Driver Locations Harvesting Attack on pRide

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Abstract. Privacy preservation in Ride-Hailing Services (RHS) is intended to protect privacy of drivers and riders. pRide, published in IEEE Trans. Vehicular Technology 2021, is a prediction based privacy-preserving RHS protocol to match riders with an optimum driver. In the protocol, the Service Provider (SP) homomorphically computes Euclidean distances between encrypted locations of drivers and rider. Rider selects an optimum driver using decrypted distances augmented by a new-ride-emergence prediction. To improve the effectiveness of driver selection, the paper proposes an enhanced version where each driver gives encrypted distances to each corner of her grid. To thwart a rider from using these distances to launch an inference attack, the SP blinds these distances before sharing them with the rider.

In this work, we propose a passive attack where an honest-but-curious adversary rider who makes a single ride request and receives the blinded distances from SP can recover the constants used to blind the distances. Using the unblinded distances, rider to driver distance and Google Nearest Road API, the adversary can obtain the precise locations of responding drivers. We conduct experiments with random on-road driver locations for four different cities. Our experiments show that we can determine the precise locations of at least 80% of the drivers participating in the enhanced pRide protocol.

Keywords: Ride-Hailing Services, Privacy and Censorship, Attacks

1 Introduction

According to a recent research by MordorIntelligence®, the global Ride-Hailing Services (RHS) market, valued at USD 113 billion in 2020, is expected to reach
USD 230 billion by 2026. With such a huge reach, individual privacy and security issues are always of primary concern. Ride-Hailing Service Providers (SP) like Uber, Lyft, Ola provide services in many parts of the world. Among other features, the SP facilitates ride booking and fare payment options for their customers, namely riders who subscribe with the SP for RHS. Drivers of vehicles such as cars and motorcycles sign-up with the SP in order to offer rides. At the time of subscription, the SP collects private information of riders and drivers in order to provide services effectively as well as required by local governance laws. In addition, the SP collects statistics of riders and drivers for every ride that is offered in its network. This naturally brings up the topic of individual data privacy concerns from both riders as well as drivers over their data held by the SP. Also, curious or malicious drivers or riders might be interested in learning more about the other parties. There are a number of works and their analysis in the literature that look at privacy-preserving RHS, we list some of them in Section 5.

Huang et al. proposed pRide \cite{1}, a privacy-preserving online RHS protocol that aims to provide the optimum driver in a global perspective thereby minimizing the unnecessary travel distance to pick the rider. The protocol makes use of a deep learning model to predict emergence of new ride requests in a ride-hailing region to enable the SP to make use of such prediction while matching optimum drivers to ride requests. They show that by using such a prediction model in a global perspective, the overall distance travelled by a matching driver is minimized compared with matching a nearest driver in the local region. The protocol proposes to use a Somewhat Homomorphic Encryption (SHE) scheme to encrypt rider and driver locations. The advantage of using a homomorphic encryption scheme is that it allows computations on ciphertexts so that the result of computation is available only after decryption. Fully Homomorphic Encryption (FHE) schemes that support potentially any number of homomorphic operations have high cost in terms of large ciphertexts and high computation latency. Hence, many practical applications that know, a priori, the bound on the number of homomorphic operations, prefer to use SHE schemes. In the pRide paper, the authors use the FV cryptosystem \cite{2} in the implementation of their scheme. Even though applications make use of semantically secure cryptosystems, careful analysis is required to make sure no unintended security holes are introduced while adapting the cryptosystem to their applications.

The pRide protocol, described in more detail in Section 2, has two parts, the basic protocol and an enhanced version. We discuss the basic protocol in this paragraph. In the initialization phase, SP divides the area of its operation into grids, the details of which are made available to all parties. SP keeps a record of ride requests emanating from each grid over specific time epochs and trains a prediction model using this information. It then uses this information to predict the grid-based distribution of requests for the next period, denoted by $PR(g)$, namely the prediction result for grid id $g$. Drivers, registered with the SP, submit their current grid id to the SP so that the SP can maintain the driver distribution map. A rider who wishes to hail a ride, picks a (public key, secret
key) pair, encrypts her coordinates and sends the ciphertext and public key to SP along with the ride request. When SP receives the ride request, it performs a search for a suitable driver in a preset order of grids around the rider’s grid and obtains a list of candidate drivers using the driver distribution map. SP then forwards the ride request to all candidate drivers. To offer their ride, drivers respond to SP by encrypting their location using the rider’s public key. SP then homomorphically computes the square of the Euclidean distance between rider and drivers’ encrypted locations and forwards the same to the rider along with $PR(g)$ where $g$ is the driver’s grid id. Rider decrypts the distance and picks the shortest distance $D_0$. It then performs two checks over the list of sorted distances. First, is $D_i - D_0 < D_0 - D_{diag}$?, where $D_i$ is the distance for $i^{th}$ driver and $D_{diag}$ is the length of the diagonal of the grid, and second, does the model predict no new ride request emerging in the driver’s grid within a short time period? When both these conditions are satisfied, the rider informs SP about the selected index $i$ after which the SP facilitates secure ride establishment with the rider and selected driver.

In order to optimize their ride matching, the paper proposes enhanced pRide built on top of the basic pRide protocol, but having a different method to pick the optimum driver. They show that they get better results when a driver also provides her encrypted distance to the farthest corner of her grid. This way the rider can use that distance, instead of $D_{diag}$ in the aforementioned check to select the optimum driver. However, the authors notice that if such a distance is decrypted by an adversarial rider, she can launch an inference attack to obtain driver’s locations. In order to thwart such an attack, the paper proposes a novel method where the driver provides SP with her encrypted distances to the four corners of her grid. SP then picks random integers to homomorphically blind the distances before sharing the same with the rider. Rider then decrypts the blinded distances and applies a private comparison algorithm which determines the result of the inequality $D_i - D_0 < D_0 - D_{maxdist}$, where $D_{maxdist}$ is the distance between the driver and the farthest corner of her grid $g$. Finally, using this inequality and $PR(g)$, it outputs the optimum selected driver.

As described earlier, in the enhanced pRide protocol, the SP homomorphically blinds the encrypted distances with random integers before sharing them with the rider. In this paper, we show that such a blinding scheme is insecure, whence an adversary rider can recover the underlying distances and then deduce the locations of at least 80% of the drivers responding to a single ride request of the rider when using the enhanced pRide protocol.

1.1 Comparison with ORide [12] Protocol

The pRide paper shows that their enhanced scheme is more effective with the same level of security as that of the basic version with only a small compromise in its efficiency. In addition, by way of experiments, they show their computation
cost is significantly better compared to a state-of-the-art protocol named ORide [12]. We note here that the method in the basic pRide protocol where the SP employs the homomorphic property of SHE to compute the Euclidean distance between driver and rider to share the encrypted distances with rider is identical to what is described in the ORide paper. The part that is different is that in the ORide paper to pick the nearest driver, only drivers inside the rider’s grid are chosen as candidate drivers, whereas in the pRide protocol, only drivers outside the rider’s grid are candidate drivers so as to optimize in a global perspective.

In [5], Kumaraswamy et al. demonstrated a driver locations harvesting attack by honest-but-curious riders on the ORide protocol, where they determine the exact locations of 40% of drivers participating in the ORide protocol. In the same paper, the authors also provide a mitigation solution wherein a driver gives her perturbed location instead of her actual location. The aforementioned attack on the ORide protocol and the mitigating solution are both applicable to the basic pRide protocol.

In [10], Murthy et al. demonstrated a driver locations harvesting attack, again by honest-but-curious adversary riders, using triangulation on the ORide protocol, where they show that they can determine the exact locations of all participating drivers in the ORide protocol. Further, they extend their method onto the mitigation solution suggested by [5] and show that they can determine locations of between 25% to 50% of the participating drivers.

As mentioned earlier, in the pRide protocol, the method where the rider obtains encrypted driver distances is identical to that in the ORide protocol. Due to this, any location harvesting attack on ORide, like in the cases of [5] and [10], are also directly applicable to the basic pRide protocol.

1.2 Our Contribution

We present a passive driver location harvesting attack on the enhanced pRide protocol. The honest-but-curious adversary rider issues a single ride request with a search radius ($SR = 1$), such that grids adjacent to the rider’s grid are searched (as explained in the pRide paper, Section V-B-4, pp. 6). In our attack, the adversary rider receives, per driver, a set of encrypted blinded distances between the driver’s location and each corner of the driver’s grid. One would expect that such a blinding process would make it hard for the rider to deduce anything about the underlying distances.

Rider decrypts the ciphertexts received from SP to obtain blinded distances. Next, by computing the Greatest Common Divisor (GCD) of the blinded distances and eliminating common factors, the rider recovers the blinding values after which the distances are easily obtained. Rider now has the four distances from driver to each corner of the driver’s grid. Using these distances, the rider computes four equiprobable driver locations in each of the four grids adjacent to the rider’s grid. This is due to the fact that the distances are in random order and, so, there is no correlation between each corner of the grid and its distance to the driver. Rider knows the distance between herself and each responding driver. Now, using the distance between herself and a particular responding driver (say,
δ), the rider draws a rider-circle with center as her location and radius = δ. Probable driver locations that lie on the rider-circle are filtered in and in case multiple such locations are obtained, Google Nearest Roads API [2] is used to output one location that is closest to a motorable road. We conduct our experiments using rectangular grids on four different cities around the world and the results are summarized in Table 1. We show that we can obtain exact driver locations of up to 80% of drivers who respond to a rider’s request.

Our attack invalidates Theorem 4, pp. 9, of the pRide paper [4], which states that pRide is adaptively $L_{access}$ semantically secure against semi-honest adversaries, where $L_{access}$ gives the access pattern of the SP and rider, which is simply the list of drivers that respond to a specific ride request. Hence, when our attack is combined with that in [10], the driver location security of the pRide paper is fully compromised, and so is the mitigation solution of [5] if applied to the basic pRide protocol. We stress that the attack from [10] is not directly applicable to the pRide protocol, but works only in combination with our attack.

The rest of the paper is organized as follows. Section 2 describes the pRide protocol. Section 3 describes our attack. Section 4 gives details about our experiments and results. Section 5 gives some of the recent works in privacy-preserving RHS, followed by conclusions.

2 Overview of pRide Protocol

In this section, we provide an overview of the pRide protocol followed by a description of the threat model adopted therein. For more details, the interested reader is referred to the original paper [4].

Remark: Unless qualified as enhanced or basic, we will use the term pRide protocol to refer to the complete pRide protocol, consisting of both the basic and enhanced parts.

2.1 pRide Protocol

pRide is a privacy-preserving online ride-hailing protocol augmented with a grid-based rider emergence prediction. The key objective of the protocol is to achieve optimum driver selection in a global perspective instead of picking the nearest driver as done in other works [12,13]. Selecting such a driver might be a better choice in order to minimize the overall empty travel distance traversed by drivers to pick up riders in the whole system. The prediction of requests based on deep learning plays an important role in driver selection.

The protocol has two parts, the basic protocol and an enhancement, built on top of the basic protocol, are summarized in the following steps. Steps 1 to 10 constitute the basic pRide protocol, followed by steps of the enhanced pRide protocol.

1. The three parties involved in the pRide protocol are: driver, rider and service provider (SP). The SP does not collude with either rider or drivers. The SP as
well as the users, namely, drivers and riders, are honest-but-curious entities who execute the protocol correctly, but are keen on knowing about each other’s sensitive information. The protocol aims to protect all users’ privacy from other riders and drivers, such that the precise location of one party is not learnt by the other party during the ride matching process. However, only after a driver is matched with a rider, they start to communicate through a secure channel.

2. During system initialization, the SP divides its area of its operation into rectangular grids of suitable sizes (size is based on sufficient ride density so as to maintain rider anonymity) and publishes the same. For example, a city like New York City together with its surrounding boroughs, where the SP is allowed to provide rides as permitted by local authorities, can be termed as the SP’s area of operation.

3. Drivers, available to offer rides, submit their real-time grid id to the SP to enable it to maintain a driver distribution map.

4. Rider, wishing to hail a ride, generates a key pair (public key \( p_k \), private key \( s_k \)) from the FV SHE scheme [1], encrypts her location using \( p_k \), and submits a ride-request along with her location ciphertext, her current grid id and \( p_k \) to the SP. The FV SHE scheme works on integers, hence, the coordinates of users are encoded as integers using UTM format[1].

5. SP keeps a record of ride requests in each grid and maintains a real-time ride request distribution map in every time period. It makes use of Convolutional long short-term memory (Convolutional LSTM [15]) to train a prediction model with the ride request distribution information. Based on a temporal sequence of grid information, SP obtains prediction result \( PR(g) \), a non-negative integer which predicts the number of requests in the next time period for grid id \( g \).

6. As soon as SP receives the ride request, it performs a driver search with a search radius \((SR)\) in a preset order of grids starting with the grid nearest to rider. The rider’s grid is not searched so as to avoid the nearest driver who would always be found in the rider’s grid. When \( SR = 1 \), only grids adjacent to the rider are searched. Using the driver distribution map, SP creates a list of candidate drivers and forwards the ride-request to all such drivers.

7. When the \( i^{th} \) driver \( d_i \) receives the ride-request, she encrypts her location using \( p_k \) and forwards it to SP.

8. SP homomorphically computes the square of the Euclidean distance between the rider and drivers’ locations. It then forwards these distances to rider along with driver id \( i \) and \( PR(g_i) \), \( g_i \) is \( i^{th} \)’s grid id.

9. Rider uses \( s_k \) to decrypt the distances and sorts them to obtain the smallest distance \( D_0 \). For each distance in the sorted list, she runs the following two checks to pick the optimum driver:

(a) \( 2D_0 - D_i > D_{diag} \), where \( D_i \) is the distance for \( i^{th} \) driver and \( D_{diag} \) is the length of the diagonal of the grid.

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[1] Universal Transverse Mercator: a map-projection system for geographical locations [19].
(b) $PR(g_i)$, where $g_i$ is the driver’s grid id, which checks if no new ride request is emerging in a short time in grid $g_i$.

10. As soon as both the aforementioned conditions are satisfied, rider determines the optimum driver and informs the same to SP to continue with secure ride establishment between rider and selected driver.

11. In order to improve the effectiveness of driver selection, the authors notice that they can minimize the empty distance travelled by the driver by using $D_{maxdist}$ instead of $D_{diag}$ in the ride selection check (Step 9), where $D_{maxdist}$ is the distance between the driver and the farthest corner in her grid. However, the authors realize that an adversary rider, after decryption, can use $D_{maxdist}$ to launch an inference attack to obtain driver’s precise location. They, therefore, propose enhanced pRide to thwart such an attack.

12. In the enhanced pRide protocol, each driver, in addition to sending encryption of her coordinates, also sends the encryption of distances to each corner of her grid to the SP.

13. To pick the optimum driver, rider now needs to perform the check $2D_0 - D_i > D_{maxdist}$, for each driver $i$, using a private comparison algorithm, as explained below (Steps 15, 16 and 17).

14. As in the earlier basic pRide protocol, rider receives a list of distances to each of the candidate drivers, decrypts them and selects the smallest $D_0$.

15. In order to find the optimum driver, for each $D_i$, $i > 0$, rider sets $D' = 2D_0 - D_i$, encrypts $D'$ as $\widetilde{D'}$ and sends $\widetilde{D'}$ and $i$ to SP.

16. SP receives encrypted distances to each of the four corners of the $i$th driver’s grid as $(\widetilde{V}_{ll}, \widetilde{V}_{lu}, \widetilde{V}_{rl}, \widetilde{V}_{ru})$. SP generates random positive blinding integers $e$ and $r$, and homomorphically blinks each of the ciphertexts as

$$
\begin{align*}
\widetilde{V}' &= e \cdot \widetilde{D'} + \widetilde{r} \\
\widetilde{V}_{ll} &= e \cdot \widetilde{D}_{ll} + \widetilde{r} \\
\widetilde{V}_{lu} &= e \cdot \widetilde{D}_{lu} + \widetilde{r} \\
\widetilde{V}_{rl} &= e \cdot \widetilde{D}_{rl} + \widetilde{r} \\
\widetilde{V}_{ru} &= e \cdot \widetilde{D}_{ru} + \widetilde{r}.
\end{align*}
$$

(1)

It then sends each of these blinded values to rider.

Remark: Homomorphic addition of two ciphertexts, and homomorphic multiplication of ciphertext with plaintext can be done very efficiently in SHE.

17. Rider decrypts each of these blinded values and compares $V'$ with each of $(V_{ll}, V_{lu}, V_{rl}, V_{ru})$. If $V'$ is greater than all the four values, then it implies that $D' > D_{maxdist}$.

18. Rider then uses this comparison result and $PR(g)$ value as in the basic pRide protocol to select the optimum driver and informs the same to SP. If these checks fail, then the Steps 15 through 18 are repeated until an optimum driver is obtained by walking through each entry in the candidate driver list.

The authors evaluate the performance of their enhanced pRide protocol over real-world datasets. Their results show that their protocol is effective in saving
empty distance as well as in maintaining drivers’ privacy during the ride matching process. Finally, they compare the basic and enhanced versions of pRide and prove that the latter is more effective in choosing the optimum driver with the same level of privacy. The security of their protocol is based on the apparent hardness of retrieving the blinding parameters when given only the blinded values.

In our attack described in Section 3, we show that we can determine the underlying distance values when given only their blinded values, where blinding is done as described in Step 16. We then go on to use the distances to get the precise coordinates of responding drivers.

2.2 Threat Model

We consider the same threat model considered in the pRide protocol, where all parties, namely the SP, drivers and riders, are honest in executing the protocol. Riders submit valid requests by encrypting their correct coordinates to the SP, and the drivers also submit the encryptions of their current coordinates to the SP. SP does not collude with either drivers or riders. Drivers do not collude with riders.

All parties are honest-but-curious in the protocol. Thus, each party is curious to know more about the sensitive information of the other party. In particular, riders are curious to know about drivers’ locations and vice-versa. pRide also considers the case of an adversary rider who follows the protocol correctly but launches an inference attack by performing private computations on received driver coordinates to infer drivers’ precise locations, and so the authors propose enhanced pRide to thwart such an attack. Their paper aims to preserve driver and rider location information from SP, and to preserve driver location information from rider.

In this paper, we consider the same threat model to model the adversaries. The ride request issued by an honest-but-curious adversary rider is indistinguishable from a ride request issued by any other legitimate rider in the protocol. In a real-life scenario, a competitor SP with the intention of harvesting driver information of another SP, can mount such an attack without being detected by the target SP.

3 Our Attack

In this section, we present our driver location harvesting attack on the enhanced pRide protocol by a honest-but-curious adversary rider (R). R issues a single ride request as per the pRide protocol. SP will not be able to distinguish between a ride request issued by an adversary rider versus another by a legitimate rider. In this section, for ease of exposition, we explain the recovery of location of one particular driver \( D_p \), who has responded to ride request by \( R \), shown in Figure 1. \( D_p \) is located at distance \( \delta \) from \( R \). Our attack extends easily to all responding drivers, since each response is handled independently by the SP.
3.1 Retrieving Distances

\( R \) issues a ride request as per the \( \text{pRide} \) protocol with search radius \( SR = 1 \). By this, only the grids adjacent to the rider’s grid are searched by \( \text{SP} \) for candidate drivers.

We recall here the steps of \( \text{pRide} \) and enhanced \( \text{pRide} \) protocols from Section 2.1. In Step 14, the rider \( R \) obtains the distances between herself and all the responding drivers in the clear (distance between \( R \) and \( D_p \) is \( \delta \)). In addition, from Step 16, \( R \) receives the ciphertexts \((\tilde{V}'_{ll}, \tilde{V}'_{lu}, \tilde{V}'_{rl}, \tilde{V}'_{ru})\), which after decryption gives \((V'_{ll}, V'_{lu}, V'_{rl}, V'_{ru})\). We know that \( \tilde{D}' \) is the encryption of \( 2D_0 - \delta \), and

\[
\begin{align*}
V' &= e \cdot \tilde{D}' + \tilde{r} \\
V'_{ll} &= e \cdot \tilde{D}'_{ll} + \tilde{r} \\
V'_{lu} &= e \cdot \tilde{D}'_{lu} + \tilde{r} \\
V'_{rl} &= e \cdot \tilde{D}'_{rl} + \tilde{r} \\
V'_{ru} &= e \cdot \tilde{D}'_{ru} + \tilde{r},
\end{align*}
\]

where \( e \) and \( r \) are the blinding integers chosen by \( \text{SP} \).

\( R \) then computes the difference of every pair from \((V'_{ll}, V'_{lu}, V'_{rl}, V'_{ru})\), decrypts them using her secret key and stores them as \((P, Q, R, S, T, U)\), in no particular order.

The differences, thus obtained, are

\[
\begin{align*}
P &= V'_{ll} - V'_{lu} = e \cdot (D'_{ll} - D'_{lu}) \\
Q &= V'_{ll} - V'_{rl} = e \cdot (D'_{ll} - D'_{rl}) \\
R &= V'_{ll} - V'_{ru} = e \cdot (D'_{ll} - D'_{ru}) \\
S &= V'_{lu} - V'_{rl} = e \cdot (D'_{lu} - D'_{rl}) \\
T &= V'_{lu} - V'_{ru} = e \cdot (D'_{lu} - D'_{ru}) \\
U &= V'_{rl} - V'_{ru} = e \cdot (D'_{rl} - D'_{ru}).
\end{align*}
\]

It can be easily seen that the GCD of any two of \((P, Q, R, S, T)\), say \( P \) and \( Q \), will give either \( e \) or its multiple. The latter case will occur when \((D'_{ll} - D'_{lu})\) and \((D'_{ll} - D'_{rl})\) are not relatively prime, and by eliminating any common factors between them, we can hope to retrieve the exact value of \( e \) with a high probability.

**Remark:** The probability of \( n \) randomly chosen integers being coprime is \( \frac{1}{\zeta(n)} \), where \( \zeta \) is the Riemann Zeta function [20], and for two such integers the probability is \( \frac{6}{\pi^2} \). This means in about 60% of cases we can find the value of \( e \) straightaway, and in rest of the cases we can try to eliminate common factors.

Notice that each of the \( D_{xy} \) values are squares of the Euclidean distance between the driver’s location and each corner of her grid. Let the driver’s coordinates (to be determined) be \((x, y)\) and the known corners of her grid be \((x_1, y_1), (x_2, y_2), \ldots\).
\((x_3, y_3)\) and \((x_4, y_4)\). W.l.o.g,

\[
D_{ll} = (x_1 - x)^2 + (y_1 - y)^2 \tag{4}
\]

\[
D_{lu} = (x_2 - x)^2 + (y_2 - y)^2. \tag{5}
\]

Hence, \(P = e \cdot \left(\left( (x_1 - x)^2 + (y_1 - y)^2 \right) - \left( (x_2 - x)^2 + (y_2 - y)^2 \right) \right)\), which simplifies to

\[
P = e \cdot \left( (x_1 - x_2)(x_1 + x_2 - 2x) + (y_1 - y_2)(y_1 + y_2 - 2y) \right). \tag{6}
\]

By eliminating common factors, if any, we obtain

\[
P' = e \cdot \frac{P}{(\text{GCD}(x_1 - x_2, y_1 - y_2) * \text{GCD}(2, x_1 + x_2, y_1 + y_2))}. \tag{7}
\]

And similarly, we get \(Q', R', S', T', U'\). Finally, \(\text{GCD}(P', Q', R', S', T', U')\) gives the value of \(e\).

Remark: The coordinates of each of the grids are known at system initialization time. Hence, any common factors between the coordinates can be computed offline.

In Step \[\text{[15]}\] rider has the value of \(\tilde{D}'\), using which the value of \(\tilde{r}\) is obtained from \(V' = e \cdot \tilde{D}' + \tilde{r}\). And, finally, using \(e\) and \(\tilde{r}\), \((D_{ll}, D_{lu}, D_{rl}, D_{ru})\) and, hence, \((D_{ll}, D_{lu}, D_{rl}, D_{ru})\) are obtained.

Remark: In case we obtain a negative value for \(\tilde{r}\), it implies that our recovery of \(e\) is in error.

### 3.2 Retrieving Driver Locations

\(R\) does not know the correlation between the \(D_{xy}\) distances and the corners of the grid as they are distances given in random order. In addition, since the search radius \(SR = 1\), any of the four grids adjacent to the rider’s grid can be a potential grid of driver \(D_p\).

Using the four distance values \((D_{ll}, D_{lu}, D_{rl}, D_{ru})\) as radii and each of the respective grid corners as center of circles, rider obtains four points in each grid where all the four circles intersect. These points, in their respective grids, represent the equiprobable locations of driver \(D_p\). Figure \[\text{[2]}\] gives a pictorial view of our attack. Adversary rider \(R\) is located in grid \(g\). Driver \(D_p\) is located in grid \(g_4\), at a distance \(\delta\) from \(R\). Each of the four probable driver locations in each adjacent grids \(g_1\) through \(g_4\) are shown as small blue dots in each grid.

Using the distance between \(R\) and \(D_p\), namely \(\delta\), \(R\) draws a rider-circle of radius \(\delta\) around herself. As long as the driver has reported her correct coordinates, it is guaranteed that at least one of the 16 equiprobable driver locations will lie on the circumference of the rider-circle. If more than one such location is obtained, then the rider makes use of Google Nearest Road API \[\text{[2]}\] to find the nearest road to each of such locations. Since we assume that the driver is located on a motorable road, the adversary algorithm will output the location closest to the nearest road.
3.3 Analysis of our Attack

As described in Section 2.1, the pRide protocol makes use of a semantically secure cryptosystem, namely the FV SHE scheme [1], to encrypt the locations of drivers and rider, using which driver distances are computed homomorphically. In order to pick the closest driver, the distances need to be sorted which will need a high-depth circuit resulting in an inefficient implementation with SHE. Hence, the rider, in the basic pRide protocol, receives all encrypted distances, decrypts and sorts them to pick the closest driver efficiently. Using the distances to all drivers, the rider is able to perform the attacks described in [5] and [10], on the basic pRide protocol.

As described in Section of 2.1, the enhanced pRide protocol, SP homomorphically blinds the distances to the four corners of drivers’ grid, using random positive integers (Eqn. 1). However, as we show in Section 3.1, this blinding method is insecure.

The mitigation solution of [5], where the locations are perturbed, can be applied to the pRide protocol. While the attack of [10] is still applicable on the basic pRide protocol, we look at our attack on its enhanced version, when the mitigation solution is applied to the pRide protocol. In that case, in response to a ride request, the driver would pick a uniform random location inside a circle of radius \( \tau \) around her original location. She then sends the encryption of that random location to the SP, as well as the encrypted distances from the random location to each of the corners of her grid. We note that \( \tau \) should not be too large, as that would have an adverse effect on driver selection by rider. Our attack, where we retrieve the distances to grid corners, described in Section 3.1, would be applicable without any change. However, one of the retrieved location(s), in this case, would be the random location picked by the driver instead of her actual location. The adversary could then apply the attack of [10] to uncover the actual driver locations, with a high probability. Since the retrieved locations might not
be on a motorable road due to perturbation, the effectiveness of being able to use Google Nearest Road API to retrieve driver locations need to studied.

4 Experiments and Results

We use Sagemath 8.6 [16] to implement our attack described in Section 3.1 where we retrieve driver distances. The attack, described in Section 3.2 where we retrieve the driver locations, was implemented in Python and used the Google Nearest Road APIs for Python [3]. Both parts of the attack were executed on a commodity laptop with 512 GB SSD and AMD Ryzen 5 processor. Our Sagemath and Python programs are available at: https://github.com/shyamsmurthy/nss2022.

4.1 Experiment Details

Our experiments were run on grids of size about $4km^2$ superimposed on maps of 4 large cities around the world, namely, Los Angeles, London, New York City and Paris. The size of the grid is comparable to what is reported in the pRide paper. We have done experiments with the number of drivers as 5, 15 and 25 per grid, in each case distributed randomly throughout each grid but located on motorable areas. We note here that the number of drivers does not have a bearing on our attack since the SP encrypts and blinds each driver’s distances independent of one other.

In each of the maps, we picked random driver locations situated on motorable roads. Next, a rider location was picked from a random grid in the map. As explained in Section 3.1 grids adjacent to the rider’s grid was examined and distances between drivers in those grids and the rider were made available to the rider. Except for the predicted result ($PR$) values, this is same as what is available to the rider in the pRide protocol. The $PR$ values do not have any bearing on our attack since they do not have any effect on either blinding or encryption of distances.

Next, from each of the adjacent grids and for each driver in such grid, the distances from each such driver to her respective grid corners were computed, and blinded using random integers picked from the range $[1, 2^{24}]$, as the maximum UTM (northing) value of $10^7$ can be represented using 24 bits. In addition, a distance value known to the adversary is also blinded using the same random integers. These blinded distances were made available to the adversary rider. Again, this exactly mimics the behaviour of the enhanced pRide protocol.

Finally, we run the attack described in Section 3 to retrieve the distances followed by retrieving the driver locations.

Remark 1: It is claimed that the security of the pRide protocol relies on the hardness of obtaining the blinding parameters when given only the blinded values. We show in our attack that the adversary can recover the blinding parameters with a high probability.
Remark 2: In our experiments, we have used a search radius $SR = 1$. Our attack methodology can be easily extended to higher values of search radius. Since the order of grid traversal is known a priori, the new attack has to compute equiprobable locations in each of the possible grids and continue with our driver retrieval attack, as described in Section 3.2.

4.2 Results

The results of our experiments are tabulated in Table 1. The pRide paper uses a $64 \times 64$ grid over the city of Chengdu, China, and mentions a maximum of 16000 drivers in their experiments, which translates to about 4 drivers per grid on average. As it can be much larger in high density areas in the city, we run our experiments with 5, 15 and 25 drivers per grid. It takes less than 1 second to recover the locations of 25 drivers.

In order to retrieve the distances, we first recover the blinding integers $e$ and $r$ as described in Section 3.1. As shown in Table 1, we can retrieve at least 80% of the distances successfully, averaged from 10 runs of the experiments for each driver count over each city. In the unsuccessful cases, we find that the value of the blinding value $e$ retrieved by our algorithm is a multiple of the actual value of $e$, and we report this as a failure.

Next, we use the successfully retrieved distances to obtain the precise driver locations. Here, we use our attack described in Section 3.2. We see that this part correctly retrieves close to 99% of the driver locations. Hence, our overall driver location harvesting algorithm retrieves at least 80% of the drivers participating in the enhanced pRide protocol.

| City       | Number of participating drivers (per grid) | %age of driver coordinates correctly recovered |
|------------|------------------------------------------|-----------------------------------------------|
| Los Angeles| 5                                        | 80                                           |
|            | 15                                       | 95                                           |
|            | 25                                       | 89                                           |
| London     | 5                                        | 85                                           |
|            | 15                                       | 81                                           |
|            | 25                                       | 86                                           |
| New York City | 5                                        | 90                                           |
|            | 15                                       | 95                                           |
|            | 25                                       | 93                                           |
| Paris      | 5                                        | 85                                           |
|            | 15                                       | 93                                           |
|            | 25                                       | 88                                           |
5 Related Works

There is a large body of work on privacy-preserving RHS which consider preserving privacy of drivers and riders. ORide [12] and PrivateRide [13], both proposed by Pham et al., were some of the early works that aimed to preserve rider privacy against SP and drivers. While PrivateRide makes use of a cloaking region to maintain privacy, ORide scheme is based on SHE to encrypt driver and rider locations so as to make use of homomorphic properties of SHE to select nearest driver. Kumaraswamy et al. [5] proposed an attack that aims to determine locations of drivers participating in the ORide protocol. In their attack, an adversary rider can reveal locations of up to 40% of drivers who respond to a single ride request. They provide a countermeasure to thwart the attack while preserving sufficient anonymity. Murthy et al. [10] proposed an attack that uses triangulation by four colluding adversaries to obtain locations of all drivers participating in the ORide protocol.

Luo et al. [7] proposed a privacy-preserving ride-matching service also named pRide. Their protocol involves using two non-colluding servers: SP and CP (a third-party crypto server), and uses Road Network Embedding (RNE) [14] such that the road network is transformed to a higher dimension space to enable efficient distance computation between the network entities. However, the disadvantage of their scheme is the use of two non-colluding servers which incurs inter-server communication costs. Yu et al. [22] proposed lpRide protocol which also uses RNE but uses a modified version of Paillier encryption scheme [11] to preserve privacy of participating entities. Vivek [17] demonstrated an attack on the lpRide protocol where they show that any rider or driver can learn the coordinates of other participating riders. TRACE [18] is a privacy-preserving dynamic spatial query RHS scheme proposed by Wang et al., that uses a quadtree structure and provides high-efficiency in terms of complexity and communication overhead. Kumaraswamy et al. [6] demonstrated an attack on the TRACE protocol where the SP can identify the exact locations of riders and drivers. Xie et al. [21] proposed a protocol that also uses RNE to efficiently compute shortest distances. Their scheme makes use of property-preserving hash functions where the SP can not only compute the rider to driver distances, but also pick the nearest driver. This way they eliminate the need for an auxiliary crypto server. All the works listed earlier picks the nearest driver to fulfil a ride request. pRide [4], proposed by Huang et al., does not match the nearest driver but considers a global matching strategy with the aim of reducing the empty distance travelled by driver to pick the rider. Murthy et al. [10] gave an attack on the ORide protocol, using triangulation, where they recover locations of all participating drivers. In addition, by using more number of colluding adversaries, they show they can recover locations of up to 50% of drivers participating in the variant of ORide protocol that uses the mitigation solution of [5].
6 Conclusions

In this paper, we presented an attack on enhanced pRide [4] protocol, a privacy-preserving RHS. We show that an honest-but-curious adversary rider can determine the coordinates of about 80% of drivers responding to the rider’s ride request as per the pRide protocol.

From Section 1.1, we see that locations of all drivers participating in the basic pRide protocol can be recovered by one or more adversary riders. As per the protocol, the rider chooses the optimum driver when given the plaintext distances to all drivers, and this fact is exploited by the adversary. Alternatively, the SP can select the optimum driver homomorphically. Since sorting and searching are high-depth circuits, it is not efficient to perform these operations using SHE schemes. However, FHE schemes can be explored to evaluate their suitability for practical RHS solutions.

The enhanced pRide protocol needs to perform comparisons and in order to preserve privacy, the values are blinded. However, since the order needs to be preserved, the blinding values are the same for all the comparands, which leads to the attack. Other secure order-preserving techniques need to be explored. However, as shown in [9], careful analysis is needed which would otherwise lead to further attacks.

In summary, we show that although protocols may seem secure in theory, a thorough analysis should be done which otherwise would expose severe vulnerabilities and security holes, as demonstrated by our attack in this paper.

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