Privacy preserving spatio-temporal databases based on k-anonymity

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ABSTRACT

The development of location-based services and mobile devices has led to an increase in the location data. Through the data mining process, some valuable information can be discovered from location data. In the other words, an attacker may also extract some private (sensitive) information of the user through the data mining process and this may make threats against the user privacy. For example, the attacker can mine user’s location data for deciding the home address of the user. Thus, location privacy protection becomes an important requirement to the success in the development of location-based services. In this paper, we propose a grid-based approach as well as an algorithm to guarantee k-anonymity, a well-known privacy protection approach, in a location database. To do this, we assume that the service server will provide services but in a defined area and the grid will cover the area in which the service server takes effect. Then, the user’s location will be hidden in an anonymization area. The anonymization area will be chosen by cells that forms a rectangle area so that this area contains at least k distinct users. Moreover, in practice, the location of a user usually accompanies with a temporal data. And, indeed, the information about the combination of spatial and temporal data may also disclose some other sensitive information of the user. Thus, the paper also proposes an approach for guaranteeing k-anonymity for the combination of spatial and temporal database. The proposed approach considers only the information that has significance for the user’s location privacy protection becomes an important requirement to the success in the development of location-based services. In this paper, we propose a grid-based approach as well as an algorithm to guarantee k-anonymity, a well-known privacy protection approach, in a location database. To do this, we assume that the service server will provide services but in a defined area and the grid will cover the area in which the service server takes effect. Then, the user’s location will be hidden in an anonymization area. The anonymization area will be chosen by cells that forms a rectangle area so that this area contains at least k distinct users. Moreover, in practice, the location of a user usually accompanies with a temporal data. And, indeed, the information about the combination of spatial and temporal data may also disclose some other sensitive information of the user. Thus, the paper also proposes an approach for guaranteeing k-anonymity for the combination of spatial and temporal database. The proposed approach considers only the information that has significance for the data mining process while ignoring the un-related information. Finally, the experiment results show the effectiveness of the proposed approach in comparison with the literature ones.

Key words: Location Privacy, Privacy Preserving, data mining, k-anonymity, spatio-temporal databases

INTRODUCTION

Today, advances in location technologies and wireless communication technologies enable the widespread development of location-based services (LBSs)\(^1\). When using the service, the user may face with risks because the location of the user can disclose some private information. For example, the attacker can keep track of information in each time the user uses the service. From there he can find the area where the user uses the service more frequently. Thus, it is necessary to protect the location information of the user from attacker\(^2\)–\(^5\). The user’s location privacy should be protected in two stages.\(^6\)–\(^9\). In the first stage, the location privacy should be protected at the time of using services. One popular method is to obfuscate the location with the service provider in order to hide the user’s location information\(^9,10\). The solution focuses on preventing the user’s location from an illegal observation at the time of service calls. We proposed an approach to hide the user’s location in\(^11,12\). In the next stage, the location privacy should be protected at the time when the user’s location information is stored in the database for data mining purposes. With this stage, the location information should be hidden before such data are shared to organizations or companies. In this paper, we focus on protecting the user’s location information when such information are stored in the database. It is assumed that when a user uses a location based service, he will provide his real location to the service server and the server will save such location information. Then, some organizations, companies or individuals will collect such location data. By using the data mining process\(^13,14\), they can obtain some valuable information. Because such location information maybe disclose some user’s privacy. For example, the attacker can queries the database to get some results, then, he can also link some priori knowledge with the results to get some sensitive information. Therefore, such location data should be protected before they are collected by organizations. Fortunately, some techniques protecting user privacy have been proposed such as k-anonymity, cryptography\(\ldots\)\(^1\). Among them, k-anonymity\(^15\) is one of the most important methods for privacy protection. The
The main idea behind k-anonymity is that some attributes in data can often be considered as pseudo-identifiers to uniquely identify the records. Thus, such attributes should be also protected.

This paper proposes a technique to anonymize the user’s spatio-temporal data to achieve k-anonymity. This approach will use a grid and anonymize the user’s location to an anonymization rectangle. The grid must cover all space where the server provides services. This approach considers also the data mining process by finding the area where has more users using the service. The paper also presents an algorithm to connect the location attribute and time attribute in a spatio-temporal database to achieve k-anonymity.

The rest of this paper is organized as follows. In section 2, we briefly summarize related works. Section 3 presents our approach to anonymize the user’s location. Next, section 4 introduces an algorithm to connect the location attribute and time attribute to achieve k-anonymity. Finally, section 5 shows some conclusions.

**RESEARCH METHODS**

**K-anonymity**

K-anonymity is an approach that protects data from individual identification. Intuitively, k-anonymity states that data must be anonymized in a way such that every combination of values of released attributes can be indistinctly matched to at least k respondents. Recently, some approaches have been introduced to ensure privacy protection when releasing data mining results. With these approaches, we first define the set of attributes, called Quasi-Identifiers (QI), whose values can be used, possibly together with external information, to re-identify the real data. For example, data about sex, the ZIP code, date of birth may not explicitly identify an individual but such data can be linked to external information to obtain name, address and city. Basically, the greater the value of k, we can get the better the protection of privacy. However, if the data is anonymized too much (that means the value of k is too big). This leads to the case that data quality for data mining process is not good. Therefore, we need the balance between data privacy and data quality and it is considered as an important factor in privacy preserving in data mining. We consider an algorithm not only to anonymize the location data but also considering the result of data mining process in this paper.

**K-Anonymity in Data Mining**

There are two possible approaches to guarantee k-anonymity in data mining:

1. Anonymize the original table and perform mining on its k-anonymous version.
2. Perform mining on the original table and anonymize the result. This approach can be performed by executing the two steps independently or in combination.

The first approach gives two benefits. First, it guarantees that data mining is safe because data mining is executed on a k-anonymized version of original table. Second, it allows data mining to be executed by others than the data holder, enables different data mining processes and different uses of the data. This is convenient, for example, when the data holder may not know a prior how the recipient may analyze and classify the data. With the second approach, Data mining can then be performed by the data holder only, and only the sanitized data mining results are released to other parties. This may therefore affect applicability.

The paper will use the first approach to guarantee k-anonymity. This allows data mining to be executed by many organizations, or companies to obtain suitable results.

**GRID-BASED APPROACH TO GUARANTEE K-ANONYMITY FOR LOCATION DATA**

When a user uses location services, he must provide his real location to the service server that provides LBSs and this information will be saved in the service server database. After that, attackers collect the user’s location information; he can find some sensitive information about the user. For example, an attacker may query the database and a result, which has just one tuple, is returned, he also has knowledge that at this location, there is just one user who is using the service. Therefore, he can decide that this tuple is for this user and can find some private information of this user. Clearly, the linking between the user's location and external knowledge can reveal the private information of the user.

To protect the information about the user from linking information, k-anonymity technique has been proposed. With this approach, the location of the user is indistinguishable from k-1 other locations. Therefore, the attacker cannot distinguish the tuple which actually contains the user’s location with other tuples. In this section, we will propose a grid approach to hide the true location of the user. We assume that the service server will provide services but in a defined area and the grid will cover the area in which the service server takes effect. First, we will have some definitions.
Definitions

Definition: A Grid $G$ is a uniform grid which contains cells, a cell is not necessary a square-shaped, it can be in a rectangle-shaped but all cells must cover the whole space. The grid has a starting point. Figure 1 a shows a grid with a starting point $S$.

Definition: An anonymization area includes cells and contains location of some users. Figure 1 b presents an area with a user $U$.

The user's location will be hidden in an anonymization area. We will create an anonymization area by choosing cells to form a rectangle area so that this area contains at least $k$ distinct users. Figure 2 shows an anonymization area with three users.

Moreover, through the data mining process, the data miner usually desires to find areas which have more users using the service. Therefore, the anonymization area should be in well-proportioned shaped. We will consider the example in Figure 3, to obtain 3-anonymity, anonymization area $A_1$ and $A_2$ are acceptable. However, anonymization $A_1$ is better in this example.

Definition: A cell is defined as a pair $(x, y)$ where $x$ is the order number of this cell in $x$ direction and $y$ is the order number in $y$ direction. For example, in Figure 4, cell $A$ is defined as $(2, 1)$.

Definition: The distance of two cells $(x_1, y_1)$ and $(x_2, y_2)$ in direction $x$ is defined as $|x_1 - x_2|$. Similarly, the distance of two cells in direction $y$ is defined as $|y_1 - y_2|$. We call the distance of two cell in direction $x$ is $d_{x}$ and in direction $y$ is $d_{y}$.

$$\text{Dis}[(x_1, y_1), (x_2, y_2)] = (d_{x}, d_{y})$$

with

$$d_{x} = |x_1 - x_2| \quad d_{y} = |y_1 - y_2|$$

Definition: An anonymization rectangle is defined as $[(x_1, y_1), (x_2, y_2)]$ where $(x_1, y_1)$ and $(x_2, y_2)$ are the left-top cell and right-bottom cell of cells in the rectangle. For example, the colored rectangle in Figure 4 b is defined as $[(2, 1), (4, 2)]$.

Normally, data miners usually desire to find an area that the number of the user in it is maximal and this area is usually not too big. Therefore, we also provide thresholds to limit the area. These thresholds are also the limitation that the data miners want to limit the area containing users. Figure 5 shows the maximum area which has threshold $t_x$ and $t_y$.

With our approach, the following rule is considered:

Area $A$ the number of users using the service in $A$ $A$ is an anonymization rectangle. Our approach will find areas and the number of users in these areas. We want to guarantee k-anonymity in the database; therefore, the number of users in any area must be greater $k$. Moreover, these areas must smaller the maximum area.
Definition: We have an anonymization rectangle $A$, threshold $tx$ and $ty$.

$A$ is safe if

$$\begin{align*}
\text{dis}_x &\leq tx \\
\text{dis}_y &\leq ty
\end{align*}$$

$\text{dis}_x$ is the distance-$x$ of any two cells in $A$ and $\text{dis}_y$ is the distance-$y$ of any two cells in $A$.

Algorithm

With $k$-anonymity approach, attributes whose values can be used, possibly together with external information, to re-identify the data, will be included in Quasi-Identifiers ($QI$). Because the attacker can use the location attribute and link to external knowledge in order to find some sensitive information of the user, the location attribute need to be included into $QI$. The $QI$ will be in the following format:

$$QI = \{Q_1, \ldots, Q_n, L\}.$$  

$L$ is the location attribute.

We assume that the location attribute does not depend on other attribute of $QI$. Therefore, we can anonymize $QI$ through two stages. The first stage is to anonymize $Q_1, \ldots, Q_n$, and the second stage is to anonymize the location attribute $L$. Our approach will focus on the second stage and not care the first stage.

In our approach, we use a grid to anonymize the location of the user. Therefore, we will anonymize the user’s location to grid cell at the first step. As discussed before, our approach will consider the rule:

**Area $A$ the number of users using the service in $A$**

The algorithm will find all areas that is smaller the maximum area (the area which is defined by thresholds $tx$ and $ty$). We will choose areas that have the most users in it. It means that users use the service more frequently in these areas. Certainly, we only choose the area which is safe.

In some cases, areas, which are not safe, are returned. In these cases, additional steps will be operated. We notice that the variable $k$, which is provided, is usually smaller the minimum number of users in an area, which the data miner desire to receive. Therefore, if

the number of users in an area is smaller $k$, we consider this area is not signification to the data mining process. In these cases, we will anonymize the location of users in this area to the closest anonymized area which is safe.

The algorithm for guaranteeing $k$-anonymity in location database is described as follows:

**Input:** $k$, threshold $tx$, threshold $ty$, location table $T$

**Output:** $k$-anonymization location table $T'$

**Method:**

Create a grid which covers the space where the server provides services.

Anonymize all location data of tuples in $T$ to grid cell.

While (exist a tuple which has not been marked)

{ 

For each tuple in $T$ and this tuple has not been marked

{ 

Find the safe anonymization area and the number of distinct users in this anonymization area is maximum.

}

From the set of anonymization areas has just found, we will choose the area in which the number of distinct users is maximal. We call this area as maximal anonymization area.

If (the number of distinct users in this maximal anonymization area $< k$)

{ 

Anonymize all location data of tuples in this area to closet anonymization area which is safe and mark the corresponding tuple in $T$.

}

Else

{ 

Anonymize location attribute of users, which belong to this maximal anonymization area, to this area and mark the corresponding tuple in the table $T$.

}

}

Return anonymized table.

In our algorithm, we ignore the case when the number of distinct users in the maximal anonymization area is smaller $k$ at the first loop. The reason for this had been mentioned above.

To explain the algorithm, we will consider an example: We have a location table with attributes **No.**, **ID**, **Location** and other data as in Table 1. Location attribute is a pair $(a, b)$ which describes the true location of the user in x and y direction. Threshold $tx$ is 2 (cells), $ty$ is 2 (cells) and $k$ is 3.

At the first step, we will anonymize all location data of tuples to grid cell. The grid cell size is 100*100 and the result is in Figure 6.
Table 1: A location table

| No. | ID | Location   | Data |
|-----|----|------------|------|
| 1   | u1 | (156, 150) | ...  |
| 2   | u2 | (460, 263) | ...  |
| 3   | u1 | (335, 158) | ...  |
| 4   | u5 | (448, 192) | ...  |
| 5   | u7 | (295, 191) | ...  |
| 6   | u8 | (388, 284) | ...  |
| 7   | u6 | (229, 365) | ...  |
| 8   | u4 | (572, 189) | ...  |
| 9   | u5 | (649, 118) | ...  |
| 10  | u3 | (320, 225) | ...  |
| 11  | u9 | (240, 224) | ...  |
| 12  | u11| (127, 358) | ...  |
| 13  | u10| (164, 167) | ...  |

At the first loop, we will find the safe anonymization area, in which the number of distinct users is maximum, for each location data of tuple. For example, tuple No. 9 has two anonymization areas which satisfy the condition. Two areas are described in Figure 7a. We can choose one among two these areas. The process is similar to other tuples. Finally, the maximal anonymization area is described in Figure 7b. We choose this area because the number of distinct users in this area is maximal.

Because the number of users in this maximal anonymization area is greater than k (value of k is 3). We will anonymize all location of users, which belong to this area and mark the corresponding tuple. In this case, location attribute of tuples No. 1, 3, 5, 6, 10 and 11 will be anonymized to anonymization rectangle \([(2, 1), (3, 2)]\).

At the second loop, the maximal anonymization area in Figure 8 is chosen. Location attribute of tuples No. 2, 8 and 9 will be anonymized to anonymization rectangle \([(4, 1), (5, 2)]\).

At the third loop, the maximal anonymization area in Figure 9 is chosen. However, the number of distinct users in this area is 2 and this value is smaller than k. Therefore, all users in this area will be "moved" to the "closest" anonymization area which is safe. In this case, the maximal anonymization area that was found in the first loop is chosen. Therefore, location attribute of tuples No. 7 and 12 will be anonymized to anonymization rectangle \([(2, 1), (3, 2)]\).

Similarity, next loops will be processed in the same way. Finally, we will have Table 2, which satisfies 3-anonymity:

K-ANONYMITY FOR SPATIO-TEMPORAL DATABASES

Discussion

In practice, the location of a user usually accompanies with a temporal data. For example, the user A was in location “U1” and used the service at “March 10, 2010”. The information about spatio-temporal...
Table 2: 3-anonymity table

| No. | ID | Location   | Data |
|-----|----|------------|------|
| 1   | u1 | [(2, 1), (3, 2)] | ...  |
| 2   | u2 | [(4, 1), (5, 2)] | ...  |
| 3   | u1 | [(2, 1), (3, 2)] | ...  |
| 4   | u5 | [(4, 1), (5, 2)] | ...  |
| 5   | u7 | [(2, 1), (3, 2)] | ...  |
| 6   | u8 | [(2, 1), (3, 2)] | ...  |
| 7   | u6 | [(2, 1), (3, 2)] | ...  |
| 8   | u4 | [(4, 1), (5, 2)] | ...  |
| 9   | u5 | [(4, 1), (5, 2)] | ...  |
| 10  | u3 | [(2, 1), (3, 2)] | ...  |
| 11  | u9 | [(2, 1), (3, 2)] | ...  |
| 12  | u11| [(2, 1), (3, 2)] | ...  |
| 13  | u10| [(2, 1), (3, 2)] | ...  |

data maybe also disclose some user’s sensitive information. In case he also has some knowledge that there is just one user, who used the service at that time and location, he will find that all tuples in the result will belong to a user. Therefore, time attribute also need to be included into QI. The structure of QI will be: \( QI = \{Q_1, \ldots, Q_n, L, T\} \). L is location attribute and T is time attribute.

The process, which anonymizes this QI to guarantee k-anonymity, is also similar to the process proposed in section 3. First, we will anonymize \( Q_1, Q_2 \ldots Q_n \) attributes. After that, L and T will be anonymized. We notice that we need to protect both spatial and temporal data. In the previous section, we introduced an approach to anonymize the location of the user. Therefore, we also need an approach to anonymize the temporal data.

Authors extend the notion of k-anonymity in the context of databases with timestamped information in order to naturally define k-anonymous views of temporal data. With this approach, time attributes can be generalized to the most common ones, as year, month or week. For example, Table 3 is the original table. We can generalize time attributes in this table to "week". We assume that we have 52 weeks in a year. The value "2009-01-03" will be generalized to value "week 1". We notice that all time data have the same year. Therefore, the value "week 1" also means that this is week 1 of year 2009. Similarly, the value "2009-01-12" will be generalized to "week 2". Table 4 is a 2-anonymous version of the original table.
We can also generalize time attributes in original table to "month". Value "2009-01-03" will be generalized to value "2009-month 1". Similarly, value "2009-02-07" will be generalized to "2009-month 2". Table 5 is another 2-anonymous version of the original table. For more details, refer to the previous section.

In order to apply k-anonymity to the database with spatio-temporal data, we notice that the location of a user accompanies with a temporal data. Therefore, when we anonymize the location of the user, we also consider the time attribute, which accompanies with the location attribute. We also notice that the data mining process result may not be significant or data is unusable if we generalize the time attribute too much.

We will consider the example in Figure 7. User u1, u3, u7, u8, and u9 are in the maximal anonymization area. We add time values to these tuples in the original table as follows:

According to the example in section 3.2, these tuples will be anonymized to the anonymization rectangle $[(2, 1), (3, 2)]$. Therefore, time attributes of these tuples are also generalized to the most common ones. In this case, time attributes will be anonymized to 2009. This interval is too long if the data miner wants statistics in each month. To avoid this case, we can also set a threshold to time attribute. Moreover, we also need to anonymize the time attribute at the same time with the location attribute. We will consider the example in Table 6. The time threshold is 2 months, threshold $tx$ is 2 (cells), $ty$ is 2 (cells) and $k$ is 2. The algorithm in section 3.2 will find all anonymization areas which are safe and choose the maximal anonymization area in which the number of distinct users is maximal. The result is in Figure 7 b. However, as discussed above, this result does not satisfy the time constraint. Therefore, the new algorithm to guarantee k-anonymity in the spatio-temporal database must choose another anonymization area which satisfies both time and location constraints. Figure 10 shows an acceptable result which satisfies all constraints. Location attributes of tuples No. 3, 5 will be anonymized to $[(2, 0), (3, 1)]$ and time attributes will be generalized to "2009-month 8_9". The result is in Figure 10 a. Similarly, location attributes of tuples No. 6, 10 will be anonymized to $[(2, 2), (3, 3)]$ and time attributes will be generalized to "2009-month 11_12" as in Figure 10 b. Tuple No. 1 will be "moved" to maximal anonymization area in Figure 10 b while tuple No.11 will be "moved" to maximal area in Figure 10 a.

In this paper, we will generalize the time attribute into intervals, which are in the formation $[a, b]$. Value $a$ is the lowest and values $b$ is the biggest of time value. For example, we will consider the following table:
Table 5: Another 2-anonymous table

| UID | QI  | Data          |
|-----|-----|---------------|
| u1  | q1  | 2009-month 1  |
| u2  | q1  | 2009-month 1  |
| u3  | q1  | 2009-month 1  |
| u4  | q1  | 2009-month 1  |
| u5  | q2  | 2009-month 2  |
| u6  | q2  | 2009-month 2  |

Table 6: A spatio-temporal table

| No. | ID | Location | Time    | Data |
|-----|----|----------|---------|------|
| 1   | u1 | (156, 150)| 2009-01-03 | ...  |
| 3   | u1 | (335, 158)| 2009-07-09 | ...  |
| 5   | u7 | (295, 191)| 2009-08-12 | ...  |
| 6   | u8 | (388, 284)| 2009-11-07 | ...  |
| 10  | u3 | (320, 225)| 2009-12-25 | ...  |
| 11  | u9 | (240, 224)| 2009-06-19 | ...  |

Figure 10: Maximal anonymization areas for spatio-temporal data

Table 7: Time attribute generalization

| No. | QI  | Data |
|-----|-----|------|
| 1   | q1  | 2010-01-12 |
| 2   | q1  | 2010-02-25 |
| 3   | q1  | 2010-01-16 |
| 4   | q1  | 2010-02-08 |
With our approach, these time attributes in table 7 will be generalized to [2010-01-12, 2010-02-25].

Similar to the location attribute, which data miners usually desire to find an area that the number of the user in it is maximal and this area is usually not too big, with the time attribute, we also set a threshold \(t_{time}\). Therefore, all intervals, which are the result of generalization, will be smaller than this time threshold. This threshold is also the limitation that the data miners want to limit time intervals. It also means that the data miner will mine the valuable information from the data but time intervals are not bigger than the time threshold.

As defined before, anonymization rectangle \(A\) is safe if the distance of any two cells in both direction \(x\) and \(y\) is smaller than thresholds \(tx\) and \(ty\). However, in a spatio-temporal database, the time attribute also accompanies with the location attribute. Therefore, we will redefine the safe anonymization rectangle \(A\) as follows:

Definition: The distance of two time values, \(a\) and \(b\), is \([a - b]\). We call this subtraction as time-distance(\(a, b\)).

Definition: We have an anonymization rectangle \(A\), threshold \(tx\) and \(ty\) and \(t_{time}\).

\[
A \text{ is safe if } \begin{cases} 
\text{dis}_x \leq tx \\
\text{dis}_y \leq ty \\
\text{dis}_time \leq t_{time}
\end{cases}
\]

\(\text{dis}_x\) is the distance-x of any two cells in \(A\), \(\text{dis}_y\) is the distance-y of any two cells in \(A\), \(\text{dis}_time\) is the time-distance of the time value of any two tuples which have location attribute value in \(A\).

Clearly, a trade off between location anonymization and time generalization is very important to achieve \(k\)-anonymity in a spatio-temporal database. In the next section, we will introduce an effective algorithm to anonymize location and time attributes in spatio-temporal database in order to guaranteeing \(k\)-anonymity.

**Algorithm**

As discussed before, the structure of \(QI\) will be:

\(QI = [Q_1, \ldots, Q_m, L, T]\).

\(L\) is location attribute and \(T\) is time attribute.

To guarantee \(k\)-anonymity in database with this structure of \(QI\), we can anonymize \(QI\) through two stages.

The first stage is to anonymize \(Q_1, \ldots, Q_m\) and the second stage is to anonymize the location attribute \(L\) and \(T\). Again, we will not care the first stage and focus on the second stage.

In our algorithm, we will anonymize the location and time value of tuples in the original table to corresponding safe anonymization rectangles and intervals. The algorithm will choose the areas in such a way that the results of the anonymization should be significant to data mining. These areas are also where users use the service more frequently. With other areas which are not good to the data mining, the algorithm will "move" them to closet significant area.

At the first step, we build a grid and then hide the user’s location data to the grid. With our approach, we want to find all areas that satisfy all thresholds and the number of distinct users, who uses the service in these areas, is maximal. Therefore, we will find all safe anonymization areas for the time and location value of each tuple, which has been not anonymized, and choose the safe area that the number of distinct users in this anonymization area is maximum. We call this area as \(\text{tuple_maximal_anonymization_area}\).

In our algorithm, the \(\text{find_safe_max_anonymization()}\) function will be responsible for this work. After the previous step, we get a set \(X\), which contains all \(\text{tuple_maximal_anonymization_area}\) for each tuple. From this set, we will choose the \(\text{tuple_maximal_anonymization_area}\) which has the number of distinct users in this area is maximum. We call this area as \(\text{maximal_anonymization_area}\). Finally, we will anonymize all the location data and time data of tuples, which belong to this \(\text{maximal_anonymization_area}\), to corresponding value, namely \(\text{maximal_anonymization_area}\) for location data and an interval for time data. Approaches for anonymizing the location data and time data are discussed before.

**Name:** \(\text{k-anonymization Algorithm}()\)

**Input:** \(k\), threshold \(tx\), threshold \(ty\), threshold \(t_{time}\), spatio-temporal table \(T\)

**Output:** \(\text{k-anonymization location table } T’\)

**Method:**

Create a gird \(G\) which covers the space where the server provides services. Anonymize all location data of tuples in \(T\) to grid cell. \(X = \emptyset\)

While (exist a tuple which has not been marked)

{} For each tuple in \(T\) and this tupe has not been marked

{} \(\text{tuple_maximal_anonymization_area} = \text{find_safe_max_anonymization}()\);

{} \(X = X U \text{tuple_maximal_anonymization_area}\);

{} \(\text{Maximal_anonymization_area} = \text{choose the tuple_maximal_anonymization_area which has the}\)
number of distinct users in this area is maximum from X.
If (the number of distinct users in this maximal anonymization area < k)
    Anonymize all location and time data of tuples in this area to closest anonymization area which is safe.
    Mark the corresponding tuple in the table T.
} Else
    Anonymize location attribute of users, which belong to this maximal anonymization area, to this area and generalize all time data of these tuples to an interval.
    Mark the corresponding tuple in the table T.
} Return anonymized table.
When the number of distinct users in the maximal anonymization area is smaller than k, we will consider this area is not significant to the data mining process. Therefore, we will anonymize all location and time data of tuples in this area to "closest" safe anonymization area. We discussed this idea in section 3.2.
The find_safe_max_anonymization() function will choose the safe area for the time and location data of each tuple that the number of distinct users in this anonymization area is maximum. At the first step, this function will find all safe areas according to the time and location value which is input parameter. Among them, it will choose the safe area that the number of distinct users in this anonymization area is biggest.
Name: find_safe_max_anonymization()
Input: a tuple t contains time and location data, threshold tx, threshold ty, threshold t_time, spatio-temporal table T, Grid G
Output: tuple_maximal_anonymization_area for tuple t and a set O which contain tuples belong to tuple_maximal_anonymization_area
Method:
Arrange T in order to tuples t1, t2, t3 ... in T will satisfy t1.time < t2.time < t3.time
Give set Y = all anonymization area which contain t.location and satisfy both thresholds tx and ty
Variable count_max = 0
tuple_maximal_anonymization_area = null;
For each y in Y
    Variable count_y = 0
    R = all tuple i in T and i.location belongs to y
    For each t’ in R and index of t’ in R <= the index of t
        if time-distance(t’.time, t.time) <= t_time
            tuple tp
            For each tuple tr in R and index of tp in R >= the index of t
                tp = tr;
            if time-distance(tp.time, t’.time) > t_time
                Exit For
        end if
    end for
    if index_of_tp_in_R – index_of_t’ in R – 1 > count_y
        count_y = index_of_tp_in_R – index_of_t’ in R – 1
        Give set O = all tuples in R from (index_of_t’ in R) to (index_of_tp_in_R – 1)
    end if
    if (count_y > count_max)
        count_max = count_y
tuple_maximal_anonymization_area = y
        Remember set O
    end if
} Return tuple_maximal_anonymization_area, O
This function will return the tuple_maximal_anonymization_area and a set O contains tuples which satisfy location and time constraints. tuple_maximal_anonymization_area always accompanies with a set O. Therefore, when this area is chosen as maximal_anonymization_area, all tuples in O will be anonymized.

EXPERIMENTS
We show the experiment for the evaluation of the effectiveness of proposed approach. With our tests, the data mining process wants to find the time interval, when users use the service more frequently. The data mining process will work with the original table and k-anonymous table version, which generated by our algorithm. We will compare these two results by getting the overlapped interval between two results. Clearly, the proposed approach is effectiveness if this overlapped interval is large. We will use a ratio to describe this effectiveness:

\[ \frac{R_{time}}{O_{time}} = \frac{overlapped_t}{original_result_t} \]

original_result_t is the result which the data mining process works with original table. overlapped_t is the overlapped interval between the results of original table and our k-anonymous version. As discussed, the larger the ratio, the more effective the approach.
We will evaluate the approach with a spatio-temporal table with more than 2000 records. The number of distinct users is more than 50. The grid cell size and k are changed in each test case. In each case, we will change the maximum area and maximum time interval which data miner desires to be processed from data mining process. The maximum area is max area column and the maximum time interval is max interval column in the Table 8.

In Table 8, k will be 5, 10, and 20 for each test. The ratio value is the average of three tests when k is 5, 10 and 20. The result shows that in most case the ratio is larger than 80%. It also means that our approach will generate a k-anonymous version of the original table in which the data mining process can find significant information as when working in original table.

CONCLUSIONS AND DISCUSSIONS

In this paper, we propose a technique for anonymizing the spatio-temporal database. With this technique, we can anonymize the location and time data easily. We also consider the data mining process result to develop an algorithm, which tradeoffs between data privacy and data quality. In the future, we will focus on improving the algorithm in order to guarantee k-anonymity in a big spatio-temporal database more efficiency.

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CONFLICT OF INTEREST

We claim that there is no conflict of interest in this article.

AUTHOR CONTRIBUTION

Anh Truong is the only author of this article.

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Table 8: Results of experiment

| tx*ty (m*m) | t_time (days) | k  | Cell size (m) | max area (m*m) | max interval (days) | Ratio Rtime (%) |
|------------|---------------|----|--------------|----------------|---------------------|-----------------|
| 90*90      | 30            | 5,10,20 | 30           | 200*200        | 120                 | 88.97           |
| 90*90      | 30            | 5,10,20 | 30           | 400*400        | 150                 | 87.53           |
| 90*90      | 60            | 5,10,20 | 30           | 200*200        | 120                 | 88.31           |
| 90*90      | 60            | 5,10,20 | 30           | 400*400        | 150                 | 86.42           |
| 150*150    | 30            | 5,10,20 | 50           | 300*300        | 120                 | 84.62           |
| 150*150    | 30            | 5,10,20 | 50           | 500*500        | 150                 | 85.02           |
| 150*150    | 60            | 5,10,20 | 50           | 300*300        | 120                 | 84.19           |
| 150*150    | 60            | 5,10,20 | 50           | 500*500        | 150                 | 83.97           |
| 300*300    | 30            | 5,10,20 | 100          | 500*500        | 120                 | 81.74           |
| 300*300    | 30            | 5,10,20 | 100          | 800*800        | 150                 | 80.36           |
| 300*300    | 60            | 5,10,20 | 100          | 500*500        | 120                 | 79.92           |

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Bảo vệ tính riêng tư cơ sở dữ liệu không-thời gian dựa trên k-anonymity

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Tóm tắt
Sự phát triển của các dịch vụ dựa trên vị trí và các thiết bị di động đã dẫn đến việc sinh ra các dữ liệu vị trí. Thông qua quá trình khai thác dữ liệu, các thông tin có ích sẽ được khai thác từ dữ liệu vị trí này. Điều này cũng đồng nghĩa với việc kẻ tấn công có thể lợi dụng để rút trích các thông tin riêng tư của người sử dụng từ các dữ liệu này. Vì dự, kẻ tấn công có thể xem thông tin vị trí của người dùng để xác định địa chỉ nhà của họ. Bởi vậy, việc bảo vệ thông tin vị trí trở thành một yêu cầu quan trọng. Trong bài báo này, chúng tôi giới thiệu hướng tiếp cận dùng lưới tương thích cũng như một giải thuật để đảm bảo k-anonymity cho các cơ sở dữ liệu vị trí. Để làm điều này, chúng tôi giả thiết rằng các dịch vụ vị trí sẽ cung cấp dịch vụ trong một vùng không phân chia và một lối tương thích sẽ được tạo ra trong vùng này. Sau đó, vị trí của người sử dụng sẽ được ẩn danh trong một vùng ẩn danh. Các vùng ẩn danh này sẽ được lựa chọn theo nguyên tắc là có ít nhất k người sử dụng trong vùng ẩn danh. Chúng tôi cũng đề xuất hướng tiếp cận để đảm bảo k-anonymity cho dữ liệu kết hợp cả không và thời gian. Hướng tiếp cận được đề xuất sẽ chỉ xét các thông tin có ý nghĩa cho quá trình khai thác dữ liệu trong khi bỏ qua các thông tin không liên quan khác. Cuối cùng, các kết quả thực nghiệm chỉ ra sự hiệu quả của giải pháp đề xuất khi so sánh với các giải pháp khác.

Từ khoá: Tính riêng tư vị trí, Bảo vệ tính riêng tư, khai thác dữ liệu, k-anonymity, cơ sở dữ liệu không-thời gian.

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