Uniqueness in the City: Urban Morphology and Location Privacy

We investigate the potential for privacy leaks when users reveal their nearby Points-of-Interest (POIs). Specifically, we investigate whether and how a person's location can be reverse-engineered when that person simply reveals their nearby POI types (e.g. 2 schools and 3 restaurants). We approach our analysis by introducing a "Location Re-identification" algorithm that is computationally efficient. Using data from Open Street Map, we conduct our analysis on datasets of multiple representative cities: New York City, Melbourne, Vancouver, and Zurich. Our analysis indicates that urban morphology has a clear link to location privacy, and highlight a number of urban factors that contribute to location privacy. Our findings can be used in any systems or platforms where users reveal their proximal POIs, such as recommendation systems, advertising platforms, and appstores.

CCS Concepts: • **Security and privacy → Human and societal aspects of security and privacy**; • **Information systems** → *Data mining*;

Additional Key Words and Phrases: Location Privacy, re-identification, POI, uniqueness, urban Morphology

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1 INTRODUCTION

This paper investigates a deceivingly simple question: by revealing the types of nearby Points-of-Interests (POIs), do we reveal our actual location? For instance, simply revealing that there are 2 schools and 3 restaurants nearby a user, is it possible to reverse-engineer the actual location of the user? There are many systems that rely on knowledge of nearby POIs, such as recommendation systems and advertising platforms. Even appstores, for example, can promote travel apps when the user is near an area with tourist attractions. Furthermore, POIs are freely and easily accessible through a variety of platforms, hence they are becoming increasingly used for conveying users' context.

Conventionally, an assumption has been made is that recommendation systems can preserve privacy by only requiring knowledge of the types of POIs near a user, and not the actual location coordinates of the user. However, as we show in this paper, a lot more can be inferred, depending on the city within which the user is, and the actual uniqueness of the user's location.

Our analysis uses the notion of location uniqueness: a unique location is one that has a unique combination of POIs. We expect that such locations are easier to reverse-engineer, because there are not many such locations in a city. In fact, we intuitively refer to the concept of location uniqueness in our everyday life. For instance, when speaking of a person just arriving in New York City by air, New Yorkers will immediately think of the person now at LGA, JFK or EWR — any of the three airports in New York. Similarly, talking of theater, Broadway will occur to almost everyone. Thus, places with distinct functions are very likely to have a high level of location

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uniqueness (and therefore relatively low privacy when revealing nearby POIs). These anecdotal observations inspire us to consider that location uniqueness in cities may be much higher than we may assume.

To make our analysis computationally tractable, we propose a "Location Re-identification" algorithm and develop a model to study the lower bounds of location uniqueness. Instead of trying to reverse-engineer the exact GPS coordinates of a user, we simply try to figure out the candidate areas surrounding any existing POIs. This key insight enables us to avoid intractable calculations, allows pre-computation, and thus is much faster and computational efficiency for our purposes.

Using POI data from four representative cities of New York, Melbourne, Vancouver and Zurich, we conduct an extensive assessment on location uniqueness through our proposed model, and systematically analyze the role of spatial granularity, POI density, POI composition as well as geographical factors contributing to location uniqueness. Our results show that locations can be highly unique in different cities, where a spatial granularity of radius 2km can uniquely identify 75%, 53%, 87% and 64% of all locations in New York, Melbourne, Vancouver and Zurich, respectively. Meanwhile, location uniqueness is closely related to multiple factors: denser POI regions tend to contain more infrequent POI types, and regions closer to the city centre tend to be more unique. The extensive results highlight that sharing or revealing nearby-POIs can lead to privacy breaches, and we highlight a number of factors and strategies that can be used to mitigate this.

2 RELATED WORK

2.1 POI Identification and Recommendation

Recent studies analyzed the POI identification with crowd-sourced data to generate entries for landmarks [9], discover places with events happening [10], and identifying users' visited POIs from their trajectories [20]. Moreover, some research focused on individual level POI recommendation. Bin et al. [11, 12] studied personalized recommendation by leveraging users' multi-aspect preferences, and Xin et al. [14] consider users' preference transition to achieve relevant recommendation. Other previous work has considered POIs in the context of geographical and temporal influence [25, 30, 31]. Instead of identifying and recommending POIs, we study how POIs can uniquely identify the locations of city. Our findings provide useful guidance for building privacy-aware location-based service systems in the future.

2.2 POI-based Urban Property Study

POIs have been utilized for urban land-use in transportation research since the early 20th century. POIs have been used to describe the characteristics of travel behaviour between different types of land use, such as the traffic between residential zones and industrial zones. Voorhees [21] described how travel between different types of origins and destinations roughly follows gravitational laws, with different types of destinations generating certain types of "pull" towards the origins. In fact, it is suggested that individuals organize spatial knowledge according to anchor points, POIs, or generally salient locations that form the cognitive map that the individual uses to navigate [18]. Besides geographical points, such as landmarks, anchor points can be path segments, nodes or even distinctive areas, similar to urban properties categorized by Lynch [17]. McGowen et al. [19] tested the feasibility of a model that predicts activity types based solely on GPS data from personal devices, GIS data and individual or household demographic data. Ye et al. [24] proposed a framework which uses a mixed hidden Markov model to predict the category of user activity at the next step and then predict the most likely location given the estimated category distribution. Yang et al. [23] first modelled the spatial and temporal activity preference separately, and then used a principle way to combine them for preference inference. Other models treat the urban as a system of markets to simulate the linkages between different industrial sectors[22]. While some other dynamic models capture the dynamics of urban growth and land use changes by both rule-based models [6] and empirical estimation models [8, 16]. Different from these static or dynamic models to characterizing the urban environment, we utilize POIs to distinguish the uniqueness of the locations of the city. Our findings highlight the surprising high location uniqueness in cities and analyze the relationship between location uniqueness and multiple factors, and therefore contribute to our understanding of urban property from a novel angle.

2.3 POI-based Human Behavior Study

More broadly, land use affects various aspects of travel behaviour, such as trip generation, distance travelled and choice of mode of transport [4]. Thus, POIs have also been utilized for human behavior study. Crucially, these effects seem to vary substantially according to the time of the day and week [5].

POI have often been used to estimate travel behaviour since the early 1990s [2]. Such kind of method is usually with high complexity and intense data requirements [1], and it has even been noted that it is difficult to find a representative set of participants willing to commit to a long-term data gathering effort [3]. POI is also utizlied to prediction human future demand[15]. Based on the understanding of user behavior inferred from the POI, lots of applications can be supported such as route recommendation[28], tourism recommender systems[13, 27], human mobility investigation [26], and novel urban computing applications [29][7, 32, 33]. Rather than attempt to develop applications leveraging POI, we instead explore the problem of how the POIs information indicate the uniqueness of a city, which has never been studied before.

3 DATASET

In our analysis we use publicly available POI data on Mapzen Metro Extract (https://mapzen.com/data/metro-extracts/), which is extracted and updated weekly from OpenStreetMap (http://www.openstreetmap.org/). To investigate a variety of POI compositions and morphologies, we carefully selected four cities to represent cities of different sizes in 4 countries: New York, Melbourne, Vancouver and Zurich. We provide a description of these cities as follows:

New York As a global city, New York is the largest city in the United States, with the world's largest natural harbour and the most active financial market. Because of its special status, and size, we choose New York city as the representative of metropolis.

Melbourne Melbourne is the second-most populous city in Oceania. Compared to New York city, Melbourne has half the population but ten times the land area. We choose Melbourne as another representative metropolis.

Vancouver Vancouver is the third-largest metropolitan area in Canada. Although the population and land area of Vancouver are smaller than New York, Vancouver's population density is similar to New York. We choose Vancouver as the representative of median city.

Zurich Zurich is the biggest city of Switzerland. With a similar population size to Vancouver, Zurich is also a typical median city. Meanwhile, because of the popularity of OpenStreetMap in Europe, the POI data of Zurich is expected to be richer than the other cities.

We summarize the basic information of these four cities and the statistics of their recorded POI data from Mapzen in Table 1.

	Country	Population($million$)	Land area(mi^2)	POI	POI types
New York	U.S.	8.538	304.6	26202	125
Melbourne	Australia	3.848	3,857	17735	145
Vancouver	Canada	0.647	44.39	5267	74
Zurich	Switzerland	0.391	33.93	22000	147

Table 1. Basic statistics for each city in our analysis.

4 METHOD

Here we describe our approach to measure location uniqueness. To quantify location uniqueness, we first define the problem of location re-identification. Then, we present our computationally efficient re-identification model.

4.1 Problem Definition

Location Re-identification: We count the frequency of all POI types within a given radius r around a particular location l, which gives us a POI type distribution vector P ($P = [n_{p_1}, n_{p_2}, ... n_{p_m}]$), where n_{p_i} represents the frequency of POI type p_i within radius r around l. Then, we try to re-identify this location through P from a location pool L and result in a number of possible locations L_C, known as *candidate*.

Through the proposed location re-identification task, we are able to study location uniqueness: locations with unique surrounding POIs will end up with few *candidate* locations, while other locations with common POIs nearby will result in lots of *candidate* locations across the city.

As we analyze location uniqueness through POIs, it is unnecessary to consider regions without POIs in the location pool L since these places can never be identified. We therefore represent location pool L as a number of spatial circles centering at each POI, which ensure that all instances in L have at least one POI and may be used for re-identification.

4.2 Model

It is indeed true that one can develop an algorithm to re-identify a location point and search for all its *candidate*s with high accuracy, say comparing the POI type distribution vector P through a sliding circle of the same radius in the city. However, such brute-force algorithms turn out to be impractical for our purposes, since its computational requirement is exponential: at every move, the distance between the sliding circle center and every POI in the city has to be recalculated, and even an improved approach like checking locations around POIs also involve lots of calculations and comparisons.

So as to tackle the computational challenge and provide a first glance into location uniqueness, we relax our demand on accuracy. Instead of identifying the exact location, we attempt to find larger regions within which those possible locations lie in. In this way, we provide a lower bound in location uniqueness.

Specifically, our model takes in a given POI type distribution vector P around location l within radius r, and first sorts P based on the overall POI frequency observed in the entire city. Our model then selects the most infrequent/unique POI type p_l in P and finds all p_l in the city from location pool L. As p_l is observed within radius r around location l, conversely every *candidate* location must be within a distance of r around each p_l, which therefore forms a bounding circle of radius r around p_l. Thus, the POI type distribution vector P must result from an observation of a radius r circle lying within a big circle of radius $2r$ centered at each p_l. We then add further constraints: since P comes from an observation of radius r circle lying within a big circle of radius $2r$ centered at each p_l, to be eligible for a *candidate*, the radius $2r$ circle around p_l should overlay no fewer than $n_(p_i)$ for POI type p_i, thus further narrowing down the *candidate* locations. The model is illustrated in Fig.1.

Since our proposed model does not involve many distance calculations and comparisons, but instead focuses on the POI statistics within radius $2r$ circle around p_l, the computational complexity is greatly reduced. Our model also makes possible pre-calculation: POI statistics within $2r$ around each POI points can be pre-calculated once and saved as a dictionary since this process is independent of the location-to-be-re-identified, and thus further speeds up the entire process.

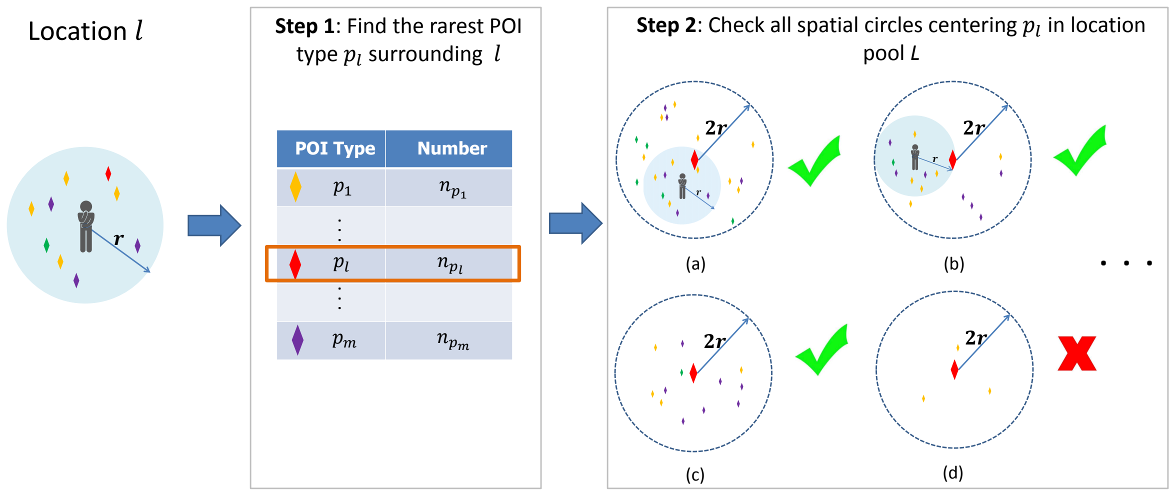


Fig. 1. Illustration of our proposed location re-identification model. Different POI types are represented by diamonds of different colors. We first pick out the rarest POI type p_l found near location l within radius r (denoted by "red" diamond in the figure), then we select all spatial circles centering at POI p_l from the location pool L. The spatial circles have radius $2r$ since the user should be no farther from the center than r so that he/she can "see" p_l, therefore the radius of $2r$ ensures that all POIs the user "sees" lie within the big circle. We further check if the $2r$ circle involves all POIs revealed by the user. The model will return possible *candidate* locations, including l (subfigure (a)), locations sharing exact POI compositions within radius r (subfigure (b)), as well as locations sharing similar POI components (subfigure (c)), but filter out spatial circles where it is impossible to reveal POI type distribution vector P (subfigure (d)). Thus the proposed model provides a lower bound of location uniqueness in a time efficient manner.

5 ANALYSIS

We conduct multiple analyses on our datasets from the 4 cities. In addition to measuring location uniqueness in these cities, we also look at the role of different factors in shaping location uniqueness, including spatial granularity, POI density, POI composition as well as distance to city center.

5.1 Experiment Setup

To best capture the city structure, for each city, we uniformly sample 1,200,000 experiment locations lying in the bounding box of the city given by Mapzen Metro Extract and conduct POI type statistics of the location point within a varying radius of 0.1 km, 0.25 km, 0.5 km, 1 km, 2 km, 4 km to represent different levels of spatial granularity. Intuitively, this radius reflects the range that a user considers when reporting nearby POIs. In some cases, a user may use a short range (e.g. 100 meters), while in other cases a longer range may be considered (e.g. 4 kilometers).

Using a varying radius in our analysis ensures that we preserve the multi-level fine-grained POI compositions in the city. We then filter out uninteresting experiment locations with few surrounding POIs (which represent unpopulated areas such as sea, mountain and fields) and concentrate on POIs and location privacy in populated regions. Finally, we adopt our proposed attack model to measure and analyze a lower bound of location uniqueness in cities.

5.2 Location Uniqueness

We first examine location uniqueness in the four cities. The results of our experiments show that location uniqueness in these cities is surprisingly high. As presented in Fig. 2, under spatial granularity r = 2km, over 87% of randomly selected locations in Vancouver can be uniquely identified through their surrounding POI types, while the same figure for New York, Melbourne and Zurich is 75%, 53% and 64%, respectively. Meanwhile, the percentage of randomly chosen locations which can be narrowed down to fewer than three candidate areas of similar POI compositions are 84%, 68%, 91% and 72% in New York, Melbourne, Vancouver and Zurich, and the percentage of being identified within three candidate areas are 92%,75%, 93% and 75%. These results suggest that POI composition, or urban functional structure, is highly unique in cities all over the world, and consequently can pose a considerable threat to location privacy.

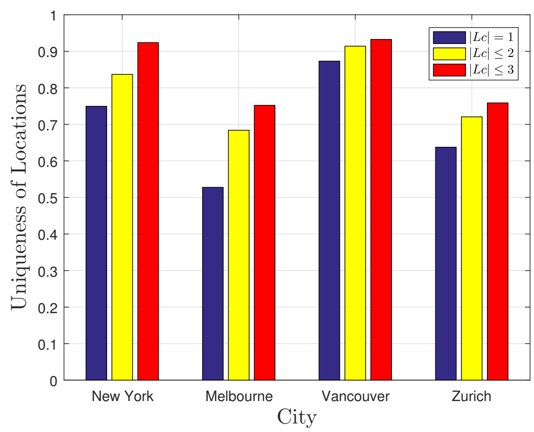


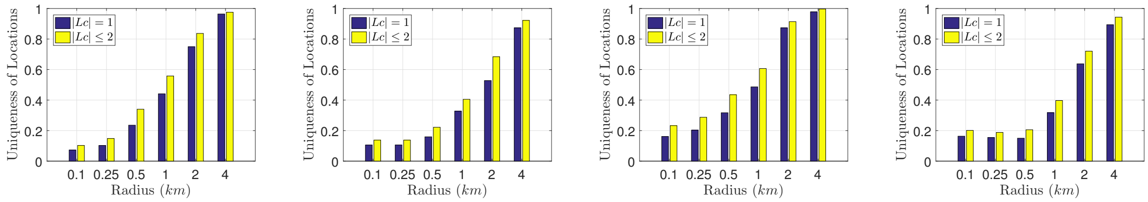
Fig. 2. Location Uniqueness in New York, Melbourne, Vancouver and Zurich, spatial granularity $r = 2km$. The chart shows the ratio of locations that can be re-identified down to a single ($|L_c| = 1$), two ($|L_c| = 2$) and three ($|L_c| = 3$) locations.

5.3 Spatial Granularity

We look at how location uniqueness varies under different spatial granularity, where spatial granularity is represented by radius r. Fig. 3 shows the the percentage of locations which can be identified within one or two candidate locations, with respect to radius. It can be observed that as the radius increases, the location uniqueness increases. When the radius is 0.1km, approximately 10% of locations can be uniquely identified, while almost all locations can be uniquely identified when the radius gets to 4km. In other words, if one stands in a city and reveals his nearby POIs within 0.1km, the chance of successfully finding the user is around 10% while if he/she reveals POIs within a radius 4km, his/her location is very easy to accurately identify. Thus users should be especially careful to reveal POIs around them with a large radius.

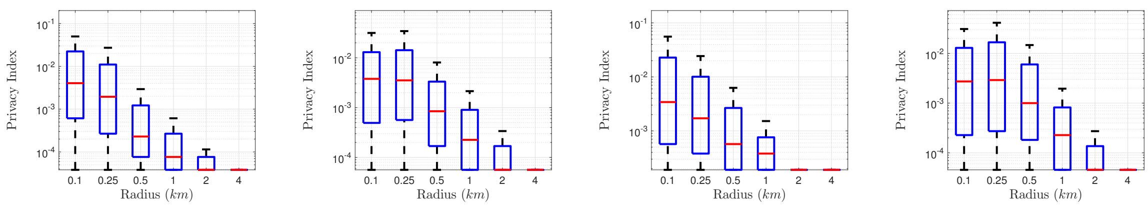
To obtain a global picture of location uniqueness in these four cities, we also generate boxplots of the mean privacy index with respect to radius, as shown in Fig.4. We define the privacy index of a location as the number of candidate re-identified locations divided by the total number of locations. This metric aims to describe 'what is the percentage of other places in the city which share highly similar POI composition as this location?'. Thus, the smaller the privacy index, the greater level of uniqueness of that location, and therefore less location privacy.

Fig. 4 shows that under most circumstances, the privacy index decreases as the radius increases. In other words, a location is not that unique if one only looks at their immediate surroundings; however, the location becomes



(a) New York City (b) Melbourne (c) Vancouver (d) Zurich

Fig. 3. Percentage of locations which can be identified within one ($|L_c| = 1$) or two ($|L_c| = 2$) possible regions in the city with respect to radius.



(a) New York City (b) Melbourne (c) Vancouver (d) Zurich

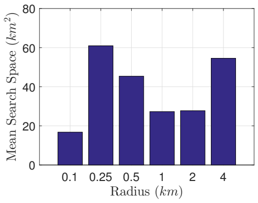
Fig. 4. Privacy index with respect to Radius.

increasingly unique if one considers a larger radius. This result is in accordance with our intuition that "there are many locations in a city where a restaurant can be found within 100 meters; but locations where there is a restaurant and a factory within 250 meters are scarcer". It is worth mentioning that despite the general trend, certain locations can be easily identified with a small radius, as indicated by the fact that the lower quartile values in Fig. 4 can be quite low. This in turn motivates us to further analyze the relationship between location uniqueness and POI density as well as POI composition afterwards.

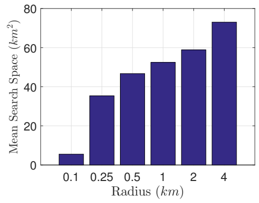
Besides the privacy index of each location, which is effectively a probability, we can quantify the privacy of each location by considering the actual geographic search space (in square kilometers) associated with each location. This measure is especially important from a privacy point of view since it represents the mean area an attacker will have to search in order to accurately locate the user, and is therefore a useful metric to measure the level of privacy for each user. As shown in Fig. 5, we analyze the relationship between spatial granularity (i.e. r) and the mean geographic search space of the locations that have identical nearby POIs (defined as $mean(\pi r^2 |l_c|)$). We observe that there is a considerable difference between the cities. For Melbourne and Vancouver, a larger radius results in larger search spaces. In contrast, for New York City and Zurich, location privacy is best preserved with a radius of 0.25km and 0.5km, respectively. We attribute these differences to the morphological differences between the cities.

5.4 POI Density

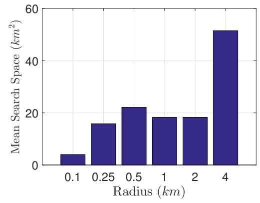
Next, we analyze the relationship between POI density and location uniqueness. Fig. 6 presents the spatial distribution of POI density in the four cities, where the black background represents land and the greyish lines shows the shape of the primary road network. In Fig. 6, locations with more POIs are highlighted by a brighter color. As Fig. 6 shows, POIs usually spread around the road network and are clustered in the downtown area of city. Similarly, Fig. 7 shows the spatial distribution of location uniqueness. It is possible to notice that these two spatial distributions are visually similar, which suggests that the distribution of unique locations are very likely relevant to the distribution of POI.



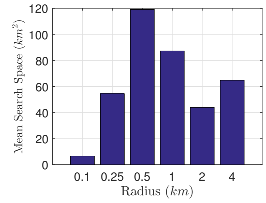
(a) New York City



(b) Melbourne



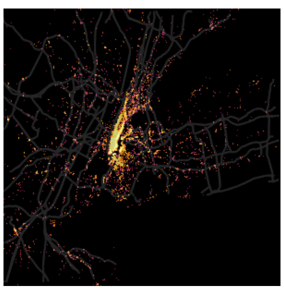
(c) Vancouver



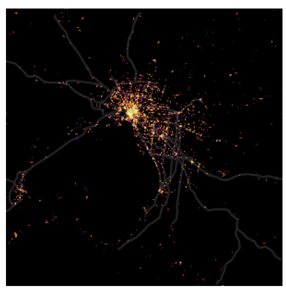
(d) Zurich

Fig. 5. Mean search space with respect to radius.

We further analyze the relationship between location uniqueness and POI density in Fig. 8. Taking New York for example, as Fig. 8(a) shows, locations become increasingly unique with the growth of POI density. This conclusion is supported by the results from different cities with different search radius (r) in Fig. 8. In other words, it is easier to re-identify a location in denser regions.

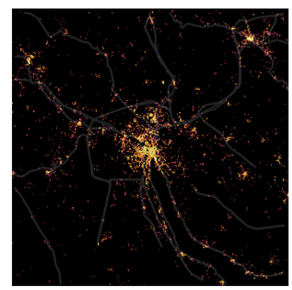


(a) New York City



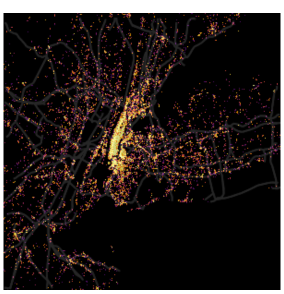
(b) Melbourne

(c) Vancouver

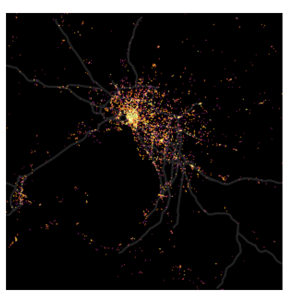


(d) Zurich

Fig. 6. Spatial distribution of POI density. Brighter color means higher density.

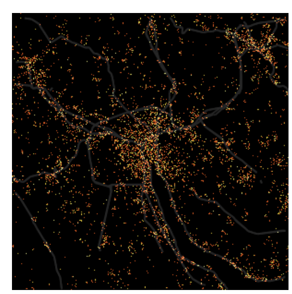


(a) New York City



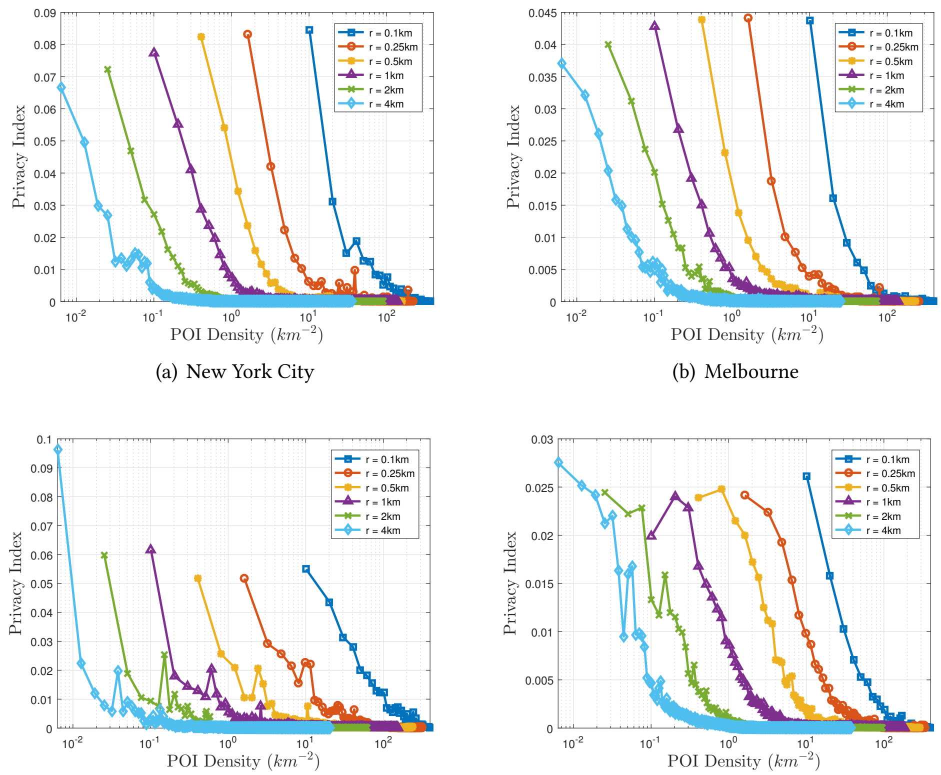
(b) Melbourne

(c) Vancouver



(d) Zurich

Fig. 7. Spatial distribution of location uniqueness. Brighter color means higher uniqueness.



(a) New York City (b) Melbourne

(c) Vancouver (d) Zurich

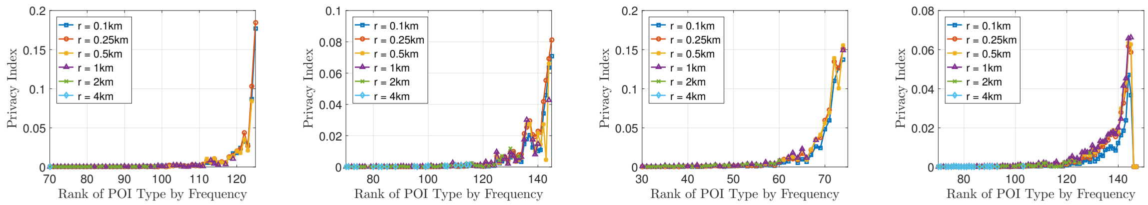
Fig. 8. Relationship between location uniqueness and POI density.

City	Infrequent POIs
New York	green market, hunting stand, music venue, catering
Melbourne	video store, surgery, statue, water point
Vancouver	nursery, waste disposal, co-op housing
Zurich	nightclub, research institute, barn, spa, conference center

Table 2. Selected Infrequent POIs for different cities.

5.5 POI popularity

We investigate the effect of infrequent POIs on location uniqueness. As shown in Fig. 9, if there are infrequent (i.e. rare) POIs near a location, the location tends to have higher level of uniqueness. In contrast, if only frequent POIs appear near a location, the uniqueness level is low. The rare POIs for each city are shown in Table 2. It is worth noting, however, that under certain circumstances, even if the nearby POIs are frequent, the location can still be quite unique. This is shown, for example, in the Melbourne plot: when the POI rank is around 140, certain locations can become quite unique.



(a) New York City (b) Melbourne (c) Vancouver (d) Zurich

Fig. 9. Relationship between location uniqueness and POI Uniqueness/Ranking. POIs of rank 1 are the most popular in their city.

5.6 Distance to City Center

As illustrated in Fig.10, we find a trend that location uniqueness decreases when the location gets farther from the city center. Vancouver, however, exhibits the opposite pattern: location uniqueness is highest when around 3 km away from city center, which may be explained by the fact that the bounding box of Vancouver is much smaller than other cities, and that the center indicated by the map is not the actual district center of the city.

6 DISCUSSION

6.1 Strategies for Reducing Privacy Leaks

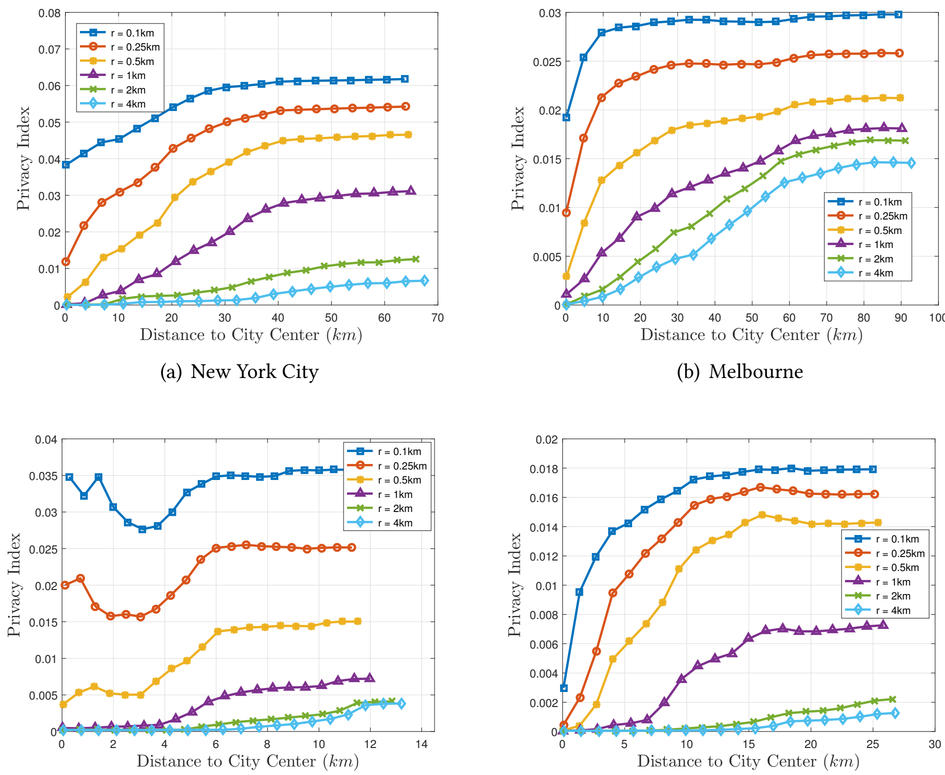
Our analysis reveals the extent to which privacy leaks can occur when sharing one's nearby POIs. For example, we found that when one reveals the POIs within a 2km range, there is an 87% chance that they can be precisely pin-pointed if they are in Vancouver, while this can be as low as 53% in Melbourne. One way to protect privacy is to use a shorter radius. We found that using a radius of 100 meters, there is a 10% chance that the location can be uniquely identified. When the radius is much larger, say 4km, then almost all locations can be uniquely identified.

In other words, our findings show that a location is not that unique if one only reveals their immediate surroundings. However, the location becomes increasingly unique as one considers a larger radius. It is important to note that in our analysis we have only considered one-off single-sharing scenarios. Yet, it is quite conceivable that a mobile user, roaming across the city, may be sharing their nearby POIs on multiple occasions. Our analysis suggests that if those instances of sharing happen close in time, then an attacker may combine the two shared datasets (thus effectively considering one larger radius) and possibly have a better chance of identifying the location of the user.

Finally, the results show that it is easier to re-identify a location in denser regions, or when there are rare POIs nearby. There are a couple of sharing strategies that can take these findings into account to preserve privacy. Sharing of POIs could be reduced by avoiding to share when in dense locations, or using a shorter radius when in dense locations. In addition, sharing could be masked by avoiding to reveal rare or infrequent nearby POIs. Finally, a strategy could combine all these parameters non-deterministically, and randomly choose certain POIs to hide (preferably infrequent POIs).

6.2 Generalizability of our Findings

In our analysis we have considered multiple cities in different continents, for the purpose of ensuring that our findings are reliable and transferable. We have found a number of patterns that exist in all cities, thus establishing stronger confidence in our results. However, it is also interesting to consider the differences across cities, so



(a) New York City
(b) Melbourne
(c) Vancouver
(d) Zurich

Fig. 10. Relationship between location uniqueness and distance to city center.

that we can better understand which of our findings are likely to be localized and contextualized for each city independently.

There are certain general patterns evident in all cities in our analysis: all cities show high level of location uniqueness and therefore face the same general threats to location privacy. As the radius for spatial granularity increases, locations become more unique. Moreover, POI density is a reliable indicator of location uniqueness: higher POI density tends to suggest higher level of uniqueness and thus more susceptible to privacy attacks. Meanwhile, the uniqueness of POIs also greatly determines the level of location uniqueness: unique POIs that do not frequently appear in the city make it easier to re-identify a location. Since POIs generally aggregate near the city center, the distance to the city center can also help distinguish location uniqueness: the closer to the city center, the location is more likely to be unique.

Yet there are some interesting differences between the cities in our analysis. On one hand, smaller cities as Vancouver and Zurich show greater location uniqueness when the spatial granularity is high, which is perhaps due to the fact that the chance of observing infrequent POIs with high spatial granularity is greater in smaller cities. Furthermore, the mean search area shows different patterns for each city, where Melbourne and Vancouver show greater location privacy when the radius is larger, while New York and Zurich have higher level of location privacy when the radius is neither too small nor too big. Furthermore, even though all cities demonstrate that the existence of rare POIs lead to reduced location privacy, the actual type of these POIs varies between different cities, as shown in Table 2.

6.3 POIs as Context

POIs are a commonplace and publicly available data resource. Many online map services, some of which are free, provide access to this information, including Google Maps, FourSquare, Open Street Map and Baidu Map. POIs are simply categories or labels that have been geo-coded and attached to specific coordinates across cities.

While a lot of UbiComp research has focused on localization techniques, context-aware computing has largely not shown great interest in the potential benefits of considering POIs. Perhaps this has been the case because freely open and high-quality POI databases have only recently become relatively popular, and due to crowdsourcing efforts they are becoming increasingly complete.

Yet, POIs have the potential to enrich a system's contextual understanding, especially for location-aware systems. In some ways, GPS and localization coordinates are valuable for navigation, but our community still lacks techniques that can leverage nearby POIs to build a contextual model of a user's location: for a user to know "where am I" is not only a matter of localization, but also contextualization. For instance, visiting a new city requires localization for navigation purposes, but contextualization is required for exploring and experiencing the city.

Our results show that revealing our immediate surroundings does tell much about where we are. While our work has considered this finding from the perspective of an attacker, it is also interesting to consider it from the perspective of context-aware systems. Conceptually, our findings suggest that if our personal device can only "see" or know our immediate surroundings, it may not have a good idea about the type of location where we are. We show that by gradually expanding the range of consideration, from 100 meters to 4 kilometers, it becomes increasingly easier to re-identify the user's location.

It could be argued that this finding puts a bound on location-based context awareness, and the geographic range that should be considered when developing location-based services. Consider the scenario where a user's device wishes to personalise its behaviour based on the nearby POIs. For example, this could be the case for a travel app that detects nearby tourist attractions. The device may simply query OpenStreetMaps, or FourSquare, to find out what nearby POIs exist. A key question here is to determine what range should the query consider. Should it consider only immediate POIs, or farther ones too? Our findings show that if only immediate surroundings are considered, then the personalisation that can be achieved is quite "generic", since not enough can be inferred about a person's location when using a limited range. As that range grows to 4 kilometers, we show that the information is rich enough to uniquely identify the location, and therefore offer a richer personalisation experience. Similarly, in dense location a shorter range can be considered.

6.4 Computational Complexity

In this paper, we show that it is possible to consider a city's POIs as a means of investigating the nature of location uniqueness. In our analysis we consider whether given a location and its surrounding POIs, can we identify similar places in this city ? Our results provide key insights for location privacy: is it safe for users if location-based service providers such as POI recommendation systems make public their surrounding POIs? Should users themselves reveal their nearby POIs? If not, under what conditions is such kind of sharing acceptable?

Despite its great significance, quantifying location uniqueness is far from computationally trivial. The key challenge comes from the computational complexity. Brute-force methods generally require huge amounts of distance computation and comparisons between different location points and their nearby POIs so as to judge if they share similar POI compositions, which becomes too computationally expensive to get a fine-grained understanding of location uniqueness in different cities. Instead, we propose a simple enough model to give a global understanding of location uniqueness and its implications for city structure and location privacy with fine-grained spatial granularity, which is memory and computational efficient.

6.5 Limitations and Future Work

We make use of POI data of four cities in North America, Oceania and Europe for this study. There is a limitation in the dataset selection as Open Street Map does not provide sufficient POI information, especially for countries in Asia and Africa. In the future, we plan to adopt multiple data sources, such as Google Map and Baidu Map to study location uniqueness in the world on a more global scale.

In this work, we mainly aim at taking the first glance into the problem of location uniqueness and privacy. Therefore, we propose a computationally efficient model to study a lower bound of location uniqueness so as to provide preliminary results on the problem. A more accurate model can be used to study the problem and conversely design a framework to ensure user location privacy when sharing POI information.

Finally, our work only considers static and honest users. Mobility has not been taken into account, and it is conceivable that mobile users who share their nearby POIs on multiple occasions may be revealing even more information that makes it possible to retrace their steps. Honesty has been assumed throughout our analysis, meaning that users share all nearby POIs within a radius, and do not selectively hide POIs.

7 CONCLUSION

In this paper we investigate the possibility of re-identifying the actual location of a person based on their surrounding POIs. This type of analysis quantifies the potential for privacy breaches when revealing nearby POIs. We propose a computationally efficient "Location Re-identification" method, and conduct extensive experiments on POI datasets of four representative cities of New York, Melbourne, Vancouver and Zurich from Open Street Map. Our results highlight the surprisingly high location uniqueness in these cities. We further analyze the relationship between location privacy and spatial granularity, POI density, POI combination and distance to city center, so that we help understand under what circumstances location privacy may be compromised. Our findings contribute to the understanding of urban morphology and provide guidance for future location privacy-preserving system and platforms where users reveal their nearby POIs, such as recommendation systems, advertising platforms, and appstores.

APPENDIX

We provide a pseudocode of our proposed Location Re-Identification Algorithm as shown in Algorithm 1:

ALGORITHM 1: Location Re-Identification Algorithm

Input: Location $l(x, y)$, POI locations in the city $poi(label, x, y)$, radius r
Output: Candidate location $l_c(x, y)$
// get the POI distribution vector P at l within radius r;
P = zeros(1,num(poi.label));
for j *in* poi **do**
    if *distance*($l.x, l.y, j.x, j.y$)<r **then**
        $P(j.label) = P(j.label)$+1;
    end
end
p_l = rarest($P.label$) // get the label of rarest POI type found in P ;
l_c = [] ;
$C = poi(poi.label == p_l)$ // find all p_l type POIs in the city ;
C_p = cell(num(C)) // save nearby POI type distribution within radius $2r$ centering at POI type p_l ;
for c *in* C **do**
    for j *in* poi **do**
        if *distance*($c.x, c.y, j.x, j.y$)<$2 * r$ **then**
            C_p(c)($j.label$) = C_p(c)($j.label$)+1 ;
        end
    end
end
// check if the original location may appear in the radius $2r$ circle centering at POI type p_l ;
for c *in* C **do**
    if *(C_p(c)(j)>= P(j) for all j in poi.label)* **then**
        l_c.append([$C.x, C.y$])
    end
end

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