Location Privacy Preservation of Vehicle Data in Internet of Vehicles

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Agenda

- Introduction
- Motivation
- Background: Privacy Techniques
- Overview of privacy techniques and Proposed attacks, with solutions
- Experiment
- Evaluation and Analysis of Results
- Conclusion and Future Work
Introduction
Internet of Vehicles (IoV)

- **Background**
  - A branch from the Internet of Things (IoT) network.
  - Evolution of traditional Vehicular Ad Hoc Networks (VANETs) with new enabling technologies such as Cloud and 5G.
  - Data exchange is involved in IoV.

- A simple form of IoV data may include an ID, a timestamp, and the location of a vehicle.

- **In this paper, we focus on protecting the identity of individuals being revealed from sharing location data in IoV applications.**
Challenges for IoV Location Privacy

- Location data is unevenly distributed. Applying state-of-the-art privacy protection such as differential privacy protection to each single point will overwhelm sparse locations with noise.
- Preservation of location patterns and traceability is important for IoV applications.
- Design an efficient data structure to represent IoV location data due to high velocity and volume.
Traditional location privacy research in VANETs: replace the true vehicle ID with a pseudonym.

- **Pro’s:** anonymity and trace-ability
- **Con’s:** storage burden for preloading the digital certificates to vehicles [Raya and Hubaux, 2007], relies on Tamper-Proof Device [Wang et al., 2016], or Trace Authority (TRA) [Zhong et al., 2019]

“Geo-indistinguishability” of fitness tracking social network

- **Pro’s:** protects large locations [Bates et al., 2018] and popular locations [Yin et al., 2018].
- **Con’s:** does not protect sensitive locations accessed by less unique users.

Lack of consensus on the definition of location privacy.

There are few holistic views of location privacy breaches and mitigation at different stages of an IoV application.
Our Contribution

1. We examine potential attacks of location privacy for IoV traffic condition service.

2. We provide a novel birds eye view of existing location privacy preserving techniques and provide a scheme of evaluating these techniques for IoV traffic condition service.

3. We show that instead of locations that are accessed frequently, the locations with less unique visitors are extremely sensitive. We use k-d tree data structure to aggregate locations into groups and apply Differential Privacy (DP) to protect sensitive locations. We show that our strategy produces differentially private data, good preservation of utility by achieving similar regression accuracy to the original dataset on an Long Term Short Term Memory (LSTM) neural network traffic predictor.
Motivation
Model Setting and Problem Statement

- **Setting:** Storage of IoV data in Cloud.
- **Data composition:** ID, timestamp, location.
- **Cloud application:** Provide traffic condition services with three stages:
  1. **Traffic update** from vehicle to cloud.
  2. **Traffic data storage** in cloud.
  3. **Traffic query** from vehicles or third party to cloud.
Potential Attacks of Location Privacy for IoV Traffic Condition Service

Attack 1: Simple UserID **background attack**.

**Assumption:** Cloud uses the same ID for each user. Adversary does not know a user’s ID but has background information about the user.

**Scenario:** Each day Officer Tom checks in at a military base that only he has access to. The adversary happens to know this, as well as the location of the military base. The adversary finds out Tom’s user ID by this query: “SELECT * FROM DB WHERE UserID = (SELECT UserID FROM DB WHERE location = X)”, where X is the location of the military base. Now the adversary can learn the location of Officer Tom even when he is not at the military base.
Potential Attacks of Location Privacy for IoV Traffic Condition Service

Attack 2: Dynamic UserID **background attack**.

**Assumption:** Cloud uses different ID’s for each user. Adversary still has background information about the user as in Attack 1.

**Scenario:** The adversary runs the query: “SELECT count(*) FROM DB WHERE location = X”, where X is the location of Officer Tom’s military base. The Cloud will return a value, 0 or 1 indicating whether Officer Tom is there or not at the current time.
Attack 3: **Untrusted** Cloud attack.

**Assumption**: Cloud is the adversary and users are innocent. The Cloud contains traffic conditions of various locations that a user may be interested in but does not have this particular user’s location.

**Scenario**: If Tom queries the Cloud regarding a particular location, then the Cloud can infer that Tom may be interested in this location. If the Cloud’s method for identifying individual users are unclear, the Cloud can still determine which locations are popular and which are not based on the number of queries about a particular location.

**Note**: This attack is less likely to happen in practice, but it is important to be considered.
Background: Privacy Techniques
Formal definition of privacy: A randomized function $K$ gives $\epsilon$-differential privacy if for all datasets $D$ and $D'$ differing on at most one row, and all $S \subseteq Range(K)$, $Pr[K(D) \in S] \leq \exp(\epsilon) \times Pr[K(D') \in S]$.

Offers a framework to develop privacy solutions:
1. $A$ is an algorithm used to compute traffic flow at locations
2. $D$ is the database with Tom’s record
3. $D'$ is the database without Tom’s record
4. Adds a random noise to the answer of $A$
5. Make $D$ indistinguishable from $D'$ by a factor of $\epsilon$

Constrained to aggregate data analysis
Private Information Retrieval [Chor et al., 1997]

Technique to protect the users that query the database.

1. User’s query is encrypted and given to the database
2. Database runs computation on encrypted query
3. An encrypted result is returned to the user
4. Decryption is done on the user’s side
Garbled circuit provides an environment for secure (and therefore private) computation between two parties, where the receiving party (evaluator) is only able to perform computation on the encrypted result of the sending party’s (garbler’s) message.

1. The garbler takes input values to a gate and encrypt them.
2. The garbler performs the gate operation on the input values prior to encryption to obtain the output value.
3. Each encrypted input is paired with the corresponding output and the value is stored together in the re-arranged truth table.
4. The evaluator receives the garbled gate from the garbler.
5. The evaluator completes decryption of exactly one ciphertext from the garbled truth table through a process called “oblivious transfer.”
Overview of privacy techniques and Proposed attacks, with solutions
## Location Privacy Metrics in IoV for Traffic Condition Service

<table>
<thead>
<tr>
<th>Privacy Concerns</th>
<th>Dynamic Pseudonym</th>
<th>Differential Privacy</th>
<th>Private Information Retrival</th>
<th>Trusted Agency + Garbled Circuit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location Privacy at Traffic Update</td>
<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Location Privacy at Traffic Storage</td>
<td>✓</td>
<td>✓ ✓</td>
<td></td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Location Privacy at Traffic Query</td>
<td>✓</td>
<td></td>
<td>✓ ✓</td>
<td>✓ ✓</td>
</tr>
</tbody>
</table>

The number of ticks represents the effectiveness of a technique for a particular privacy concern.
## Location Privacy Parties in IoV for Traffic Condition Service

<table>
<thead>
<tr>
<th>Parties</th>
<th>Dynamic Pseudonym</th>
<th>Differential Privacy</th>
<th>Private Information Retrival</th>
<th>Trusted Agency + Garbled Circuit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Third Party Agency</td>
<td>Trusted</td>
<td>N/A</td>
<td>N/A</td>
<td>Trusted</td>
</tr>
<tr>
<td>Cloud</td>
<td>Not Trusted</td>
<td>Trusted</td>
<td>Not Trusted</td>
<td>Not Trusted</td>
</tr>
<tr>
<td>Vehicle</td>
<td>Trusted</td>
<td>Not Trusted</td>
<td>Trusted</td>
<td>Trusted</td>
</tr>
</tbody>
</table>
The Cloud is the adversary and the vehicle and Trusted Agency (TA) are trusted.

A user’s real identifier is mapped to a list of pseudonyms that change at a predetermined time.

Only the TA is able to determine the real identity of the mapped pseudonyms.

Susceptible to Attack 2: Dynamic UserID background attack.
Differential Privacy

- The Cloud is trusted but the vehicle is not.
- The user will attempt to gain information about other users using seemingly harmless queries.
- Strong privacy at traffic storage: Noise is added to the database rows to maintain data privacy and utility at the same time.
- No location privacy protection for traffic update and query:
  1. Vehicles are constantly checking in their locations to the Cloud with updates. This breaks Differential Privacy if the Cloud is not dynamically updating its records.
  2. If an adversarial user queries the Cloud regarding traffic information in various locations they may be able to obtain a picture of what the general traffic concentration appears to be.
The Cloud is the adversary and the vehicle is trusted.
The Cloud has no way of knowing what the vehicles are querying because the queries are encrypted.
If a vehicle chooses to update the Cloud at any point, its exact location will be revealed to the adversary.
This technique attempts to satisfy each metric that we are evaluating with but it is also most complex.

The Cloud is the adversary, and the vehicles and TA are trusted.

Location privacy at update and storage: the Cloud only receives encrypted data to store and cannot directly decrypt this without some assistance from the TA, which does not expose the location of the vehicle without the vehicle's permission.

Location privacy at query: on a query about traffic related to a certain location, the Cloud is not aware of the value that is being requested for.
Experiment
We investigate Differential Privacy to centrally stored location data using the Gowalla location-based social network check-in data.

Although the dataset is not strictly IoV data, it shares similarity with IoV data by having location, timestamp, and ID in each row. The data is preprocessed to be more suitable for the experiment.
We generalize individual locations to location groups by splitting the geometric plane using $k$–$d$ tree such that each group has roughly the same amount of locations. Each row of the aggregated data includes timestamp, location group, and unique count of users. We then apply Laplace noise to the user count to achieve $\epsilon$–Differential Privacy for the location data.
Data Cleaning

Original Gowalla Locations Including Outliers

Normalized Gowalla Locations Without Outliers
In order to prepare a differentially private dataset for sharing and publishing, it is important to make sure a contingency table is built on top of the original generalized data and before Differential Privacy is applied.

For our data, building a contingency table means to create continuous dates for each location group and unique user combination.

We calculate the minimum and maximum dates in the dataset, and add missing dates to all location groups with user count set to 0.
Generalization: Gowalla Location Groups and User Counts ($k - d$ tree depth = 6)
From the first glance, this dataset shares similar distributions as the original dataset. At a closer look, we can notice the noise added to each location group.
Evaluation and Analysis of Results
In order to quantify the utility of our differentially private dataset, we measure and compare the regression accuracy of a traffic predictor when it is trained by the original dataset and the differentially private dataset.

We use an LSTM traffic predictor utilized in [Fu et al., 2016] and train two models using 2009-02-04 to 2010-08-31 of the original and differentially private datasets as training data respectively, and then we use the 2010-09-01 to 2010-10-23 of the original dataset as test data. The model is trained with a sliding window of 7 (representing one week) and iteration of 600.
After successfully training our predictors, we measure the regression accuracy of the predictors in terms of explained variance score, Root Mean Squared Error (RMSE) and R2 score using the metrics package of Python scikit-learn. The following table shows the comparison of predictions made by models trained by different versions of location data for Gowalla location group 63. We observe that the predictor trained with 0.1—differentially private data has very close accuracy to the model trained with original data.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Orig model</th>
<th>$DP \epsilon = 0.1$</th>
<th>$DP \epsilon = 0.5$</th>
<th>$DP \epsilon = 1.0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explained variance score</td>
<td>0.713</td>
<td>0.670</td>
<td>0.390</td>
<td>0.469</td>
</tr>
<tr>
<td>RMSE</td>
<td>45.676</td>
<td>48.893</td>
<td>56.583</td>
<td>50.343</td>
</tr>
<tr>
<td>R2 score</td>
<td>0.513</td>
<td>0.442</td>
<td>0.253</td>
<td>0.409</td>
</tr>
</tbody>
</table>
In general, the predicted data by all DP-data-trained models are reasonable compared to the real data.
Conclusion and Future Work
We conduct a thorough study of location privacy in IoV traffic condition service through investigation of potential attacks and mitigation.

Based on this knowledge, we develop a novel overview of location privacy preservation scheme.

For experiment, we develop a Differential Privacy strategy to centrally store location data and demonstrate the preservation of data utility quantitatively.
Many avenues are open for research on the techniques we have proposed here.

Private Information Retrieval (PIR) can be studied much more extensively to determine its overall effectiveness and to examine whether there is another variant of PIR or some existing technique coupled with PIR to satisfy location privacy using the three metrics designed in this section.

Conducting some experiments on the Trusted Agency (TA) and Garbled Circuit technique could also be an important step to implement a robust location privacy preserving technique as it provides the most utility and the most privacy of all models observed in this paper.
Thank You!