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Trade-off Between Location Quality and Privacy in Crowdsensing: An Optimization Perspective

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***Abstract*—Crowdsensing enables a wide range of data collection, where the data are usually tagged with private locations. Protecting users' location privacy has been a central issue. The study of various location perturbation techniques, e.g. k-anonymity, for location privacy has received widespread attention. Despite the huge promise and considerable attention, provable good algorithms considering the trade-off between location privacy and location information quality from the optimization perspective in crowdsensing are lacking in the literature. In this paper, we study two related optimization problems from two different perspectives. The first problem is to minimize the location quality degradation caused by the protection of users' location privacy. We present an efficient optimal algorithm OLoQ for this problem. The second problem is to maximize the number of protected users, subject to a location quality degradation constraint. To satisfy different requirements of the platform, we consider two cases for this problem: overlapping and non-overlapping perturbations. For the former case, we give an efficient optimal algorithm $\mathsf{OPUM_O}$. For the latter case, we first prove its NP-hardness. We then design a $(1-\epsilon)$-approximation algorithm $\mathsf{NPUM_N}$ and a fast and effective heuristic algorithm $\mathsf{HPUM_N}$. Extensive simulations demonstrate that OLoQ, $\mathsf{OPUM_O}$, and $\mathsf{HPUM_N}$ significantly outperform an existing algorithm.**

***Index Terms*—Crowdsensing, location data quality, location privacy, k-anonymity.**

I. Introduction

OVER the last decade, there has been an explosion of smart devices, e.g. smartphones and tablets. In 2015, there were available 3.2 billion smartphone subscriptions, with 6.2 billion predicted to be available in 2021 [13]. Current smart devices are embedded with increasingly powerful processors and a multitude of sensors (e.g., GPS, thermometer, microphone, camera). The ubiquity of mobile devices into everyday life can provide sufficient geographic coverage, especially in densely populated areas. The mobile crowdsensing paradigm serves as a critical building block for the emerging Internet of Things (IoT) applications [19, 23, 24, 29, 30, 39], which takes advantage of the widely distributed mobile devices for sensing and collecting ubiquitous data, such as P-Sense to monitor air pollution [11], Nericell to sense road and traffic conditions [20], and Ear-Phone to construct urban noise maps [25]. The sensing data are usually tagged with locations to form a database or a map for information release or decision making.

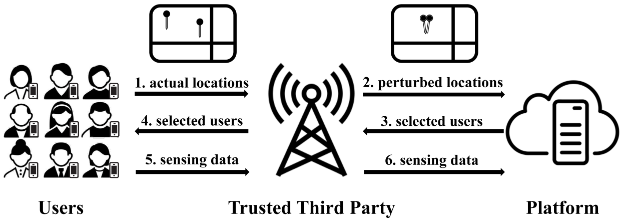

Figure 1: Location privacy preserving crowdsensing system

It is essential to achieve location privacy protection, since mobile users' locations are tightly correlated with their identities and vulnerable to malicious attacks. Upon preserving location privacy in crowdsensing, various methods are proposed including information caching [27], spatial cloaking [33], data perturbation with noise [40] and microaggregation [36]. The goal is to prevent the servers or platforms from inferring users' actual locations. However, these privacy preserving methods need to hide the users' actual locations, which usually degrade the location (information) quality [6].

Location privacy and location quality are two conflicting concerns in crowdsensing. On the one hand, disclosing users' actual locations to the platform may severely discourage their participation, because users are increasingly wary of location privacy. On the other hand, the platform desires the actual locations of users to ensure the location quality. It is necessary to strike a good balance between location privacy and location quality in crowdsensing. To quantify the impact of location privacy protection on location quality, we define the *location quality degradation* as the maximum distance between users' actual locations and their corresponding perturbed locations. Note that the summation of squared location errors (SSE) [28] has also been used to measure location quality in the literature. Although minimizing the SSE is not our objective, our simulation results demonstrate that a low location quality degradation also implies a low SSE.

In this paper, we study the trade-off between location quality and location privacy. Location quality and location privacy are two conflicting concerns in crowdsensing, which naturally leads to a duality relation. On the one hand, for the isolated users, the distances between their actual locations and perturbed locations might be very large, because they have

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to share the same perturbed locations with the other users to protect their location privacy. Thus, if all users' location privacy must be protected, this may cause a large location quality degradation. On the other hand, if the location quality degradation is a constraint, it might not be possible to find perturbed locations for the isolated users to protect their location privacy, because they are too far from the others. Depending on the preference of the crowdsensing platform, we consider the optimization from two perspectives. If it desires to protect all users' location privacy, the problem can be formulated as the **Location Quality Degradation Minimization (LQDM)** problem: minimizing the location quality degradation, while guaranteeing the location privacy for all users; if it desires to bound the location quality degradation, the problem can be formulated as the **Protected User Maximization with Location Quality Degradation Constraint (PUM)** problem: maximizing the number of users whose location privacy is protected, subject to a location quality degradation constraint. For the second problem, we consider overlapping and non-overlapping cases to satisfy various requirements of the platform. The difference is whether one user is allowed to be tagged with more than one perturbed location. The rationale behind the overlapping case is that the sensed data at one location can well represent the results at nearby locations in many crowdsensing applications, e.g., noise, temperature and signal coverage. Note that we focus on only the overlapping case for the **LQDM** problem because the non-overlapping case often results in large location quality degradation due to the constraint of including all users.

A. Contributions

We summarize **the main contributions** as follows:

- To the best of our knowledge, we are the first to consider the trade-off between location privacy and location quality in crowdsensing from optimization perspective.
- We first study the problem of optimizing the location quality in terms of the location quality degradation, while guaranteeing the location privacy for all users. We design an efficient optimal algorithm to minimize the location quality degradation among all users.
- We then investigate the problem of maximizing the number of users whose location privacy is protected, while guaranteeing the location quality with a location quality degradation bound. Specifically, there are two cases depending on the platform's requirement: overlapping and non-overlapping. For the former case, we design an efficient optimal algorithm. For the latter case, we prove its NP-hardness and design a near-optimal approximation algorithm and a fast and effective heuristic algorithm that achieves near-optimal performance in simulations.

The remainder of the paper is organized as follows. In Section II, we give a brief review of existing location privacy preserving mechanisms in the literature. In Section III, we formally introduce the system model and give a precise problem description. In Section IV, we present a polynomial-time optimal algorithm for **LQDM** and analyze its properties. In Section V, we study the **PUM** problem under the overlapping perturbation and non-overlapping perturbation cases and design corresponding algorithms. Section VI demonstrates the experimental evaluations. Section VII concludes this paper.

II. Related Work

A. Location Privacy Approaches

There is a rich collection of literature on location privacy in general frameworks. Surveys for location privacy-preserving methods can be found in [4, 9]. Following the discussions in [9], we classify location privacy-preserving techniques to three types: location generation [15, 38], cryptographic techniques [19] and differential privacy [14]. Along the line of location generation, various methods are proposed including position dummies [15], mix zone [2], pseudonym [10], and k-anonymity [38].

Much effort has also been made to protect location privacy in crowdsensing systems [1, 8, 14, 18, 34, 35]. This line of work aims at preventing location privacy leakage from sensing reports submitted by crowdsensing users. Gao *et al.* [8] designed a partner selection algorithm and construct several trajectories that are closer to the users. Agir *et al.* [1] proposed a scheme which estimated the expected location-privacy level at the user-side locally in real-time, which satisfies each user's privacy requirement adaptively. Vu *et al.* [34] utilized Voronoi diagram to partition a space into cells that contain at least k users in each, without considering to minimize the cloaking area. Differential location privacy in the crowdsourced spectrum sensing was preserved in [14, 18, 35]. However, a significant problem neglected in these works is to optimize the crowdsensing platform's location quality, while protecting the users' location privacy.

B. Location Information Quality

As pointed out by Krause *et al.* in [17], it is challenging to balance between location privacy and location quality. Rodhe *et al.* [26] considered two strategies based on different types of system servers to reconstruct the data distribution and investigated the impact of location privacy preserving mechanisms on the quality of information. Xiao *et al.* developed a directed-graph based cloaking algorithm for protecting location privacy in location-based service, while meeting user-specified quality of service requirements [37]. Murshed *et al.* proposed a subset-coding scheme to achieve almost lossless data integrity in [21].

Another related topic is the microaggregation problem: divide a set of data into several disjoint subsets, such that the size of each subset in more than k and the sum of squared error is minimized. This problem has been studied to strike a balance between privacy protection and information loss reduction [5, 16, 28]. However, the location quality degradation minimization is not considered in this problem.

III. System Model and Problem Formulation

In this section, we introduce the system model and give a precise problem description.

A. System Model

We consider a location-based crowdsensing system consisting of a set $\mathcal{U} = \{1, 2, \ldots, n\}$ of n users, a trusted third party [32, 36] (e.g., a cellular service provider) and a crowdsensing platform. Each user carries an advanced mobile device with sensing capabilities and wishes to earn rewards by completing crowdsensing tasks. The user registers with the platform and communicates with the platform via an app installed on his mobile device. Developed by the platform, the app is assumed to pass the strict vetting process of the trusted app store and has no unauthorized access to user's locations.

We assume that the platform is honest but curious, which is commonly used to characterize a reasonable crowdsensing platform. Particularly, the platform is trusted to faithfully follow the protocol but also interested in learning users' locations. We assume that the platform can have arbitrary prior knowledge for attempting to breach the users' location privacy.

A precision-aware location privacy preserving crowdsensing system is shown in Figure 1. The platform publishes crowdsensing tasks and collects location aware sensing data from the users. The trusted third party, which is a cellular service supposed to protect the location privacy. The workflow of the system is as follows:

1) All the users report their actual locations $\mathcal{L} = \{l_1, l_2, \ldots, l_n\}$ to the trusted third party for location privacy protection.
2) The trusted third party processes the actual locations and reports a set of perturbed locations $\{h_1, h_2, \ldots, h_m\}$ to the platform, where a perturbed location h_j is tagged to at least k users.
3) The users tagged with perturbed locations are reported to the platform, and the rest users are discarded.

B. Problem Formulation

To formally formulate our studied problems, we introduce the following necessary concepts. In order to preserve location privacy, one solution is to make a user's location indistinguishable from at least $k-1$ others' locations. This property is proposed in [31] and called k*-anonymity*.

k*-anonymity*: To protect user's privacy, it requires that at least k reports are combined together before releasing.

Location perturbation: Location perturbation is defined as deliberately degrading the quality of location information about a user's location in order to protect that user's location privacy. Similar definition has been proposed as obfuscation [6]. However, the mechanism in [6] cannot be directly applied to crowdsensing. We have discussed the difference between LBS and crowdsensing in Section II-A.

Location quality degradation: The location quality degradation is the maximum of a set of distances between users' actual locations and their corresponding perturbed locations..

Perturbed group: A perturbed group is a set of users $\mathcal{S} \subseteq \mathcal{U}$ tagged with the same perturbed location, denoted by $(h, \mathcal{S})$, satisfying k-anonymity.

Apparently, the perturbation operation for protecting users' location privacy causes inevitable location errors, which can diminish the quality of the crowdsensing results. Thus it is necessary to strike a good balance between location privacy and location quality in crowdsensing. Therefore, it is essential to control the location quality degradation while preserving users' location privacy. Towards this goal, we consider the following two related optimization problems from two different perspectives in this paper:

1) **Location Quality Degradation Minimization (LQDM)**: Given a set of n users' actual locations and an integer $k \leq n$, form a set of perturbed groups, denoted by $\mathcal{H}$, including all users to minimize the location quality degradation.
2) **Protected User Maximization with Location Quality Degradation Constraint (PUM)**: Given a set of n users' actual locations, an integer $k \leq n$, and a location quality degradation bound δ, form a set of perturbed groups, denoted by $\mathcal{H}$, to include a maximum number of users, such that the location quality degradation is no more than δ.

Depending on the platform's requirement, we consider two cases: *overlapping perturbation*, where one user is allowed to be tagged with more than one perturbed location, and *non-overlapping perturbation*, where one user is tagged with at most one perturbed location. The rationale behind the overlapping case is that the sensed data at one location can well represent the results at nearby locations in many crowdsensing applications, e.g., temperature and signal coverage. We denote the **PUM** problem under these two cases by $\mathbf{PUM_O}$ and $\mathbf{PUM_N}$, respectively. Note that we focus on only the overlapping case for the **LQDM** problem because the non-overlapping case often results in large location quality degradation due to the constraint of including all users.

Note that in the literature, the summation of squared location errors (SSE) [28] has been used to measure data quality. In this paper, we use the location quality degradation, Some large errors are still detrimental to the crowdsensing application with a small SSE. Whereas, a small location quality degradation guarantees that none of the errors exceeds this value. Although we do not focus on minimizing the SSE, extensive simulations show that our algorithm achieves a lower SSE, compared to an existing k-anonymity location privacy preserving algorithm.

C. Geometric Problem Transformation

Both **LQDM** and **PUM** problems can be transformed into equivalent geometric problems. Before the transformation, we introduce the following definition.

Let $\mathcal{P}$ denote a plane. For any two points $p \in \mathcal{P}$ and $q \in \mathcal{P}$, we use $||p, q||$ to denote the Euclidean distance between p and q. A disk centered at c of radius r is denoted by $D(c, r)$. We say $D(c, r)$ *covers* p, if $p \in D(c, r)$, i.e., $||p, c|| \leq r$. Let $B(c, r)$ denote the closed boundary of $D(c, r)$. Given a set $\mathcal{L}$ of n points, let $\mathcal{D}(\mathcal{L}, r)$ denote a set of disks of radius r centered at points in $\mathcal{L}$.

Definition 1 (k-enclosing Disk)**.** *Let $\mathcal{L}$ be a set of n points on the plane $\mathcal{P}$. Given an integer $k \leq n$, a k-enclosing disk is a disk that covers at least k points in $\mathcal{L}$.*

The transformed **LQDM** and **PUM** problems are:

1) **LQDM**: Given a set $\mathcal{L}$ of n points on the plane $\mathcal{P}$ and an integer $k \leq n$, find a minimum r and a set of k-enclosing disks $\mathcal{D} = \{D(h_1, r), D(h_2, r), \ldots\}$, such that any $l_i \in \mathcal{L}$ is covered by at least one disk in $\mathcal{D}$.
2) **PUM**: Given a set $\mathcal{L}$ of n points on the plane $\mathcal{P}$, an integer $k \leq n$ and a constant δ, find a set of k-enclosing disks $\mathcal{D} = \{D(h_1, \delta), D(h_2, \delta), \ldots\}$, such that a maximum number of points in $\mathcal{L}$ are covered by disks in $\mathcal{D}$.

To solve these problems, we need the following definitions and claims from [7].

Definition 2 (Depth of a Point)**.** *Given a point $p \in \mathcal{P}$ and a disk set $\mathcal{D}(\mathcal{L}, r)$, the depth of p with respect to $\mathcal{D}(\mathcal{L}, r)$, denoted by $d_{\mathcal{D}(\mathcal{L},r)}(p)$, is the number of disks in $\mathcal{D}(\mathcal{L}, r)$ covering p.*

Definition 3 (Depth of a Disk)**.** *Given a point $l_i \in \mathcal{L}$ and a disk set $\mathcal{D}(\mathcal{L}, r)$, the depth of $D(l_i, r)$, denoted by $d_{D(l_i,r)}$, is the maximum depth of all points $p \in D(l_i, r)$:*

$$d_{D(l_i,r)} = \max_{p \in D(l_i,r)} \{d_{\mathcal{D}(\mathcal{L},r)}(p)\}.$$

Claim 1. *Given two points $p, q \in \mathcal{P}$, $p \in D(q, r)$ if and only if $q \in D(p, r)$.*

Claim 2. *The depth of a point $p \in \mathcal{P}$ in $\mathcal{D}(\mathcal{L}, r)$ is the number of points in $\mathcal{L}$ covered by $D(p, r)$.*

Definition 4 (Critical Radius)**.** *Given any $l_i \in \mathcal{L}$, a radius r is a critical radius, if $d_{D(l_i,r)}$ decreases, when r is decreased by an arbitrarily small amount.*

At last, we have three geometrical facts as follows.

1) The point on $D(l_i, r)$ with maximum depth must be an intersection point on $B(l_i, r)$, if $B(l_i, r)$ intersects with the boundary of any other disk in $\mathcal{D}(\mathcal{L}, r)$. Then we only focus on the intersection points on $B(l_i, r)$ for computing $d_{D(l_i,r)}$.
2) Given any $l_i \in \mathcal{L}$, let r_i^* denote the minimum radius r, such that $d_{D(l_i,r)} \geq k$. We can locate r_i^* within a feasible range of r using the following criteria:
   - $d_{D(l_i,r)} < k \to r < r_i^*$;
   - $d_{D(l_i,r)} > k \to r > r_i^*$;
   - $d_{D(l_i,r)} = k \to r \geq r_i^*$.
3) A radius r can be a critical radius only if $B(l_i, r)$ is tangent to $B(l_j, r)$, or $B(l_i, r)$ is concurrent with $B(l_j, r)$ and $B(l_k, r)$, where $l_i, l_j, l_k \in \mathcal{L}$. In other words, a critical radius is either $\frac{1}{2}||l_i, l_j||$, denoted by r_{ij}, or a circumradius of a triangle with l_i, l_j and l_k as the vertices, denoted by r_{ijk}.

The main notations are summarized in Table 1.

IV. Optimal Algorithm for **LQDM**

In this section, we present an efficient optimal algorithm OLoQ for the **LQDM** problem.

Table 1: Main notations

Notation	Meaning
$\mathcal{U}$	a set of users $\{1, 2, \ldots, n\}$
$(h, \mathcal{S})$	a perturbed group, where all users in $\mathcal{S}$ are tagged with h
$\mathcal{H}$	a set of perturbed groups
$\mathcal{P}$	a plane
l_i	the actual location (a point on $\mathcal{P}$) of user i
$\mathcal{L}$	the set of actual locations (points on $\mathcal{P}$) of users in $\mathcal{U}$
$D(p, r)$	the disk of radius r, centered at $p \in \mathcal{P}$
$\mathcal{D}(\mathcal{L}, r)$	the set of disks with radius r, centered at points in $\mathcal{L}$
$d_{\mathcal{D}(\mathcal{L},r)}(p)$	the depth of a point p with respect to $\mathcal{D}(\mathcal{L}, r)$
$d_{D(l_i,r)}$	the depth of a disk $D(l_i, r)$
$B(p, r)$	the closed boundary of $D(p, r)$
r_i^*	the minimum radius of a k-enclosing disk to cover l_i
p_i^*	the center of the smallest k-enclosing disk to cover l_i

A. Overview

Since r_i^* is the minimum radius, such that l_i is covered by a k-enclosing disk, the minimum radius in the optimal solution to the **LQDM** problem equals $\max_{l_i \in \mathcal{L}} r_i^*$, denoted by r^*. Thus the **LQDM** problem boils down to finding r_i^* for each $l_i \in \mathcal{L}$. Based on Fact 2) in Section III-C, it is necessary to determine a range in order to locate r_i^*. To locate the exact value of r_i^*, we need to discretize its range. By the definition of critical radius, r_i^* must be a critical radius of l_i. Thus we focus on critical radii and conduct a binary search among them for locating r_i^*. According to Fact 3), a critical radius of l_i can only be r_{ij} or r_{ijk}, where $l_j, l_k \in \mathcal{L}, i \neq j \neq k$. Once r_i^* is located, we find the point of maximum depth on $D(l_i, r_i^*)$, denoted by p_i^*. Then a set of k-enclosing disks $\mathcal{D} = \{D(p_i^*, r^*) \mid l_i \in \mathcal{L}\}$ can cover all $l_i \in \mathcal{L}$. However, not all disks in $\mathcal{D}$ are necessary. Thus we select a minimal $\mathcal{D}^* \subseteq \mathcal{D}$ covering all points in $\mathcal{L}$. The centers of the selected disks are the perturbed locations.

B. Algorithm Design

OLoQ includes one key algorithm to find the smallest k-enclosing disk covering $l_i \in \mathcal{L}$, illustrated in Algorithm 1.

In Algorithm 1, we narrow the range where r_i^* can lie and locate r_i^*. To narrow the range where r_i^* can lie, we collect the $n-1$ values of r_{ij} and sort them in a non-decreasing order. Note that each r_{ij} is corresponding to a tangent point p_{ij} of $B(l_i, r_{ij})$ and $B(l_j, r_{ij})$, which is the midpoint of line $l_i l_j$. Then the range can be narrowed to $(\underline{r}_{ij}, \bar{r}_{ij}]$.

Then we collect $\frac{(n-1)(n-2)}{2}$ values of r_{ijk} and only keep the values of r_{ijk} within the range $(\underline{r}_{ij}, \bar{r}_{ij}]$. If there is no r_{ijk} within this range, then r_i^* is $\bar{r}_{ij}$ and its corresponding p_i^* is $\bar{p}_{ij}$. Otherwise, we sort the values of r_{ijk} within the range $(\underline{r}_{ij}, \bar{r}_{ij}]$ in a non-decreasing order. Note that each r_{ijk} is corresponding to a point p_{ijk}, which is the circumcenter of the triangle with l_i, l_j and l_k as the vertices. Using binary search, we further restrict the range to $(\underline{r}_{ijk}, \bar{r}_{ijk}]$, which is the smallest range such that $d_{D(l_i,\underline{r}_{ijk})} < k$ and $d_{D(l_i,\bar{r}_{ijk})} \geq k$. Therefore r_i^* is $\bar{r}_{ijk}$, and p_i^* is the $\bar{p}_{ijk}$ corresponding to $\bar{r}_{ijk}$.

At the end, Algorithm 1 outputs (r_i^*, p_i^*), which forms the smallest k-enclosing disk $D(r_i^*, p_i^*)$ that covers l_i. We shall run Algorithm 1 for each $l_i \in \mathcal{L}$. Then the minimum radius in the optimal solution to the **LQDM** problem is $\max_{l_i \in \mathcal{L}} r_i^*$.

Next, we generate a set of k-enclosing disks $\mathcal{D}^* = \{D(h_1, r^*), D(h_2, r^*), \ldots\}$, such that any $l_i \in \mathcal{L}$ is

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Algorithm 1: Find-$k$-enclosing-Disk($l_i, k, \mathcal{L}$)
1 Sort all values in $\{r_{ij} \mid l_j \in \mathcal{L}\backslash\{l_i\}\}$ in a non-decreasing
    order and obtain a sorted list $R_{ij}$;
2 Run a binary search in $R_{ij}$ to find two consecutive
    values of $r_{ij}$, denoted by $\underline{r}_{ij}$ and $\bar{r}_{ij}$, such that
    $d_{D(l_i,\underline{r}_{ijk})} < k$ and $d_{D(l_i,\bar{r}_{ij})} \geq k$;
3 Sort all values in $\{r_{ijk} \mid r_{ijk} \in (\underline{r}_{ij}, \bar{r}_{ij}], l_j, l_k \in \mathcal{L}\backslash\{l_i\}\}$
    in a non-decreasing order and obtain a sorted list $R_{ijk}$;
4 if $R_{ijk} = \emptyset$ then
5     $r_i^* \leftarrow \bar{r}_{ij}$; $p_i^* \leftarrow \bar{p}_{ij}$ ;
6 else
7     Run a binary search in $R_{ijk}$ to find two consecutive
        values of $r_{ijk}$, denoted by $\underline{r}_{ijk}$ and $\bar{r}_{ijk}$, such that
        $d_{D(l_i,\underline{r}_{ijk})} < k$ and $d_{D(l_i,\bar{r}_{ijk})} \geq k$;
8     $r_i^* \leftarrow \bar{r}_{ijk}$; $p_i^* \leftarrow \bar{p}_{ijk}$;
9 return $(r_i^*, p_i^*)$
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Algorithm 2: OLoQ ($\mathcal{L}, k$)
$\mathcal{H} \leftarrow \emptyset$; $\mathcal{D}^* \leftarrow \emptyset$;
for $l_i \in \mathcal{L}$ do
$r_i^* \leftarrow$ Find-$k$-enclosing-Disk( $l_i, k, \mathcal{L}$ );
$r^* \leftarrow \max_{l_i \in \mathcal{L}} r_i^*$;
Sort points in $\mathcal{L}$ based on $r_i^*$ in a non-increasing order
    and obtain a sorted list $L$;
for $l_i \in L$ do
    if $l_i$ is uncovered by $\mathcal{D}^*$ then
        $\mathcal{D}^* \leftarrow \mathcal{D}^* \cup \{D(p_i^*, r^*)\}$;
        $\mathcal{H} \leftarrow \mathcal{H} \cup \{(p_i^*, \{i \mid l_i \in D(p_i^*, r^*)\})\}$ ;
return $(\mathcal{H}, r^*)$
```

covered by at least one disk in $\mathcal{D}^*$. By the previous steps, we can obtain a set of k-enclosing disks $\mathcal{D} = \{D(p_1^*, r^*), D(p_1^*, r^*), \ldots, D(p_n^*, r^*)\}$ covering all points in $\mathcal{L}$. However, not all of them are necessary. So we design Algorithm 2 to select a minimal $\mathcal{D}^* \subseteq \mathcal{D}$ covering all points in $\mathcal{L}$. The idea is to select disks iteratively. In each iteration we select a disk covering as many points as possible. Thus we sort n values of r_i^* for all $l_i \in \mathcal{L}$ in a non-increasing order and select disks sequentially according to the sorted list. If l_i has not been covered, we add $D(p_i^*, r^*)$ to $\mathcal{D}^*$. For all users whose actual locations are covered by $D(p_i^*, r^*)$, we form a perturbed group with p_i^* as their perturbed location.

The time complexity of Algorithm 1 is $O(n^2 \log n)$. The time complexity of Algorithm 2 is $O(n)$. Therefore, the time complexity of OLoQ is $O(n^3 \log n)$. It can be proved that OLoQ returns an optimal solution to **LQDM** [41].

V. Algorithms for **PUM**

In this section, we study the **PUM** problem under the overlapping perturbation and non-overlapping perturbation cases, denoted by $\mathbf{PUM_O}$ and $\mathbf{PUM_N}$, respectively. Then we design corresponding algorithms for them.

A. Optimal Algorithm for $\mathbf{PUM_O}$

In this subsection, we develop an efficient optimal algorithm $\mathsf{OPUM_O}$ for the $\mathbf{PUM_O}$ problem.

We first introduce the intuition behind $\mathsf{OPUM_O}$. We know that r_i^* is the minimum radius r, such that l_i is covered by a k-enclosing disk. It implies that for any point $l_i \in \mathcal{L}$, if $r_i^* > \delta$, then l_i can never be covered in a k-enclosing disk of radius δ. Thus we can discard such points from $\mathcal{L}$. For the remaining points in $\mathcal{L}$, we select a subset $\mathcal{D}^\delta \subseteq \mathcal{D} = \{D(p_1^*, \delta), D(p_1^*, \delta), \ldots, D(p_n^*, \delta)\}$ to cover all of them. The centers of the selected disks are the perturbed locations.

The details of $\mathsf{OPUM_O}$ are described as follows. Using Algorithm 1 in Section IV-B, we can obtain a set of k-enclosing disks $\mathcal{D} = \{D(p_1^*, \delta), D(p_1^*, \delta), \ldots, D(p_n^*, \delta)\}$. Similar to Algorithm 2, we sort the values of r_i^* for all $l_i \in \mathcal{L}$ in a non-increasing order and select a subset of disks $\mathcal{D}^\delta \subseteq \mathcal{D}$ sequentially according to the sorted list. The fundamental difference from OLoQ is that for any point $l_i \in \mathcal{L}$, if $r_i^* > \delta$, we discard l_i from $\mathcal{L}$. Then if l_i has not been covered and its corresponding $r_i^* \leq \delta$, we add $D(p_i^*, \delta)$ to $\mathcal{D}^\delta$. For all users whose actual locations are covered by $D(p_i^*, \delta)$, we form a perturbed group $(p_i^*, \{i \mid l_i \in D(p_i^*, \delta)\})$. Then p_i^* is set to be their perturbed location.

Since $\mathsf{OPUM_O}$ is similar to OLoQ, the overall time complexity of $\mathsf{OPUM_O}$ is $O(n^3 \log n)$ as well. The optimality of $\mathsf{OPUM_O}$ is guaranteed by the following theorem.

Theorem 1. $\mathsf{OPUM_O}$ *returns an optimal solution to* $\mathbf{PUM_O}$.

Proof. We first prove that each user i included in the perturbed groups is tagged with the same perturbed location as at least $k-1$ other users and then prove that the maximum number of users are included in the formed perturbed groups.

For each $l_i \in \mathcal{L}$, it guarantees that $d_{D(l_i, r_i^*)} \geq k$, based on Lines 2 and 7 in Algorithm 1. Since p_i^* is the point with maximum depth on $D(l_i, r_i^*)$, we have $d_{\mathcal{D}(\mathcal{L}, r_i^*)}(p_i^*) \geq k$. By Claim 2, $D(p_i^*, r_i^*)$ covers at least k points in $\mathcal{L}$. By Claim 1, we have $l_i \in D(p_i^*, r_i^*)$. With $r_i^* \leq \delta$, we know that $D(p_i^*, \delta)$ covers at least k points in $\mathcal{L}$ and $l_i \in D(p_i^*, \delta)$, as well. Thus there are at least k users in each perturbed group $(p_i^*, \{i \mid l_i \in D(p_i^*, \delta)\})$. Therefore each user i included in the perturbed groups is tagged with the same perturbed location with at least $k-1$ other users.

We learned from the proof above that r_i^* is the minimum radius, such that user i is tagged with the same perturbed location as at least $k-1$ other users. So we know that if $r_i^* > \delta$, then user i can never be included in a perturbed group. Because the users with $r_i^* > \delta$ are discarded, and the users with $r_i^* \leq \delta$ are included in the perturbed groups, we know that the maximum number of users are included in the formed perturbed groups. ■

B. Algorithms for $\mathbf{PUM_N}$

In this subsection, we design a near-optimal approximation algorithm $\mathsf{NPUM_N}$ and an effective heuristic algorithm $\mathsf{HPUM_N}$. The $\mathbf{PUM_N}$ problem can be proved to be NP-hard [41] by a reduction from the Disjoint Unit-Disk Cover problem, which has been proved to be NP-hard in [12].

Therefore, the **PUM$_{\mathsf{N}}$** problem is unlikely to have an efficient optimal algorithm, unless P = NP. Thus we design an approximation algorithm $\mathsf{NPUM_N}$ by applying the shifted grid technique. The shifting technique has two stages. In the first stage, the plane is partitioned into squares with each having a size of $s \times s$. By shifting the partition grid lines over unit distance, a new way of partitioning can be derived. We call each way of partitioning a "shift". Thus there are $s \times s$ shifts in total.

The second stage is to use a local algorithm to find an optimal solution within each square. Then the union of all squares' solutions is the global solution for a shift. The final solution is the one with the best performance among all shifts. A brute-force algorithm can find the optimal solution within an $s \times s$ square in exponential time. Since an $s \times s$ square can be covered with $2s^2$ unit disks compactly, there are $O(\frac{8}{\epsilon^2})$ disks in the optimal solution to cover n_p points inside the square. Since we can always move a disk in the optimal solution, such that at least 2 points are on its boundary, there are $O(n_p^2)$ disk positions. To select $O(\frac{8}{\epsilon^2})$ from $O(n_p^2)$ disks, we check $O(n_p^{16/\epsilon^2})$ disk arrangements. In each arrangement, we check n_p points' positions in $O((\frac{8}{\epsilon^2})^{n_p})$ time. Therefore, the overall time complexity of the local algorithm is $O(\frac{8^{n_p}}{\epsilon^{2n_p}} n_p^{16/\epsilon^2})$. For the shifted grid technique, we only discuss the local algorithm's complexity, because the local algorithm (Lines 6-7 in Algorithm 3) can be run in parallel in multiple squares.

Theorem 2. *The approximation ratio of* $\mathsf{NPUM_N}$ *is* $1 - \epsilon$, *where* $\epsilon > 0$ *is an arbitrarily small constant.*

Proof. Let OPT be the set of points in an optimal solution, $OPT_{(i,j)}$ be the set of points in the global solution of shift (i, j) and $OPT'_{(i,j)}$ be the set of points in OPT intersecting the lines $x = as + i$ and $y = bs + j$, where $a, b \in \{0, 1, 2, \ldots\}$. Then, we have $|OPT_{(i,j)}| + |OPT'_{(i,j)}| \geq |OPT|$, and thus

$$\sum_{i=1}^{s}\sum_{j=1}^{s}(|OPT_{(i,j)}| + |OPT'_{(i,j)}|) \geq s^2|OPT|,$$

because $\sum_{i=1}^{s}\sum_{j=1}^{s}|OPT'_{(i,j)}| \leq 2s|OPT|$, we have $\sum_{i=1}^{s}\sum_{j=1}^{s}|OPT_{(i,j)}| \geq (s^2 - 2s)|OPT|$, and thus,

$$\max_{i,j\in\{1,\ldots,s-1\}}|OPT_{(i,j)}| \geq (1 - \frac{2}{s})|OPT| = (1 - \epsilon)|OPT|. \blacksquare$$

Even though the time complexity is exponential to the maximum number of points in any square, the number of users in each square is small in practice. We conduct studies on the roma taxi dataset [3] and the San Francisco taxi dataset [22]. Table 2 shows the maximum number of users in a square.

To further reduce the time complexity, we design a fast and effective heuristic algorithm $\mathsf{HPUM_N}$ that can achieve near-optimal performance in practice, although not theoretically.

The details of $\mathsf{HPUM_N}$ are as follows. When $\mathcal{L}$ contains more than k points, we compute the disk depth $d_{D(l_i,\delta)}$ for each $l_i \in \mathcal{L}$. If $d_{D(l_i,\delta)} < k$, then we discard l_i from $\mathcal{L}$. For the remaining points in $\mathcal{L}$, we extract the point l_{min}, whose corresponding disk depth $d_{D(l_i,\delta)}$ is the minimum among all disks. Then we find the point with maximum depth on $d_{D(l_{min},\delta)}$, denoted by p^*_{min}. It is obvious that $d_{\mathcal{D}(\mathcal{L},\delta)}(p^*_{min}) \geq k$, and we obtain a k-enclosing disk $D(p^*_{min}, \delta)$. Then we add $D(p^*_{min}, \delta)$ to $\mathcal{D}^\delta$. For the remaining points covered by $D(p^*_{min}, \delta)$, we form a perturbed group $(p^*_{min}, \{i \mid l_i \in D(p^*_{min}, \delta) \cap \mathcal{L}\})$ and tag p^*_{min} to the corresponding users as their perturbed location. Then we discard these locations from $\mathcal{L}$. We keep forming perturbed groups and discarding points until there are less than k points in $\mathcal{L}$.

Algorithm 3: $\mathsf{NPUM_N}$ $(\mathcal{L}, k, \delta, \epsilon)$

```
1  Normalize the plane with respect to $\delta$;
2  $s \leftarrow \frac{2}{\epsilon}$;
3  in parallel for $i \leftarrow 1$ to $s$ and $j \leftarrow 1$ to $s$ do
4      Partition the plane into squares with each having a
         size of $s \times s$, by drawing grid lines $x = i + as$ and
         $y = j + bs$, where $a, b \in \mathbb{Z}$ ;
5      in parallel for each square do
6          Construct $s(s-1)$ unit disks s.t. at least 2 points
             in $\mathcal{L}$ are on the boundary;
7          Use a brute-force algorithm to select an optimal
             disk set for this square, which contains at most
             $2s^2$ disks;
8      Combine the selected disk sets as the global solution;
9  Pick the solution $\mathcal{D}^\delta$ that includes the maximum number
     of points among;
10 Construct $\mathcal{H}$ based on disks in $\mathcal{D}^\delta$;
11 return $\mathcal{H}$
```

Table 2: Maximum number of users in a square

Dataset	1.5×1.5 km^2	2×2 km^2	2.5×2.5 km^2
roma taxi [3]	17	22	30
SF taxi [22]	23	29	34

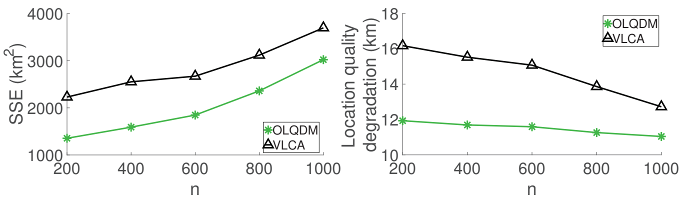
Algorithm 4: $\mathsf{HPUM_N}$ $(\mathcal{L}, k, \delta)$

```
1  $\mathcal{H} \leftarrow \emptyset$; $\mathcal{D}^\delta \leftarrow \emptyset$;
2  while $|\mathcal{L}| \geq k$ do
3      for $l_i \in \mathcal{L}$ do
4          Update $d_{D(l_i,\delta)}$;
5          if $d_{D(l_i,\delta)} < k$ then  $\mathcal{L} \leftarrow \mathcal{L} \backslash \{l_i\}$;
6      if $\max_{l_i \in \mathcal{L}} d_{D(l_i,\delta)} < k$ then break;
7      $l_{min} \leftarrow \arg\min_{l_i \in \mathcal{L}} d_{D(l_i,\delta)}$ ;
8      Find the point $p^*_{min} \in D(l_{min}, \delta)$ of maximum depth;
9      $\mathcal{D}^\delta \leftarrow \mathcal{D}^\delta \cup \{D(p^*_{min}, \delta)\}$;
10     $\mathcal{H} \leftarrow \mathcal{H} \cup \{(p^*_{min}, \{i \mid l_i \in D(p^*_{min}, \delta) \cap \mathcal{L}\})\}$;
11     $\mathcal{L} \leftarrow \mathcal{L} \backslash \{l_i \mid l_i \in D(p^*_{min}, \delta)\}$;
12 return $\mathcal{H}$
```

Theorem 3. $\mathsf{HPUM_N}$ *preserves k-anonymity location privacy.*

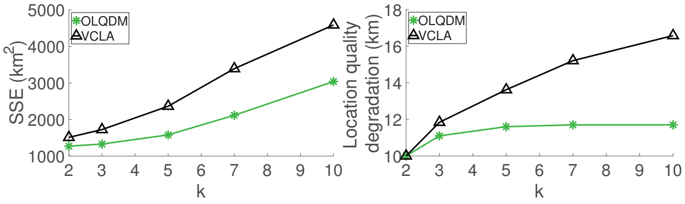
Proof. We prove that each user i included in the perturbed groups is tagged with the same perturbed location as at least $k - 1$ other users.

For each $l_{min} \in \mathcal{L}$, it guarantees that $d_{D(l_{min},\delta)} \geq k$, based on Line 5 in Algorithm 4. Since p^*_{min} is the point with



(a) (b)

Figure 2: Impact of n on OLoQ and VCLA: (a) SSE and (b) Location quality degradation (km).



(a) (b)

Figure 3: Impact of k on OLoQ and VCLA: (a) SSE and (b) Location quality degradation (km).

maximum depth on $D(l_{min}, \delta)$, we have $d_{\mathcal{D}(\mathcal{L},\delta)}(p^*_{min}) \geq k$. By Claim 2, $D(p^*_{min}, \delta)$ covers at least k points in $\mathcal{L}$. Thus there are at least k users in each perturbed group $(p^*_{min}, \{i \mid l_{min} \in D(p^*_{min}, \delta)\})$. Therefore each user i included in the perturbed groups is tagged with the same perturbed location with at least $k-1$ other users. ■

The time complexity of $\mathsf{HPUM_N}$ is dominated by the nested while-loop and for-loop. The while-loop takes $O(\frac{n}{k})$ time. The for-loop takes $O(n)$ time to update disk depth. Hence the overall time complexity of $\mathsf{HPUM_N}$ is $O(\frac{n^3}{k})$.

VI. Performance Evaluation

In this section, we evaluate the performance of OLoQ, $\mathsf{OPUM_O}$ and $\mathsf{HPUM_N}$ by comparing them with existing k-anonymity location privacy preserving algorithms [36].

A. Evaluation Setup

As we surveyed in Section II, there is no existing algorithm that aims to minimize the location quality degradation or to maximize the number of protected users. The most related work for k-anonymity location privacy is VCLA [36], which is a heuristic algorithm that uses the microaggregation approach to obtain anonymized locations and aims to minimize the summation of squared errors (SSE).

We use the CRAWDAD dataset roma/taxi [3] for our simulations. The dataset contains the mobility traces of approximately 320 taxis collected over 30 days in Rome, Italy. Each mobility trace consists of a sequence of GPS coordinates collected roughly every seven seconds along with corresponding timestamps. Because our model does not require the time information, we removed the timestamps from the whole 30-day dataset and treated all the data points as independent. We then randomly select data points as input to our algorithms. Investigating the trade-off between location quality and privacy with both spatial and temporal information will be one of our future research directions as we will discuss in Section VII.

B. Performance Metrics

We are interested in the following performance metrics.

- *SSE:* Suppose a point set $\mathcal{L}$ is divided into m groups. The sum of squared errors of perturbed group j is defined as:

$$sse_j = \sum_{p=1}^{n_j} [(x_{jp} - \bar{x}_j)^2 + (y_{jp} - \bar{y}_j)^2]$$

  where n_j is the number of users in j-th group satisfying $n_j \geq k$, (x_{jp}, y_{jp}) is the location of the pth user with $(\bar{x}_j, \bar{y}_j)$ the perturbed location of j-th group. The SSE is the sum of sse_j:

$$SSE = \sum_{j=1}^{m} sse_j = \sum_{j=1}^{m} \sum_{p=1}^{n_j} [(x_{jp} - \bar{x}_j)^2 + (y_{jp} - \bar{y}_j)^2],$$

  where SSE describes the overall group homogeneity after group formation. When nearby points are grouped together, SSE will be small and the groups are more homogeneous.
- *Location quality degradation*
- *Number of protected users*

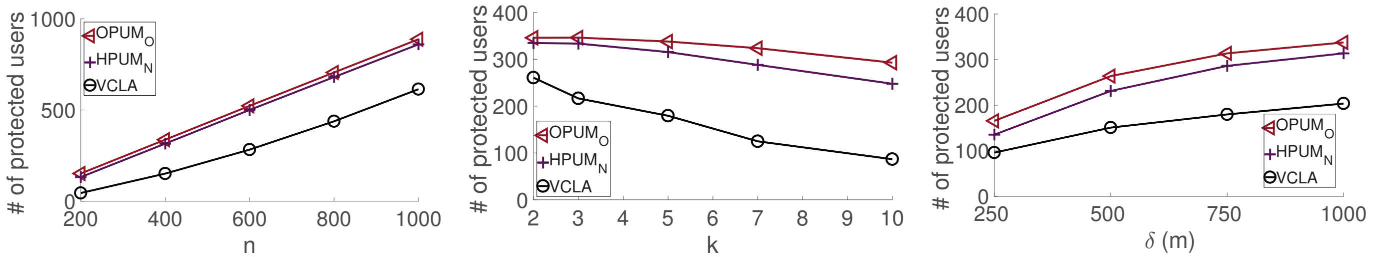
In our evaluation, we show the impact of the number of users (n) and k on OLoQ and VCLA in terms of SSE and location quality degradation. For the impact of n, we vary it from 200 to 1000 with an increment of 200, while fixing $k = 5$. For the impact of k, we set it to be $2, 3, 5, 7, 10$, while fixing $n = 400$.

Then we show the impact of the number of users (n), the value of k, and the location quality degradation bound (δ) on $\mathsf{OPUM_O}$ $\mathsf{HPUM_N}$ and VCLA in terms of the number of protected users. For the impact of n, we vary it from 200 to 1000 with an increment of 200, fixing $k = 5$ and $\delta = 500$m. For the impact of k, we set it to be $2, 3, 5, 7, 10$, fixing $n = 400$ and $\delta = 500$m. For the impact of δ, we vary it from 500m to 2500m with an increment of 500m, fixing $n = 400$ and $k = 5$. We choose this range of δ, because this error is tolerable for location quality in most crowdsensing applications. All results are averaged over 100 independent runs.

In addition, we show the impact of ϵ and k on $\mathsf{NPUM_N}$ in terms of the number of protected users. For the impact of ϵ, we set it to be $\frac{1}{750}, \frac{1}{1000}, \frac{1}{1250}$, while fixing $n = 50$ and $\delta = 500$. For the impact of k, we vary it from 3 to 5 with an increment of 1, while fixing $n = 50$ and $k = 4$. Due to the high time complexity of $\mathsf{NPUM_N}$, all results are averaged for 30 independent runs.

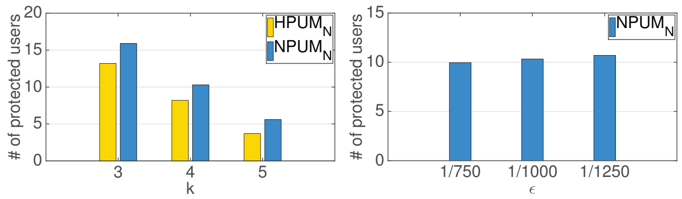
C. Evaluation Results and Analysis

Figure 2 shows the impact of n on OLoQ and VCLA. Figure 2(a) shows the impact of n on SSE. We observe that OLoQ can always introduce lower SSE, which is very essential to obtain accurate sensing data. Besides, the SSE increases with n, because sparser location distribution will lead to larger errors. In Figure 2(b), the location quality degradations of OLoQ and



(a) (b) (c)

Figure 4: Impact of n, k and δ on OPUM$_\text{O}$, HPUM$_\text{N}$ and VCLA: (a) Impact of n ($k = 5, \delta = 1000$), (b) Impact of k ($n = 400, \delta = 1000$) and (c) Impact of δ ($k = 5, n = 400$).



(a) (b)

Figure 5: Impact of k and l on HPUM$_\text{N}$ and NPUM$_\text{N}$: (a) Impact of k ($\epsilon = 10^{-3}$) and (b) Impact of ϵ ($n = 50$).

VCLA decrease with n. We also observe that OLoQ performs better than VCLA, especially with fewer users, because OLoQ minimizes the location quality degradation optimally, while VCLA heuristically aggregate locations by first choosing the farthest point and then aggregating the nearest points to it.

Figure 3 shows the impact of k on OLoQ and VCLA. Figure 3(a) illustrates that the SSE gradually increases with more stringent privacy protection in both OLoQ and VCLA. To protect more users' locations in one perturbed group, it is inevitable to diminish the location quality to some degree. OLoQ has a lower SSE, because it minimizes the location quality degradation. From Figure 3(b), we observe that, OLoQ outputs perturbed groups with minimum location quality degradation and performs significantly better than VCLA. The common trend is that, with more stringent privacy protection the location quality degradation increases in both OLoQ and VCLA.

Figure 4 shows the impact of n, k and δ on OPUM$_\text{O}$, HPUM$_\text{N}$ and VCLA. Figure 4(a) illustrates that the number of protected users increases with more users involved. OPUM$_\text{O}$ includes most protected users, because it is an optimal algorithm that allows overlapping. We can also see that the performance of HPUM$_\text{N}$ is very close to OPUM$_\text{O}$. Since OPUM$_\text{O}$ allows overlapping and already includes all the possible users with the location quality degradation constraint, the optimal solution in the non-overlapping case can never include more users than OPUM$_\text{O}$. Thus HPUM$_\text{N}$ achieves near-optimal performance. In addition, VCLA includes fewer protected users, because VCLA always chooses the farthest point to form a new group. Figure 4(b) illustrates that the number of protected users decreases, when k increases. The reason is that a larger k requires more stringent privacy protection, while the location quality degradation bound remains the same, which makes some users unprotected. We also notice that HPUM$_\text{N}$'s performance is very close to OPUM$_\text{O}$. Since the optimal solution in the non-overlapping case is no greater than that of the overlapping case, we can say that HPUM$_\text{N}$ achieves near-optimal performance. Whereas, VCLA includes fewer protected users, because it forms perturbed groups by choosing the farthest point and then aggregating the nearest points to it. Figure 4(c) demonstrates that the number of protected users increases when δ is larger. Because more users' locations can included in a perturbed group with a larger δ.

Figure 5 shows the impact of k and ϵ on NPUM$_\text{N}$. In Figure 5(a), we observe that the number of protected users decreases. A larger k requires more stringent privacy protection, while the location quality degradation bound remains the same, which makes some users unprotected. In addition, NPUM$_\text{N}$ achieves better performance than HPUM$_\text{N}$, because NPUM$_\text{N}$ has an approximation close to 1 when ϵ is very small. In Figure 5(b), we notice that the number of protected users increases, because the approximation ratio increases when the value of ϵ decreases.

VII. Conclusion and Future Work

In this paper, we considered the trade-off between location privacy and location quality in location-based crowdsensing from optimization perspective. Two optimization problems haven been studied. The first problem is to minimize the location quality degradation, while guaranteeing the location privacy for all users. We presented an efficient optimal algorithm OLoQ for this problem. The second problem is to maximize the number of protected users with a location quality degradation constraint. To satisfy different requirements of the platforms, we further considered two cases: overlapping and non-overlapping perturbations. For the former case, we gave an efficient optimal algorithm OPUM$_\text{O}$. For the latter case, we proved its NP-hardness, and designed a near-optimal $(1-\epsilon)$-approximation algorithm NPUM$_\text{N}$ and a fast and effective heuristic algorithm HPUM$_\text{N}$. Extensive simulations show that OLoQ and OPUM$_\text{O}$ achieve optimal performance. In addition, NPUM$_\text{N}$ and HPUM$_\text{N}$ achieve near-optimal performance.

There are two directions that we can work on in the future. In the current work, we assume that all users require the same anonymity level. Our algorithms can be extended to a personalized k-anonymity model, where each user can specify a different anonymity level requirement. Another direction is to

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consider temporal information privacy protection, because the crowdsensing data are sometimes time-sensitive. An attacker can infer a user's personal preference or behaviors based on the user's location information combined with its temporal information. Thus, it will be better to perturb both the spatial and temporal information.

In addition, we plan to conduct the mobile crowdsensing on constructing urban noise maps [42] as a case study. People in major cities suffer from noise pollution, which compromises working efficiency and mental health. Urban noises usually vary by locations, change over time, and consist of multiple sound sources., e.g., loud music, vehicle traffic and constructions. New York City (NYC) has opened a platform CityNoise [42] to allow people to submit the urban noise sensing data tagged with locations by using a mobile app, which is location-aware and open source. Our proposed algorithms will process the sensing data by tagging them with perturbed locations. With the processed location data, we will be able to generate the noise map and study the trade-off between location quality and privacy.

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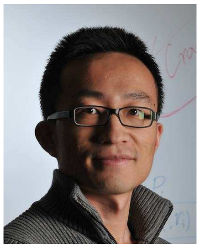

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