correctly, still needs to be aware of some leakage of location that may exist. For example, a prediction approach may incorrectly infer a Parisian living in LYON according to probabilistic results: 55% in LYON and 45% in PARIS; Even though the prediction result is incorrect, the user still leaks some location information. Therefore, how to estimate the current city exposure risk and help a user achieve his desired privacy level is a challenging objective.

This paper makes the following contributions:

1) **Profile and friend location indication model:** To properly extract location indications from users’ self-exposed information, we construct an integrated probability model. We capture location indications from two types of information: location sensitive attributes and friends list. Location sensitive attributes are the profile attributes that can indicate one or multiple locations. In this paper, we use ‘Hometown’ and ‘Work and Education’ as the location sensitive attributes. For each location sensitive attribute, we set up a location attribute indication matrix from which we can index the locations and the corresponding probabilities that a certain attribute value indicates. Besides, considering a user and each of his friends who publish current city, we estimate their location similarity according to their attribute correlations, and assign a large weight to a friend that has a high location similarity to the user. For a friend who does not reveal current city, we predict the friend’s current city using his visible location sensitive attributes, and assign him a very small weight. Finally, based on information from 371,913 users collected from Facebook, we train an integrated model that can determine the probability for each potential city where a user may reside.

2) **Current city prediction approach:** To address Challenge 2, we aggregate locations into clusters by considering the locations’ geographic relations. Then, based on the proposed profile and friend location indication model, we predict a user’s invisible current city in two steps: (i) cluster-selection: for each cluster, we sum up the probabilities of locations inside the cluster; then we select the cluster with the highest probability; (ii) location-selection: we determine a best location within the selected cluster as the user’s current city. The evaluation results demonstrate that our proposed prediction approach achieves lower error
distance and higher accuracy than the state-of-the-art approaches. Furthermore, for the users who reveal their ‘Hometown’ and ‘Work and Education’, our proposed approach can predict current city with an accuracy of 90%.

3) **Current city exposure estimator**: We define some measurements to describe the characteristics of users’ self-exposed information. Based on these measurements, we analyze how the users’ self-exposed information affects the probability that their current city may be correctly inferred (i.e., current city exposure probability). Furthermore, *Random Decision Forest* method is employed to model the current city exposure probability, and subsequently a current city exposure estimator is constructed. Given a user’s self-exposed information, the proposed exposure estimator provides two estimators — *Exposure Probability* and *Risk Level* — to quantify the current city exposure risk. The exposure estimator can also estimate the exposure risk assuming that the user hides some of his self-exposed information. Consequently, the user can easily decide which information he should hide to satisfy his privacy intention.

The rest of this paper is organized as follows. We review the literature in Sec. 2, formulate the current city prediction problem in Sec. 3, and overview our solution to the prediction problem in Sec. 4. Next, the profile and friend location indication model is devised in Sec. 5; the current city prediction approach is respectively presented and evaluated in Sec. 6 and Sec. 7. By inspecting the current city prediction results, Sec. 8 proposes the exposure estimator. Finally, Sec. 9 makes some discussions and points out future work. Sec. 10 concludes this work.

2. Literature Review

In this section, we briefly review the related work from two perspectives: city-level location prediction and privacy in OSNs.

2.1. City-Level Location Prediction

Existing city-level location prediction approaches can be classified into four categories: *relationship-based* prediction, *content-based* prediction, *hybrid content-relationship* prediction-
tion and *multi-indication* prediction.

### 2.1.1. Relationship-based Prediction

Based on the principle that the probability of being friends is declining with geographic distance, this prediction category infers a user’s location according to the visible locations of his friends \(^3\). Researchers have studied the correlation between geographic distance and social relationship on large-scale Facebook users in United States. They reveal that the probability of being friends falls down monotonically as the distance increases. Depending on this observation, they build a maximum-likelihood location prediction model and finally refine the prediction with an iterative algorithm.

### 2.1.2. Content-based Prediction

The rise of Twitter has spawned a mass of tweets. As some tweets contain location-specific data, this category of prediction approaches \(^5\)\(^,\)\(^8\)\(^,\)\(^21\) infers a user’s location relying on his location-related tweets. The basic idea of these approaches is to detect the location-related tweets and construct a probabilistic model to estimate the distribution of location-related words used in tweets. In order to raise the prediction accuracy, the basic idea is improved by various means, such as such as selecting the top K probable cities \(^5\), identifying words with a strong local geo-scope and refining the prediction with a neighborhood smoothing model \(^8\).

### 2.1.3. Hybrid Content-Relationship Prediction

Another compelling category combines the location indications from relationships and tweet content. TweetHood identifies a user’s location by exploring both his tweets and his closest friends’ locations \(^1\). Tweecalization improves TweetHood by employing a semi-supervised learning algorithm and introducing a new measurement which combines trustworthiness and the number of common friends to weight friends \(^2\). Li et al. integrate the location influences captured from both social network and user-centric tweets into a unified discriminative probabilistic model \(^24\). By considering a user who may be related to multiple locations, MLP model \(^23\) proposes to set up a complete ‘location profiles’ prediction
which infers not only a user’s home location but also his other related locations.

2.1.4. Multi-Indication Prediction

Besides users’ relationships and content, multi-indication prediction approaches explore multiple location indications from other possible location resources to infer users’ invisible location. To resolve ambiguous toponymies in tweet content, besides location indications extracted from tweets, existing work has introduced location indications from websites’ country code, geocoded IP addresses, time zone and UTC24-offset [33]. Such a multi-indication idea has also been used to Foursquare, which specifically exploits mayorships, tips and dones that users marked [30]. However, all these multi-indication prediction approaches are proposed for either Twitter or Foursquare, but not for Facebook. Our previous work reveals the statistical analyzed correlation between users’ current city and other location sensitive attributes in Facebook [6]. It also predicts a user’s current city with city-level and country-level results by using a neural network approach. However, this previous work assumed that an attribute value could map to a specific location, which is not true for many cases. Recall the example that a user works in Google might work in California, Paris or Beijing (Challenge 1 of Sec. 1).

In this paper, we consider multiple location indications by integrating relationship and profile attributes in Facebook. Compared to our previous work where an attribute value only allows to bind with one fixed location [6], an attribute value can be mapped to multiple locations with different probabilities in the newly proposed model. In addition, we consider both the friends whose current city is either visible or invisible; whereas the existing work relies on the friends who reveal their locations [3][24]. Particularly, we propose a new approach to bias the weights of friends whose current city is visible.

2.2. Privacy in OSNs

In OSNs, users are more and more concerned with privacy of their personal information [10]. A majority of users configure their privacy settings and hide some of their information from strangers. Unfortunately, previous research has pointed out the disparity
between the expectation and the reality of users’ privacy; and it has also showed that much of users’ private information is easily uncovered \[27\].

Much existing work ascribes the privacy leakage to the users themselves. On one hand, users might incorrectly manage their privacy settings due to the poor human-computer interaction or complex privacy maintainability \[27\][4]. To address this issue, researchers have designed a user-friendly interface for managing privacy settings with an audience view \[26\].

On the other hand, users only hide some of the attributes that are privacy-sensitive to them while make the others accessible to public — users on Facebook generally expose more than four attributes to strangers and 63% of users share their friend lists with the public \[13\]. As reported, such user self-exposure behavior leaves a huge chance for inferring the hidden attributes \[11\][28][20]. Many tools have been developed to infer users’ invisible information by various means such as inferring the private information through users’ other self-exposed information \[28\], their social connections \[11\][20] and social groups \[40\][22].

Some papers claim that it is hard for a user to avoid privacy leakages if he only hides the private attribute \[11\][28][30]; whereas many studies merely suggest users with a general idea of hiding other attributes so as to become more secure (e.g., hide relationships \[19\]). Unlike the above work, we provide an individual user with the exposure probability of his private current city concerning his self-exposed information. We also suggest some pointed rules for protecting users’ privacy on their current city.

3. Formulation of Current City Prediction Problem

In this section, we formulate the current city prediction problem. Facebook, as a social network containing location information, can be viewed as an undirected graph \( G = (U, E, L) \), where \( U \) is a set of users; \( E \) is a set of edges \( e(u, v) \) representing the friend relationship between users \( u \) and \( v \), where \( u \) and \( v \in U \); \( L \) is a candidate locations list composed of all the user-generated locations.

Typically, a user \( u \) in Facebook might contribute various items of information, e.g., basic profile information, friends, comments and photos. The core information of \( u \) in this paper is the user’s current city, denoted as \( l(u) \). The users are classified into two sets according to
the accessibility of users’ current city: current city available users (LA-users) and current city unavailable users (LN-users). We, respectively, use $U^L_A$ and $U^L_N$ to denote the sets of LA-users and LN-users, where $U = U^L_A \cup U^L_N$.

To predict users’ current city, we exploit the users’ location sensitive attributes and friends list. Assume that there exist $m$ types of location sensitive attributes, denoted as $A = \{a_1, a_2, \cdots, a_m\}$. Specifically, we denote a user $u$’s location sensitive attributes as $A(u) = \{a_1(u), a_2(u), \cdots, a_m(u)\}$. The users may also have a friends list, denoted as $F(u)$, where $F(u) = \{f \in U : e(u,f) \in \mathcal{E}\}$. Therefore, we use a tuple to represent a user as $u : \langle l(u), A(u), F(u) \rangle$.

Additionally, each location is associated with a unified ID ($l_{id}$). Then, with this ID, we can obtain each location’s latitude and longitude coordinate via Facebook Graph API Explorer. Therefore, a location can also be written as a tuple: $l : \langle l_{id}, lat, lon \rangle$ and the candidate locations list can be denoted as a set of location tuples: $L = \{l : \langle l_{id}, lat, lon \rangle\}_N$, where $lat$ and $lon$ respectively stand for the latitude and longitude of a location, and $N$ is the number of candidate locations in the list.

Thus, the current city prediction problem can be formally stated as: Given, (i) a graph $\mathcal{G} = (U^L_A \cup U^L_N, \mathcal{E}, \mathcal{L})$; (ii) the public location $l(u)$ for LA-users $u \in U^L_A$; (iii) the location sensitive attributes $A(u)$ and the friends list $F(u)$ for all the users $u \in (U^L_A \cup U^L_N)$, we predict current city $\hat{l}(u)$ for each LN-user $u \in U^L_N$, so as to make $\hat{l}(u)$ close to the user’s real current city.

Note that the current city of a user’s friends can be either available ($f \in U^L_A$) or unavailable ($f \in U^L_N$). Thus, we introduce two notations to represent the two groups of friends: current city available friends (LA-friends) and current city unavailable friends (LN-friends). Let denote a user’s LA-friends as $F^L_A(u)$ and LN-friends as $F^L_N(u)$, where $F(u) = F^L_A(u) \cup F^L_N(u)$.

4. Overview of Current City Prediction

The goal of current city prediction is to correctly infer a coordinate point with latitude and longitude for a LN-user, given the candidate locations list $\mathcal{L}$ and the user’s self-exposed
information including his location sensitive attributes and friends list. Figure 1 illustrates the framework of the proposed current city prediction solution. To determine the current city of a LN-user, we first train an integrated profile and friend location indication (i.e., PFLI) model to compute the probabilities of the candidate locations in which the LN-user may currently live. Next we take a two-step location selection strategy: cluster selection and location selection. Specifically, we aggregate the nearby locations into a location cluster and obtain a set of location clusters. We then calculate the probability of a user being in a cluster by summing up the probabilities of all the candidate locations belonging to this cluster; the cluster with the highest probability is picked out as a candidate cluster. Finally, we try to select the ‘best’ location from the candidate cluster as the predicted current city.

Figure 1: Framework of Current City Prediction.

To train the integrated PFLI model (see the right-hand part of Figure 1), we separately consider the location indications from location sensitive attributes and friends, and consequently obtain two sub-models: profile location indication (PLI) model and friend location indication (FLI) model. Both PLI model and FLI model calculate a probability vector in which the element stands for the probability of a user being at a certain candidate location. Note that, FLI model leverages the location indications from both LA-friends and LN-friends. By integrating the probability vectors that are generated by PLI and FLI models with appropriate parameters, a unified profile and friend location indication (PFLI) model is derived.
Next, we will elaborate the $PFLI$ model and the current city prediction approach.

5. Profile and Friend Location Indication Model

In this section, we describe the design of the probabilistic models that can suggest the probabilities of users being at each of the candidate locations. We first introduce the profile location indication ($PLI$) model; it estimates the probability of each candidate location by merely relying on a user’s location sensitive attributes. Then, we describe the friend location indication ($FLI$) model, which captures the location indications from a user’s friends. Finally, we integrate these two models and obtain the integrated profile and friend location indication ($PFLI$) model.

5.1. Profile Location Indication Model

According to Challenge 1 in Sec. 1, two problems should be considered in constructing $PLI$ model. First, a certain value of a location sensitive attribute may indicate several locations. For instance, GOOGLE, being a certain value of workplace, could indicate any city where GOOGLE sets up an office such as CALIFORNIA, BEIJING or PARIS. Therefore, for each attribute value, we consider all possible location indications with the corresponding probabilities. Second, a user may present multiple location sensitive attributes (e.g., hometown, workplace, college). Thus we integrate various location indications extracted from different location sensitive attributes.

To capture the multiple possible location indications from one attribute value, we define a location-attribute indication matrix for each ($k$-th) location sensitive attribute $a_k \in \mathcal{A}$, denoted as $\mathcal{R}_k$. The rows of this matrix represent the candidate locations ($l \in \mathcal{L}$), while the columns stand for the possible values of $a_k$. We use $l_i$ to represent the $i$-th candidate location and $a_{kj}$ to denote the $j$-th possible value of $a_k$. A cell $\sigma_{ij}^{kj}$ in the matrix calculates the indication probability of $a_{kj}$ to $l_i$ — the probability that a user, whose $k$-th location sensitive attribute $a_k$ equals $a_{kj}$, currently lives in the city $l_i$. Specifically, the indication probability equals the number of users who live in $l_i$ and have a value of $a_{kj}$ divided by the total number of users who have a value of $a_{kj}$. For instance, considering workplace, if 10 out
of 100 employees from TELECOM SUDPARIS in the whole data set state that they live in Evry, then the indication probability of TELECOM SUDPARIS to Evry is 0.1. Note that, the j-th column of $\mathcal{R}_k$ represents the multiple location indications of $a_{kj}$.

Assume that $a_k$ has $M$ possible values except null; $N$ is the total number of the candidate locations. The $k$-th location-attribute indication matrix can be written as:

$$
\mathcal{R}_k = \{\sigma_{ij}^{kj}\}_{N \times M} = \{p(l(u) = l_i | a_k(u) = a_{kj})\}_{N \times M} = [R_{k1}, R_{k2}, ..., R_{kM}]
$$

where $R_{kj}$ represents all the locations’ probabilities for a user who presents $a_{kj}$.

Based on the location-attribute indication matrix ($\mathcal{R}$), we model the probability of a user’s current city at $l_i$ by combining all of a user’s available location sensitive attributes in his profile:

$$
p_{Prof}(u, l_i) = \alpha_k \sum_{a_k \in A, a_k(u) \neq \text{null}} \sigma_k^{ij}(u, l_i)
$$

where $\sigma_k(u, l_i)$ can be easily obtained by indexing the corresponding location-attribute indication matrix ($\mathcal{R}_k$) according to $u$’s value of $a_k$ ($a_k(u) = a_{kj}$) and the given location ($l_i$), namely $\sigma_{ij}^{kj}$; $\alpha_k$ is a parameter to adjust the significance of the different location sensitive attributes.

As we discussed in Sec. 5, a user may not reveal some attributes. Therefore, in Eq. 1 the location indication from the attribute $a_k(u)$ at any location equals zero if the user’s $a_k(u)$ is invisible. If all of a user’s location sensitive attributes are invisible, we rely on his friends’ information to infer his current city, which we will discuss in the next section.

5.2. Friend Location Indication Model

In addition to a user’s location sensitive attributes, we explore location indications from users’ friends to construct FLI model. A user’s friends can be either LA-friends (current city available) or LN-friends (current city unavailable). We build up FLI model primarily
depending on LA-friends’ location indications and also considering LN-friends’ location indications as a small regulator. Accordingly, FLI model contains two components: LA-friends location indication (LA-FLI) model and LN-friends location indication (LN-FLI) model.

5.2.1. LA-FLI Model

LA-FLI model differentiates the weights of a user’s LA-friends and estimates his probability of living in location \( l_i \) by the weights of his friends who also live in \( l_i \). LA-FLI model expects to assign high weights to the LA-friends who live in the same city as the user does. However, since the user’s city is unknown, whether or not a friend and the user live in the same city cannot be directly determined. Therefore, LA-FLI model assesses the likelihood that two users live in a same city (i.e., location similarity) based on the correlation between their location sensitive attributes. Figure 2 illustrates an example to show that the location sensitive attributes can be used to distinguish the weights among various LA-friends. Focusing on LN-user \( u_2 \) and his LA-friends \( u_3, u_4 \) and \( u_5 \), we notice that \( u_2 \) and \( u_3, u_4 \) work in the same institute, while \( u_5 \) works in another company which is far away from \( u_2 \)’s workplace. In this case, it is natural to infer that \( u_2 \) is more likely to be living in the same city with \( u_3 \) and \( u_4 \) than with \( u_5 \); then \( u_3 \) and \( u_4 \) should be assigned with higher weights than \( u_5 \) because of the location similarity indicated by their workplace.

Inspired by the example, we construct an attribute-based location similarity matrix \( (W_k) \) by each \((k\text{-th})\) location sensitive attribute \((a_k \in \mathcal{A})\). In the matrix, a cell \( w_{ij}^k \) calculates the probability that two users live in the same city (i.e., location similarity) when they respectively have values of \( a_k \), and \( a_k \) regarding \( a_k \). Specifically, we compute the total

![Figure 2: An Example of Social Relations and Profile Information.](image-url)
number of friend pairs where one user has a value of $a_k$ and the other has a value of $a_k$, denoted as $|\{a_k(u) = a_k, a_k(v) = a_k\}|$; Among these friend pairs, we further count the pairs of friends who live in the same city, denoted as $|\{l(u) = l(v) \wedge a_k(u) = a_k \land a_k(v) = a_k\}|$. Then,

$$W_k = \{w_{ij}^k\}_{M \times M} = \left\{ \frac{|\{l(u) = l(v) \wedge a_k(u) = a_k \land a_k(v) = a_k\}|}{|\{a_k(u) = a_k \land a_k(v) = a_k\}|} \right\}_{M \times M}$$

where $M$ is the number of possible values of attribute $a_k$ including null.

For a certain attribute $a_k$, assume that $u$ and his LA-friend $v$ have a value of $a_k$ and $a_k$, respectively. Then, the $u$ and $v$’s location similarity on $a_k$ can be easily obtained by indexing the $i$-th row and $j$-th column of $W_k$, denoted as $w_k(u,v) = w_{ij}^k, v \in F_{LA}(u)$.

We combine multiple location similarities on all the location sensitive attributes (e.g., work, hometown) with a set of trained parameters ($\beta$) to measure $v$’s weight. This combined weight describes the probability that $u$ and $v$ live in the same city concerning all of their location sensitive attributes.

Then, LA-FLI model calculates the probability of $u$ living in $l_i$ by integrating all the weights of $u$’s LA-friends who live in $l_i$:

$$p_{LA-u}(u,l_i) = \sum_{v \in F_{LA}(u)} \sum_{a_k \in A} \beta_k w_k(u,v) p_{LA-v}(v,l_i)$$

where $p_{LA-v}(v,l_i)$ represents whether or not the LA-friend $v$ living in $l_i$. It equals 1 if $v$ states his current city is $l_i$; otherwise, it is 0:

$$p_{LA-v}(v,l_i) = \begin{cases} 1 & \text{if } l(v) = l_i \\ 0 & \text{otherwise} \end{cases}$$

5.2.2. LN-FLI Model

Before introducing LN-FLI model, we inspect the potential benefit of a user’s LN-friends for his current city prediction with another example shown in Figure 2. We observe that
u₂, being a LN-friend of u₁, does not expose his current city; whereas, the workplace of u₂, Telecom SudParis, indicates two cities — Paris and Evry — according to the current cities of the users u₃ and u₄ who are also the employees of Telecom SudParis. Thereby, a user’s LN-friends can also reveal some location indications in their exposed attributes, which may help the prediction.

Therefore, for a LN-friend v, we first rely on his exposed location sensitive attributes and use PLI model (Sec. 5.1) to predict his current city, as:

\[ p_{\text{Prof}}(v, l_i) = \sum_{a_k \in A, \alpha_k(v) \neq \text{null}} \alpha_k p(l(v) = l_i | \alpha_k(v) = \alpha_k_j) \]

Treating all the LN-friends equally, LN-FLI model integrates LN-friends’ location indications and computes the probability that u lives in \( l_i \in \mathcal{L} \) as:

\[ p_{\text{LN}}{\text{-}F}(u, l_i) = \sum_{v \in \mathcal{F}_{\text{LN}}(u)} p_{\text{Prof}}(v, l_i) \quad (3) \]

5.2.3. FLI Model

Finally, primarily relying on LA-FLI model and being adjusted by LN-FLI model with a small regulator parameter \( \lambda \), FLI model estimates the probability that u currently lives in \( l_i \) as:

\[ p_F(u, l_i) = p_{\text{LA}−F}(u, l_i) + \lambda p_{\text{LN}−F}(u, l_i) \quad (4) \]

5.3. Integrated Profile and Friend Location Indication Model

Next, we discuss how to integrate PLI model and FLI model into a unified probabilistic location indication model, so as to capture the complete location indications. Specifically, PFLI model calculates the probability of u living in \( l_i \in \mathcal{L} \) as:

\[ p(u, l_i) = \theta_p p_{\text{Prof}}(u, l_i) + \theta_F p_F(u, l_i) \quad (5) \]

Parameter Computation: To obtain a set of good parameters for the model, we first
rewrite the model as:

\[
p(u, l_i) = \sum_{a_k \in A} \theta_p \alpha_k \sigma_k(u, l_i) \\
+ \sum_{a_k \in A} \theta_p \beta_k \sum_{v \in F_{LA}(u)} w_k(u, v)p_{LA-F}(v, l_i) \\
+ \sum_{a_k \in A} \lambda \theta_p \sum_{v \in F_{LN}(u)} \alpha_k \sigma_k(v, l_i) \\
= \sum_{a_k \in A} \{[\mu_k \sigma_k(u, l_i) + \nu_k \delta_k(u, l_i)] + [\lambda_a \alpha_k \eta_k(u, l_i)]\}
\]  

(6)

where

- \( \mu_k = \theta_p \alpha_k; \ \nu_k = \theta_p \beta_k; \ \lambda_a = \lambda \theta_F \)

- \( \delta_k(u, l_i) = \sum_{v \in F_{LA}(u)} w_k(u, v)p_{LA-F}(v, l_i) \)

- \( \eta_k(u, l_i) = \sum_{v \in F_{LN}(u)} \sigma_k(v, l_i) \)

The location indications extracted from a user’s location sensitive attributes and his LA-friends are considered as primary indications, while the location indication captured from the LN-friends is only used to regulate the results. Therefore, we integrally train a good set of parameters \( \mu_k \) and \( \nu_k \); while we separately train \( \alpha_k \).

To train the parameters \( \mu_k \) and \( \nu_k \), we generate a training data set with items \((\text{label}(l_i) : \text{features}(u, l_i))\), if the probability that a LA-user \( u \) lives in \( l_i \) is larger than zero, i.e., \( \sum_{a_k \in A} [\sigma_k(u, l_i) + \delta_k(u, l_i)] > 0 \). In particular, \( l_i \) is labeled as a far location (\( \text{label}(l_i) = 0 \)), if the distance between \( l_i \) and \( u \)'s actual location is larger than a pre-defined threshold; otherwise, it is labeled as a close location (\( \text{label}(l_i) = 1 \)). Additionally, \( \text{features}(u, l_i) \) is a vector consisting of \( \sigma_k(u, l_i) \) and \( \delta_k(u, l_i) \), where \( k \in [1, m] \) represents the \( k \)-th location sensitive attribute. Based on the generated items, we use a logistic regression method to train the model in the following format:

\[
f(y | x; \sigma_1, \ldots, \sigma_m, \delta_1, \ldots, \delta_m) = h_{\sigma,\delta}(x)^y(1 - h_{\sigma,\delta}(x))^{1-y}
\]
where \( y \) is the label(\( l_i \)), \( x \) stands for the features(\( u_i \)) and \( h_{\sigma,\delta}(x) \) is the hypothesis function. Then we can apply the gradient descent method to maximize \( f(y|x;\sigma,\delta) \) and compute the parameters. In the similar way, we can train a set of parameters \( \alpha_k \).

6. Current City Prediction Approach

To address Challenge 2 of Sec. 1 we aggregate the close candidate locations into clusters and devise a two-step current city selection approach. In this section, referring to Figure 1, we elaborate the Candidate Locations Cluster, Cluster Selector and Location Selector respectively. We summarize the prediction approach at the end of this section.

6.1. Candidate Locations Cluster

We draw on the hierarchical clustering method, i.e., UPGMA (Unweighted Pair Group Method with Arithmetic Mean) [34][18], to generate location clusters. This method arranges all the candidate locations in a hierarchy with a treelike structure based on the distance between two locations, and successively merges the closest locations into clusters. Algorithm 1 elaborates the clustering process.

Figure 3 illustrates an example of the clustering results on 154 candidate locations that are located in the area with latitude in 47°N \( \sim \) 49°N and longitude in 1°W \( \sim \) 6°E. By using the hierarchical clustering method, we divide these locations into 5 clusters. We note several properties of our location clusters. First, instead of dividing areas with equal-sized grid cells [25][9], the hierarchical clustering method only considers the user-generated locations while the areas that no user mentions are out of consideration. Second, the densities inside the clusters are different; however, the average distances between all the candidate locations in any two neighboring clusters are equal (100 km in Figure 3). Third, the complexity of the algorithm is \( O(|L|^3) \), where \( |L| \) is the total number of the candidate locations.

6.2. Cluster Selector

Given a location cluster and a LN-user's location probability vector obtained by PFLI model, we sum up the user's probabilities of locations inside the cluster as the cluster
**Algorithm 1: Clustering Locations**

**Input:** All the candidate locations \( l \in \mathcal{L} \);

**Output:** Location clusters set \( \mathcal{C} = \{ c_1, c_2, \cdots, c_s \} \) (\( s \) is the number of clusters);

**Step 1:** treat all \( l \in \mathcal{L} \) as a cluster and calculate the distance between any two locations;

repeat

**Step 2:** find and merge the two closest location clusters into a new location cluster;

**Step 3:** compute the average distance between the new cluster and each of the old ones;

until all the candidate locations are organized into one cluster tree;

**Step 4:** cut the cluster tree into clusters with an ideal distance threshold

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Figure 3: Example of Candidate Locations Cluster.

---

probability. Cluster selector calculates the probabilities of all the clusters that the LN-user may reside in and then selects the cluster with the highest probability.

6.3. Location Selector

Finally, we select a best point from the selected cluster as the user’s predicted location of the current city. Three alternatives are considered. First, we select the point of the highest probability inside the selected cluster as the best point. Second, we consider the geographic centroid of the selected cluster as the user’s best point. The geographic centroid is the average coordinate for all the points in a cluster while the probability of each point is considered as its weight. Third, we calculate the center of minimum distance which has the
ALGORITHM 2: Current City Prediction

Input: A LN-user $u$’s location sensitive attributes;
$u$’s friends list and friends’ location sensitive attributes;
Location clusters set $\mathcal{C} = \{c_1, c_2, \cdots, c_s\}$ ($s$ is the number of clusters);

Output: Predicted current city for $u$: $\langle \text{lat, lon} \rangle$;

Compute location indications $p(u)$ by $u$’s location sensitive attributes and LN-friends (Eq. 7);
Obtain all of LA-friends’ current city $\mathcal{L}_{LA-F}$;
for $l_i \in \mathcal{L}_{LA-F}$ do
  $p(u, l_i) \leftarrow p(u, l_i) + p_{LA-F}(u, l_i)$;
end
for $c_x \in \mathcal{C}$ do
  $p(u)_{c_x} = \sum_{l \in c_x} p(u, l)$
end
Cluster selection: $c_h$ where $p(u)_{c_h} \geq p(u)_{c_x}, \forall c_x \in \mathcal{C}$;
Location selection from $c_h$ (Sec. 6.3);
The predicted current city of $u$: $\langle \text{lat, lon} \rangle$ minimum overall distance from itself to all the rest of locations in a cluster. We will further discuss and compare the three methods in Sec. 7.

6.4. Implementation of Prediction Approach

We summarize the current city prediction approach in Algorithm 2. In practice, to speed up the computation of location probability vector for a given LN-user $u$, we first compute location indications from $u$’s location sensitive attributes and LN-friends:

$$p(u) = \sum_{a_k \in A} (\mu_k R_{a_k}(u)) + \lambda_\alpha \sum_{v \in F^{LN}} \alpha_k R_{a_k}(v)$$ (7)

Assume $\mathcal{L}_{LA-F}$ is the set of current cities of $u$’s LA-friends. We sum location indications from $u$’s LA-friends $p_{LA-F}(u, l_i)$ (refer to Eq(2) to $p(u, l_i)$, where $l_i \in \mathcal{L}_{LA-F}$. 

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7. Evaluation on Current City Prediction

In this section, we first introduce the experiment setups including the used Facebook data set, the compared approaches and the measurements. Then, we report the experiment results.

7.1. Experiment Setup

7.1.1. Data description

We crawled Facebook by a Breadth First Search (BFS) [14] approach from March to June in 2012 and collected 371,913 users’ information including profile (e.g., gender, current city, hometown) and friends. Among all these users, 153,909 users publicly report their current city (LA-users) and 225,314 users do not reveal their current city (LN-users). All these users generate 12,863 different locations. For more details about this data set, please refer to our previous work [17].

To evaluate the prediction approach, a user’s latest work or education experience is extracted as a location sensitive attribute, named ‘Work and Education’; we also exploit a user’s ‘Hometown’ as another location sensitive attribute. In our data set, 122,899 LA-users show ‘Hometown’, 54,097 LA-users reveal ‘Work and Education’ and 115,807 LA-users publish their friend lists.

In addition to the exploited location sensitive information, some other information (e.g., a user’s geo-tagged posts) in Facebook may also leak the location. Our prediction approach can be extended to consider other location sensitive information smoothly, which we will discuss more in Sec. 9.1.

7.1.2. Approaches

We first compare the different location selection approaches introduced in Sec. 6.3 to finalize the prediction approach with a good location selector. We also evaluate the performance of non-cluster prediction approach to show the effectiveness of location cluster. Specifically, these approaches can be denoted as:
• $PFLI_{prob}$ is a cluster based approach which selects the point of highest probability from the selected cluster as the predicted location.

• $PFLI_{cent}$ is a cluster based approach which selects the geographic centroid from the selected cluster as the predicted location.

• $PFLI_{dist}$ is a cluster based approach which selects the center of minimum distance from the selected cluster as the predicted location.

• $PFLI_{noclst}$ is a non-cluster approach which selects the point of highest probability from all candidate locations as the predicted location.

The proposed approaches are also compared to several state-of-the-art methods:

• $Base_{dist}$ predicts a user’s location based on the observation that the distance between two users decreases by the increase of their friendship.

• $Base_{ann}$ maps any location sensitive attribute value to a certain location and applies artificial neural network to train a current city prediction model.

• $Base_{freq}$, borrowing the idea from the prior works based on the Twitter data set, counts the frequency of locations that emerge in a user’s friends and predicts his current city by the most frequent location.

• $Base_{freq+}$ improves $Base_{freq}$ by further using the neighborhood smoothing approach. Given a location $l$, the points that are less than 20km apart from $l$ are considered as $l$’s neighborhoods.

• $Base_{knn}$ also relies on the frequency idea for Twitter; however, it merely counts on a user’s $k$ closest friends who have the most common friends with him to compute the most frequent location.

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1Geographic centroid is the average coordinate for all the points in a cluster while the probability of each point is considered as its weight.
Among the above approaches, Base\textsubscript{dist} and Base\textsubscript{ann} are originally devised for Facebook; while Base\textsubscript{freq}, Base\textsubscript{freq}\textsubscript{+} and Base\textsubscript{knn} are on Twitter. We utilize the main ideas from Base\textsubscript{freq}, Base\textsubscript{freq}\textsubscript{+} and Base\textsubscript{knn}, and adopt them to fit our data set. By comparing our approach to Base\textsubscript{dist}, Base\textsubscript{freq}, Base\textsubscript{freq}\textsubscript{+} and Base\textsubscript{knn} which mainly depend on friendships, we test the effectiveness of integrating location sensitive attributes. By comparing to Base\textsubscript{ann}, we examine the newly introduced one-attribute/multiple-locations mapping method.

7.1.3. Measurement

Two widely used measurements: Average Error Distance (AED) and Accuracy within K km (ACC@K) \cite{5,8,24} are exploited.

Error Distance computes the distance in kilometers between a user \(u\)’s real location and predicted location, i.e., \(\text{ErrDist}(u)\). AED averages the Error Distances of the overall evaluated users, denoted as \(\text{AED} = \frac{\sum_{u \in U} \text{ErrDist}(u)}{|U|}\). In addition, we rank the users by their Error Distance in descending order and report AED of the top 60\%, 80\% and 100\% of the evaluated users in the ranked list, denoted as \(\text{AED@60\%}, \text{AED@80\%} \text{ and AED@100\%}\) respectively \cite{24}.

Given a predefined Error Distance K km, a prediction for a user is considered as a correct prediction, if the predicted Error Distance is less than K km; otherwise, the prediction is incorrect. Then, Accuracy within K km is defined as the percentage of correct predictions (i.e., the percentage of users being predicted with an Error Distance less than K km), denoted as \(\text{ACC@K} = \frac{|\{u \in U | \text{ErrDist}(u) < K\}|}{|U|}\). ACC@K shows the prediction capability of an approach at a specific pre-established Error Distance.
7.2. Experiment Results

Many relationship-based methods (e.g., $Base_{\text{dist}}$, $Base_{\text{freq}}$, $Base_{\text{freq}+}$ and $Base_{\text{knn}}$) rely heavily on users’ LA-friends whose locations are exposed. In general, such methods can work well for the users who have a certain number of LA-friends; but when they are applied to the overall users (who either have or do not have LA-friends), the performance notably decreases. We evaluate the prediction performance on two user sets: users with LA-friends and overall users, and report the evaluation results on $AED$ and $ACC@K$ subsequently.

7.2.1. Evaluation on $AED$

Table 1 and Table 2 show the $AED$s of all the compared approaches for two user sets. The smallest $AED$s, which are generated by $PFLI_{\text{prob}}$, have been highlighted in bold.

|        | $Base_{\text{dist}}$ | $Base_{\text{ann}}$ | $Base_{\text{freq}}$ | $Base_{\text{freq}+}$ | $Base_{\text{knn}}$ | $PFLI_{\text{noclst}}$ | $PFLI_{\text{dist}}$ | $PFLI_{\text{cent}}$ | $PFLI_{\text{prob}}$ |
|--------|------------------------|----------------------|-----------------------|------------------------|----------------------|------------------------|------------------------|------------------------|------------------------|
| $AED@60\%$ | 102.8                  | 6.7                  | 73.9                  | 66.6                  | 119.5                | 3.5                    | 50.6                   | 6.3                    | 3.1                    |
| $AED@80\%$ | 1368.8                 | 74.7                 | 1257.2                | 1243.1                | 1429.6               | 52.5                   | 88.2                   | 50.2                   | 49.1                   |
| $AED@100\%$ | 2671                  | 1204.0                | 2523.5                | 2498                  | 2698.5               | 981.0                  | 989.9                  | 960.8                  | 960.0                  |

Table 2: Prediction Results ($AED$) for Overall Users

In addition, the results show that the $PFLI$ model based approaches present much smaller $AED$s than all the other baselines. In particular, the results demonstrate the $PFLI$ model based approaches mapping one-attribute to multiple locations reduce the $AED$ significantly compared to $Base_{\text{ann}}$ which maps one-attribute to one-location.

By examining the results of $AED@60\%$, $AED@80\%$ and $AED@100\%$, we observe that the $PFLI$ model based approaches can predict current city with relatively small $AED@60\%$.
and $AED@80\%$; whereas, $AED@100\%$ increases by 10–23 times from $AED@80\%$. This demonstrates the large Error Distance only occurs at predictions for a small number of users.

Lastly, we compare the results in the two Tables and notice that the prior approaches ($Base_{dist}$, $Base_{freq}$, $Base_{freq^+}$ and $Base_{knn}$) predict locations with much larger AEDs for overall users than for users with LA-friends; however, for the PFLI model based approaches, AEDs differ slightly for two user sets. It demonstrates that a user’s profile can significantly contribute to the location prediction when the user’s friends’ locations are unavailable.

7.2.2. Evaluation on ACC@K

We study $ACC@K$ of the three proposed prediction approaches ($PFLI_{prob}$, $PFLI_{cent}$ and $PFLI_{dist}$) for two user sets in Figure 4. We observe that the accuracy of $PFLI_{prob}$ goes up steadily with the increase of Error Distance. $PFLI_{cent}$ may lead to very low accuracy when the pre-established Error Distance is quite small; but it can achieve higher accuracy than $PFLI_{prob}$, when the pre-established Error Distance is larger than 40 km. This reveals the properties of these two prediction approaches: $PFLI_{cent}$, which selects the geographic centroid of a cluster, generates a short average Error Distance to all the locations in the cluster but fails to pick the user’s exact coordinate once it is not the centroid; while $PFLI_{prob}$ may produce a large Error Distance if the location of the highest probability is not the user’s real location. In addition, $PFLI_{dist}$ is not competitive with the other two approaches.

Rather than solely using any one of the proposed approaches, we exploit a combined-approach strategy by flexibly selecting the best approach according to the pre-established Error Distance. Specifically, this strategy uses $PFLI_{prob}$ when the pre-established Error Distance is smaller than 40 km and otherwise applies $PFLI_{cent}$. The combination is practical and can obtain a better performance than using any single approach. We plot the combination line in Figure 4 and call it $PFLI_{cmb}$.

Figure 5 compares $PFLI_{cmb}$ to various baseline methods in terms of $ACC@K$. We observe that the proposed $PFLI_{cmb}$ outperforms all the compared baselines for both user sets. Compared to $PFLI_{nocalst}$, $PFLI_{cmb}$ increases around 1.5% and 1.2% of accuracy on average for
users with LA-friends and overall users. This proves the effectiveness of the cluster strategy with successive cluster selection and location selection.

Comparing Figure 5(a) and 5(b) we observe that the approaches $Base_{freq}$, $Base_{freq+}$, $Base_{dist}$ and $Base_{knn}$ perform much worse for overall users than for users with LA-friends. This observation again indicates that these approaches depend heavily on the friends’ locations. However, in respect of the other approaches, which integrate location indications from both location sensitive attributes and friends (including our previous work $Base_{ann}$ [6]), the prediction performance for overall users relatively approaches to the performance for users
8. Current City Exposure Estimator

In this section, we pay attention to estimating current city exposure probability for a user who hides his current city. We formulate the current city exposure estimation problem as: Given, (i) a graph $G = (U^{LA} \cup U^{LN}, E, L)$; (ii) the public location $l(u)$ for LA-users $u \in U^{LA}$; (iii) the location sensitive attributes $A(u)$ and the friends list $F(u)$ for all the users $u \in (U^{LA} \cup U^{LN})$; (iv) a pre-established Error Distance $K$ km, we forecast the current city exposure probability within $K$ km and report the exposure risk level for each LN-user $u \in U^{LN}$.

To solve this problem, we run the proposed prediction approach on an aggregation of users and conduct analysis on the aggregated prediction results. Furthermore, we apply a regression method to construct the exposure model according to the analysis observations. Relying on this model, we devise a current city exposure estimator to inform users of their current city Exposure Probability within $K$ km and Exposure Risk Level.

The Exposure Probability within $K$ km ($EP@K$) represents the probability that a user’s current city could be inferred correctly if the pre-established Error Distance is $K$ km. As it is conceptually similar to the metric $ACC@K$, we compute it by the same formula:

$$EP@K = \frac{|\{u | u \in U \wedge ErrDist(u) < K\}|}{|U|}$$ (8)

Additionally, we set up five Exposure Risk Levels according to the value of Exposure Probability, shown in Table 3. Level 5 is defined as the most risky level, which indicates an Exposure Probability higher than 0.9, while Level 1 is the safest one, which represents a small Exposure Probability lower than 0.25.

Next, we show some observations of inspections on the aggregated prediction results. We then introduce the current city exposure model and the model based estimator. Finally, we illustrate some case studies to show the use of our proposed exposure estimator. We also summarize some guidelines to reduce the exposure risk.
Table 3: Risk Level vs. Exposure Probability

| Exposure Probability | [0.9, 1) | (0.75, 0.9] | [0.5, 0.75] | [0.5, 0.25) | [0.25, 0] |
|----------------------|----------|-------------|-------------|-------------|----------|
| Risk Level           | Level 5  | Level 4     | Level 3     | Level 2     | Level 1  |

Table 4: Users Categories by Visible Attributes Combination

8.1. Current City Exposure Inspection

In this subsection, we extract several measurable characteristics from users’ self-exposed information (e.g., User Category), and inspect the current city exposure probability by these characteristics.

First, we classify users into diverse categories with respect to the combinations of visible/invisible properties of their location sensitive attributes and friends list. Table 4 lists the obtained seven User Categories. User Category measures the types and amount of users’ self-exposed information.

Figure 6: Current City Exposure Probability by User Category.

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Figure 6 inspects the Exposure Probabilities for various User Categories. From this figure, we observe that different types of self-exposed information may divulge users’ current city to different extent. For instance, users in ‘WE’ category are normally more dangerous to disclose their current city than users in ‘HT’ or ‘F’ categories. We also find that the users who publish their ‘WE’ (in ‘WE’, ‘HT+WE’, ‘WE+F’ or ‘HT+WE+F’ categories) exhibit a high Exposure Probability. This means that ‘WE’ is a very risky attribute to leak users’ current city. The results also reveal that ‘HT’ is more sensitive to disclose current city than ‘F’, although ‘F’ is generally regarded as a significant location indication.

Figure 6 also indicates that a user’s current city generally could be predicted with a higher probability if the user exposes more information. For example, users who expose ‘HT+F’ exhibit a higher exposure probability than users only revealing either ‘HT’ or ‘F’. Note that, for a user who exposes ‘HT+WE’, his current city exposure probability can be up to 90%, which approaches to the exposure probability of users who expose ‘HT+WE+F’. In other words, merely exposing ‘HT+WE’ can almost lead to the exposure of a user’s current city. To conclude, User Category, which distinguishes users by the types and amount of their self-exposed information, relates to Exposure Probability.

In addition to User Category, we study the influence of the percentage of friends with attributes (i.e., % Friends with Attributes) on Exposure Probability. % Friends with Attributes is the ratio of a user’s friends who present at least one attribute to his overall friends.

Figure 7: Current City Exposure Probability by the Percentage of Friends with Attributes.
Figure 7 displays the Exposure Probability (i.e., EP, Z axis) by % Friends with Attributes (i.e., FA, X axis) at different Error Distances (i.e., ED, Y axis). As more than 95% of the users have a % Friends with Attributes smaller than 45%, we only look at its value in a range of 0% to 45%. Generally speaking, Exposure Probability grows by the increase of % Friends with Attributes.

![Graphs showing Exposure Probability](image)

Figure 8: Exposure Probability by Cluster Confidence in Different User Categories.

In addition, we define a new metric named Cluster Confidence. It estimates the ratio of the probabilities of candidate locations in the selected cluster $c_h$ to the overall probabilities of all the candidate locations (equal 1), calculated as follows:

$$CC(u) = \frac{\sum_{l \in c_h} p(u,l)}{\sum_{l \in L} p(u,l)} = \sum_{l \in c_h} p(u,l)$$  \hspace{1cm} (9)

Cluster Confidence represents the confidence of the users’ location indications. For example, Cluster Confidence with a value of 100% means that all of a user’s location indications point to an exclusive location cluster. We further look into the change of Exposure Probability according to Cluster Confidence for each User Category.

Figure 8 reveals how Exposure Probability (i.e., EP, Z axis) varies with diverse Cluster Confidence (i.e., CC, X axis) and Error Distances (i.e., ED, Y axis) in different User Categories.
Categories. The results show that the Exposure Probability normally grows up when the Cluster Confidence gets larger. When the Cluster Confidence equals 100%, the Exposure Probability surpasses 90% within a pre-established Error Distance of 20 km almost for all User Categories. This observation indicates that the current city is more dangerous to be predicted when a user’s location indications are more likely to point to one city or to multiple cities that are in the same cluster. In other words, a user’s current city can be easily disclosed if the confidence of the user’s self-exposed information is high.

Note that, there exists an exception for the users only exposing their ‘F’: the decline of Exposure Probability when the Cluster Confidence is larger than 0.9. One reasonable explanation is that only the users with an extremely small number of friends (e.g., only one friend) can have the Cluster Confidence higher than 0.9, which might reduce the exposure risk of current city due to the limited information.

8.2. Estimating Current City Exposure Risk

8.2.1. Current City Exposure Model

In the previous section, we observe that a user’s current city Exposure Probability is probably influenced by four factors: Error Distance, User Category, % Friends with Attributes and Cluster Confidence. Taking these four factors as features, we respectively use Random Decision Forest and Linear Regression approaches to model Exposure Probability. The performance of model is evaluated by two commonly used metrics, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), with 10-cross validation, shown in Table 5. We observe that the Random Decision Forest based model outperforms the Linear Regression based model by presenting smaller MAE and RMSE. Therefore, we employ the Random Decision Forest based model to estimate current city exposure probability, denoted as RDF Exposure Model.

Furthermore, ‘Leave-one-feature-out’ approach is exploited to verify the effectiveness of the features. We use Random Decision Forest approach to train exposure models by taking out any one of the four features, namely No Error Distance, No User Category, No % Friends with Attributes and No Cluster Confidence. Table 6 compares these ‘Leave-one-feature-out’
models to the *RDF Exposure Model*. We observe that the *RDF Exposure Model* presents the best performance with the smallest MAE and RMSE. The performance degradations when removing any one of the features just verify that all the four studied features contribute to the model. *Cluster Confidence* is observed as the most sensitive feature for the model, because the performance of the *RDF Exposure Model* drops most significantly when *Cluster Confidence* is taken out.

### 8.2.2. Current City Exposure Estimator

By exploiting the proposed current city exposure model, we construct an exposure estimator to forecast the exposure risk of a user’s private current city. Figure 9 illustrates the framework of the current city exposure estimator. The exposure estimator contains three main function modules: user information handler, current city exposure model and exposure risk level decision. The inputs of the exposure estimator include a user’s self-exposed information and a pre-established *Error Distance*. Given a user’s self-exposure information, the user information handler determines *User Category*, and computes *Cluster Confidence* and *% Friends with Attributes*. Based on the pre-established *Error Distance*, the obtained *User Category*, *Cluster Confidence*, and *% Friends with Attributes*, the exposure model calculates the current city exposure probability for the user. The exposure risk module determines a risk level according to the exposure probability. Finally, the exposure estimator outputs two risk measurements of current city: *Exposure Probability* and *Risk Level*. 

| RDF Exposure Model | No Error Distance | No User Category | No % Friends with Attributes | No Cluster Confidence |
|--------------------|-------------------|------------------|-----------------------------|-----------------------|
| MAE                | 0.027             | 0.065            | 0.045                       | 0.082                 |
| RMSE               | 0.077             | 0.131            | 0.117                       | 0.166                 |

Table 5: Performance Comparison of Exposure Models

| RDF Exposure Model | No Error Distance | No User Category | No % Friends with Attributes | No Cluster Confidence |
|--------------------|-------------------|------------------|-----------------------------|-----------------------|
| MAE                | 0.027             | 0.065            | 0.045                       | 0.082                 |
| RMSE               | 0.077             | 0.131            | 0.117                       | 0.166                 |

Table 6: Feature Verification of RDF Exposure Model
8.3. Case Studies: Exposure Estimator and Privacy Protection

Table 7: Exposure Estimator Cases Study

| User | User Category | Cluster Confidence | Error Distance | % Friends with Attribute | Exposure Probability | Risk Level |
|------|---------------|--------------------|----------------|--------------------------|----------------------|------------|
| U1   | ‘HT+WE+F’     | 0.69               | 100 km         | 0.9%                     | 0.967                | Level 5    |
| U1   | ‘HT+WE+F’     | 0.69               | 20 km          | 0.9%                     | 0.883                | Level 4    |
| U2   | ‘F’           | 0.208              | 100 km         | 11.2%                    | 0.564                | Level 3    |
| U3   | ‘F’           | 0.208              | 100 km         | 0.2%                     | 0.374                | Level 2    |
| U4   | ‘WE+F’        | 0.281              | 100 km         | 2.1%                     | 0.407                | Level 2    |
| U5   | ‘WE+F’        | 0.57               | 100 km         | 2.1%                     | 0.797                | Level 4    |
| U6   | ‘HT+F’        | 0.332              | 20 km          | 20.1%                    | 0.276                | Level 2    |
| U7   | ‘HT+WE’       | 0.73               | 100 km         | 0%                       | 0.903                | Level 5    |
| U8   | ‘HT’          | 0.169              | 20 km          | 0%                       | 0.059                | Level 1    |
| U9   | ‘WE’          | 0.404              | 20 km          | 0%                       | 0.834                | Level 4    |
| U10  | ‘F’           | 0.891              | 20 km          | 17.2%                    | 0.823                | Level 4    |

Any LN-users who reveal their self-exposed information and pre-define an Error Distance can use the proposed current city exposure estimator to assess their Exposure Probability and Risk Level. To better understand the use of exposure estimator, we illustrate several use cases in Table 7. In this study, we observe that some of the LN-users are not really safe to hide their current city if they leave some other information visible. For instance, considering U9, even though only ‘WE’ is published, his current city is almost leaked with an extremely high Exposure Probability of 0.834 within an Error Distance of 20 km. In addition, for users in the same User Category, the one with a higher Cluster Confidence is more likely to divulge his current city. Looking at U4 and U5 who are both in ‘WE+F’
category, the current city of $U_5$ who exhibits a higher Cluster Confidence is more dangerous to be inferred, compared to $U_4$’s current city.

In addition, the exposure estimator can offer some countermeasures on privacy configuration against information leakage. Assume users hide some part of their exposed information, the exposure estimator estimates and reports the corresponding Exposure Probability and Exposure Risk Level. Then users can decide on a new privacy configuration accordingly. We take $U_1$ as an example and list some possible exposure risks assuming that he adjusts his privacy configuration. The results shown in Table 8 reveal that the exposure risk could be significantly decreased if $U_1$ hides his ‘HT+WE’, ‘WE+F’ or ‘WE’. The results also point out that merely hiding ‘F’ or ‘HT’ cannot protect $U_1$’s current city privacy.

Finally, according to the studies on current city exposure risk, we summarize the following general suggestions:

- As all the location indications may expose the hidden current city, close all of location sensitive information including ‘WE’, ‘F’ and ‘HT’ so as to achieve a high current city security.

- Hide the most sensitive exposed information (e.g., ‘WE’) if users want to publicly share some personal information (e.g., ‘F’), since the most sensitive information can independently lead to a quite high Exposure Probability. For example, ‘WE’ alone can lead to an Exposure Probability higher than 80%.

- According to the centrality principle which refers to the Cluster Confidence, hide ‘F’ if most friends indicate the same place where the user lives. For instance, $U_{10}$ in Table

| $U_1$ | Current status | Hide |
|-------|----------------|------|
|       | ‘HT+WE+F’ | ‘WE’ | ‘F’ | ‘HT’ | ‘WE+F’ | ‘HT+WE’ |
| Exposure Probability | 0.967 | 0.503 | 0.944 | 0.936 | 0.456 | 0.073 |
| Risk Level | Level 5 | Level 3 | Level 5 | Level 5 | Level 2 | Level 1 |

Table 8: Exposure Guidelines for $U_1$: the exposure risks if he adjusts some privacy configurations with an Error Distance of 100km
9. Discussion and Future Work

In this section, we discuss some issues which are not addressed in this work due to space limitations, and point out some future potential research directions.

9.1. Extensibility of the Current City Prediction Approach

Due to the data set limitation, we only use three features (i.e., ‘Hometown’, ‘Work and Education’ and ‘Friend’) to evaluate our proposed current city prediction approach. However, our prediction approach can be extended to consider other location sensitive attributes. For instance, for the location sensitive pages that a user follows (e.g., the page of a favorite local restaurant) or the location sensitive posts that a user published (e.g., geo-tagged posts), we can regard one page or one post as a LA-Friend and refer to LA-FLI model to explore the location indications.

9.2. Adaptability of the Exposure Estimation Approach

In addition, our exposure estimation approach can easily adapt to other current city prediction approaches by the two-step solution: (1) feature extraction (Sec. 8.1) and (2) exposure model training (Sec. 8.2). In particular, we can first extract similar features for other city prediction approaches as the inspected features in Sec. 8.1. Take Cluster Confidence as an example. For the cluster-based city prediction approaches like ours, Cluster Confidence can be extracted in the same way, i.e., the largest cluster prediction probability (Eq. 9). For the other city prediction approaches without a clustering step \[3, 24\], following the essence of Cluster Confidence, a similar feature, Prediction Confidence, can be computed as the largest city prediction probability. Likewise, we can also obtain the other features presented in our exposure model for many other city prediction approaches, while we do not discuss them further for brevity. Once the features are derived, in the second step, we can directly apply the regression methods used in Sec. 8.2 to train the exposure models for other prediction approaches.
9.3. Generalizability of the Exposure Estimator

Taking ‘current city’ as a representative attribute to study the information exposure issue, this work gives further insights on how to assess the exposure risk of other privacy-sensitive attributes (e.g., age). Denoting the privacy-sensitive attribute as PSA, the process to assess its exposure risk can be generalized into three steps: 1) Explore PSA-sensitive attributes and construct a PSA prediction model; 2) Inspect the prediction results to extract features and train a PSA exposure model; 3) Based on the exposure model, implement an exposure estimator to notify users of the exposure risk and provide suggestions to lower the risk if necessary.

Moreover, our future work will consider integrating multiple exposure models into the exposure estimator, so as to construct an exposure estimation system that can provide reliable and multi-functional exposure risk estimations.

10. Conclusion

This paper starts with two open questions regarding the security of users’ hidden privacy-sensitive attributes. To answer these questions, we first propose a novel current city prediction approach to infer users’ current city by leveraging users’ self-exposed information including location sensitive attributes and friends list. We validate the new prediction approach on a Facebook data set containing 371,913 users, and the results reveal that the users’ hidden current city may be dangerous to be predicted. Then we apply the proposed prediction approach to predict users’ current city and model the exposure probability by considering four measurable characteristics — Cluster Confidence, Error Distance, User Category and Percentage of Friends with Attributes. Based on the exposure model, we propose a current city exposure estimator to measure the exposure probability and risk level of users’ hidden current city according to their self-exposed information. The exposure estimator can also help users to adjust their privacy configuration to satisfy their privacy requirements. While this work studies the potential risk of users’ privacy-sensitive attributes with a representative attribute of current city in Facebook, the proposed idea and approach could be extended to other attributes and utilized by other OSNs.
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