Swapping trajectories with a sufficient sanitizer

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Abstract. Mobility data mining can improve decision making, from planning transports in metropolitan areas to localizing services in towns. However, unrestricted access to such data may reveal sensible locations and pose safety risks if the data is associated to a specific moving individual. This is one of the many reasons to consider trajectory anonymization.

Some anonymization methods rely on grouping individual registers on a database and publishing summaries in such a way that individual information is protected inside the group. Other approaches consist of adding noise, such as differential privacy, in a way that the presence of an individual cannot be inferred from the data.

In this paper, we we formalize the concept of sufficient sanitizer and show that the sanitization method based on swapping segments for trajectory data (SwapMob), is a sufficient sanitizer for various statistical decision problems as it not only preserves the aggregate information of the spatial database in the form of sufficient statistics but also provides privacy to the individuals. We test the utility of the data obtained after applying SwapMob sanitization in terms of Origin-Destination matrices, a fundamental tool in transportation modelling.

1 Introduction

With the pervasive use of smartphones and the location techniques such as GPS, GSM and RFID, the opportunities to deliver content depending on current user location have increased. Location Based Services (LBS) provide considerable advantages such as allowing users to benefit from live location-based information for transportation, recommendations of places of interest, or even the opportunity to meet friends in nearby locations. Such location-based data can be useful also for intelligent transportation systems, in which vehicles may serve as sensors for collecting information about traffic jams, weather, and road conditions.

However, revealing users' locations may have some privacy risks. If the data is linked to the real identities it may reveal personal preferences (e.g., sexual, political or religious orientation), or it may be used for inferring habits and know the time when a person is at home or away. To avoid such inconveniences, a variety of anonymization techniques have been developed to hide the identity of the user or her exact location, e.g, [34].

Moreover, as Giannotti et al. mention in [13], big data (in particular trajectory data) may be used to understand human behavior through the discovery of individual social profiles, by the analysis of collective behaviors, spreading epidemics, social contagion, and to study the evolution of sentiment and opinion; however, trusted networks and privacy-aware social mining must be pursued and methods for protection and anonymization for such data must be developed to enforce the data subjects' rights and promote their participation.

2 Related work

Different solutions have been proposed for anonymizing trajectories in data publishing. Terrovitis and Mamoulis [35] consider a discrete spatial domain, e.g., spatial information is given in terms of addresses in a city map. Hence, the user trajectories are expressed as sequences of points of interest (POIs). They present the use case of the RFID cards from the Octopus[5] company in Hong Kong, which collects the transaction history of its customers. The company may want to publish sequences of transactions by the same person as trajectories, for extracting movement and behavioral patterns. However, if a given user, Alice, uses her card to pay at different convenience stores that belong to the same chain (e.g., convenience stores), that company may reidentify Alice if her sequence of purchases is unique in the published trajectory database.

A similar approach in [23] is obtained by transforming sequences by adding, deleting, or substituting some points of the trajectory, while preserving also frequent sequential patterns [2] obtained by mining the anonymized data.

In [17] and [16], Hoh et al. discuss the use of mobility data for transportation planning and traffic monitoring applications to provide drivers with feedback on road and traffic conditions. For modelling the threats to privacy in such datasets, they assume that an adversary does not have information about which subset of samples belongs to a single user, however by using multi-target tracking algorithms [24] subsequent location samples may be linked to an individual that is periodically reporting his anonymized location information.

In [16] they consider the attack of deducing home locations of users by leveraging clustering heuristics used together with the decrease of speed reported by GPS sensors. Then, propose data suppression techniques by changing the sampling rate (e.g, from 1 minute to 2, 4 and 10) for protecting from such inferences.

[5] http://www.octopuscards.com/

In [17], to prevent adversaries from tracking complete individual paths, they propose an algorithm that perturbs slightly the trajectories of different individuals (to make them closer) in such a way that the adversary may not be able to follow which segment of the path corresponds to which user by using multi-target tracking algorithms. This is done with a constraint on the Quality of Service, which is expressed as the mean location error between the actual and the observed locations. They argue that adequate levels of privacy can only be obtained if the density of users is sufficiently high.

This is closely related to [3] in which Mix Zones are introduced. These are spatial areas on which users' location is not accessible, hence when users are simultaneously present on a mix zone, their pseudonyms are changed. This procedure is performed to disrupt the linkage of the incoming and outgoing path segments to the same specific user.

They design a model for location privacy protection that aims to preserve the advantages of location aware services while hiding their identities from the applications that receive the users' locations. The existence of a trusted middleware system (or sensing infrastructure) is assumed and the applications register their interest in a geographic space with the middleware, such space is called application zone. Examples of such application zones are hospitals, universities or supermarket complexes; in general it could be any open or closed space.

The regions in which applications cannot trace user movements are called mix zones, and the borders between a mix zone and an application zone are called boundary lines. Applications do not receive traceable user identities, they receive pseudonyms that allow communication between them. Such communication passes through the trusted intermediary and the pseudonyms of users change when they enter a mix zone.

To measure location privacy, Beresford and Stajano [4] define the anonymity set as the group of people visiting the mix zone during the same time interval. However, as the boundary and time when a user exits a mix zone is strongly correlated to the boundary and time when the user enters it, such information may be exploited by an attacker; therefore they use the information theoretic metric that Serjantov and Danezis [32] proposed for anonymous communications which considers the varying probabilities of users sending and receiving messages through a network of mix nodes.

This is modeled in [4] as a movement matrix which represents the frequency of ingress and egress points to the mix zone at several times. Then, a bipartite weighted graph is defined in which vertices model ingress and egress pseudonyms and edge-weights model the probability that two pseudonyms represent the same underlying person. Therefore, a maximal cost perfect matching of these graphs can be used to find the most probable mapping among incoming and outgoing pseudonyms. However, since the solution to many restricted matching problems (such as this one) is NP-hard [33], Beresford and Stajano [4] describe a method for achieving partial solutions.

Other approaches to provide privacy to LBS include the posibility of individual specification of privacy preferences [8], some are based on Private Information

Retrieval (PIR) and Oblivious Transfer [22], or are a combination of cloaking regions and PIR [12], however they use cryptographic primitives and are focused on preventing the disclosure of points of interest.

An approach that does not consider middleware to obtain location privacy is proposed in Chapter 9 from [14]. It consists of a system with an untrusted server and clients communicating in a P2P network for privacy preserving trajectory collection. The aim of their data collection solution is to preserve anonymity in any set of data being stored, transmitted or collected in the system. This is achieved by means of k-anonymization and swapping. Briefly, the protocol consists of the clients recording their private trajectories, cloaking them among k similar trajectories and exchanging parts of those trajectories with other clients in the P2P network. However, in the final step (the data reporting stage) clients send anonymous partial trajectories to the server, it filters all the synthetic trajectory data generated during the process and recovers the original trajectory.

One of the advantages of performing trajectory anonymization on the user side, as in [27] and [28], is that the anonymization process is no longer centralized. Thus data subjects gain control, transparency and more security for their data. They leverage the concept of k-anonymity for trajectories, similarly to Abul et al. [1], that propose the (k, δ)-anonymity model, which consists of publishing a cylindrical volume of radius δ that contains the trajectory of at least k moving objects. Note that this idea is an extension of the concept of k-anonymity for databases [31] and it may be related to k-anonymity for dynamic databases [30] if we consider that the records of the dynamic database represent locations. Also the concept of differential privacy [10] has been extended from databases to many other types of data. For a brief overview of privacy protection techniques and a discussion of k-anonymity and differential privacy models in different frameworks, cf. [29].

In [7], a differential privacy model for transit data publication is considered, using data from the Société de Transport de Montréal (STM). The data are modeled as sequential data in a prefix tree that represents all the sequences by grouping the sequences with the same prefix into the same branch. Their algorithm takes a raw sequential dataset D, a privacy budget ϵ, a user specified height of the prefix tree h and a location taxonomy tree T, and returns a sanitized dataset $\tilde{\mathcal{D}}$ satisfying ϵ-differential privacy. For measuring utility, in the STM case, sanitized data are mainly used to perform two data mining tasks, count query and frequent sequential pattern mining [2].

Other ϵ-differentially private mechanism for publishing trajectories called SDD (Sampling Distance and Direction) can be found in [19]. They focus on ship trajectories with known starting and terminal point, with same number of points, and consider differential privacy when two trajectories differ at exactly one location.

In [36], a differentially private algorithm for location privacy is proposed, it follows a discussion on the different notions of adjacency used for differential privacy , such as [6] and [20]. Their algorithm considers temporal correlations modeled as a Markov chain and proposes the "δ-location set" to include all probable locations (where the user might appear). The authors argue that, to protect the true location, it is enough to "hide" it in the δ-location set in which any pairs of locations are not distinguishable. However, they leave the problem of protecting the entire trace of released locations as future work.

In this paper, we present a sanitization method considering that the data are dynamic, the rate at which the information is collected is not constant, and the databases are being generated as the data is received. The rest of the paper is organized as follows in Section 3 we formalize the concept of sufficient sanitizer and provide some examples of sufficient statistcs related to traffic engineering and transportation planning. In Section 4 we define our algorithm, and discuss some of its properties of privacy and utility, in Section 5, we evaluate our method also when including the additional guarantee of preserving Origin-Destination matrices. We finish with some conclusions and future work on Section 6

3 Sufficient Sanitizer

Recall that the sufficient statistics T of data X under a statistical experiment, i.e., a family of probability models $\{P_\theta : \theta \in \mathbf{\Theta}\}$, that is parametrized by $\theta \in \mathbf{\Theta}$, contains all the information in the data about θ. More formally, $T(X) = t$ is a sufficient statistic for the underlying parameter θ if the conditional probability $P_\theta(X|T(X) = t)$ is independent of θ. Intuitively speaking, all the information in the data about the typically unknown parameter of the probability model is captured by the sufficient statistic. Therefore, by anonymizing the data while preserving the sufficient statistics is decision-theoretically optimal, in the sense of maximizing utility from optimal estimates of the parameters in the probability model.

A *sanitizer* $\mathcal{S}$ is a map from the data space $\mathbb{D}$ to a sanitized data space $\tilde{\mathcal{D}}$, i.e., $\mathcal{S}(d) : \mathbb{D} \to \tilde{\mathcal{D}}$, in such a way that the data in $\tilde{\mathcal{D}}$ has additional privacy guarantees than in $\mathbb{D}$. Thus, this notion englobes the notion of k-anonymity, differential privacy, and many other privacy enhancing technologies. A sanitizer may or may not preserve the sufficient statistics in the data for a given statistical experiment. A *sufficient sanitizer* preserves the sufficient statistics.

Next, we give three concrete examples of sufficient statistics that have utility in decision problems routinely faced in traffic engineering, city and transportation planning, etc. We end this section with a discussion on General Markov models and sufficient sanitizers.

State Counts: One of the simplest statistical experiments for mobility data can be based on an independent and identical distribution for the probability of being found in location or state i from among $k+1$ states based on a labelled partition of the support set of the trajectories into $k+1$ cells or states given by $[k] := \{0, 1, \ldots, k\}$. For such a simple experiment $\{P_\theta : \theta \in \triangle^k\}$, i.e., P_θ is a discrete probability distribution specified by the parameter θ taking values in $\triangle^k := \{\theta \in \mathbb{R}^{k+1} : \sum_{i=0}^k \theta_i = 1, \theta_i \geq 0, i \in [k]\}$, the probability k-simplex. A consistent nonparametric estimate of θ is obtained from the relative frequency of visits to each state in $[k]$ and its sufficient statistic is simply $\{N_i : i \in [k]\}$, where N_i is merely the frequency or count of the number of visits to state i.

State Transition Counts: A more useful statistical experiment for trajectory data is the time-homogeneous Markov chain model of independent random transitions. This model is more general the previous one, since it allows the probability of the next location to depend on that of the current location. Here $\{P_\theta : \theta \in (\triangle^k)^k\}$, i.e., P_θ is the transition probability matrix of a Markov chain based on a partition of the support set of the trajectories into $k+1$ labelled cells or states given by $[k]$. Recall that the transition counts $N_{i,j}$ between states i and j for each pair $(i, j) \in [k]^2$ is the sufficient statistics for such a simple Markov chain model, as it will allow us to nonparametrically estimate the transition matrix itself.

Origin-Destination Matrices: Origin-Destination Matrices (ODMs) are routinely used in transportation modelling to depict travel demand. Traffic flows can be estimated as part of trip generation modelling using Origin-Destination (OD) demand matrix, infrastructure network capacity and traffic controls. OD trip generation models serve as basis for transport planning, construction, performance assessment, and as such have potential to affect regional economies.

Although ODMs can be more general, we consider an ODM based on n states that can be the origin i and/or the destination j. Such an ODM shown in Table 1 is a matrix of size $(n + 1) \times (n + 1)$ containing flow values N_{ij}, such as number or share of trips from i to j [26]. The last row contains total arrivals to each destination j from all origins, the last column contains the total departures from each origin i to all destinations, and the bottom right element contains the total flows in the model [11].

Table 1: An Origin Destination Matrix from a spatial interaction survey

		Destinations j			
		Uppsala	Stockholm	Arlanda	Departures
Origins i	Uppsala	2000	5	20	2025
	Stockholm	10	100	10	120
	Arlanda	20	5	0	25
	Arrivals	2030	110	30	2170

ODM are constructed based on estimations from travel studies as part of traffic census: field, online and telephone traffic surveys, traffic volume counts [25], check-point intercept interviews, license plate and other video analyses, *etc.* Automatically generated data (e.g. CDR [18]) are increasingly used as a base for constructing ODMs, reducing survey costs and improving accuracy of route choice estimations. Thus, a sufficient anonymizer for ODMs from trajectory data (as SwapMOb), can allow for the utility to be gained from ODM while preserving the privacy of the individual associated with the trajectory.

ODM parameters include: cut-off departure time from Origins, cut-off arrival time to Destinations, mode of transportation, and spatial resolution or aggregation level for Origins and Destinations. In Section 5.3, we empirically assess the loss of privacy under a given metric as this spatial resolution varies for a single ODM.

General Markov models: More sophisticated Markov chain models, including those that allow dependence on past few states or those that allow the transition probabilities to depend on time with more involved sufficient statistics, can in principle be treated with the basic ideas illustrated here using simple but useful Markov chain models of mobility. Thus, any subsequent decision problem (eg. traffic flow prediction from mobility simulations based on the learnt Markov chain model), based on *sufficient sanitizers* that preserve the sufficient statistic for the model can allow for optimal decisions under the model for a desired level of privacy.

4 Proposed method: SwapMob

We propose a method for anonymization of mobility data by swapping trajectories, which works in a similar way as the mix zones but in a non-restricted space.

Our algorithm (SwapMob) simulates an online P2P system for exchanging segments of trajectories. That is, when two users are near they interchange their partial trajectories, see section 4.1. In this way, all users' trajectories are mixed incrementally, and the moving users keep generating segments of trajectories that are being swapped. In the end, each trajectory retrieved is made of small segments of trajectories of different individuals, who have met during the day, as depicted in Figure 1. Hence, the relation between data subjects and their data is obfuscated while keeping a precise aggregated data, such as the number of users in each place at each time and the locations that have been visited by different anonymous users. We formalize our method after a brief explanation of previous definitions and assumptions.

4.1 Definitions

We assume that we have a database in which the i-th observation is a tuple (ID_i, lat_i, long_i, t_i) that consists of the individual's identifier (ID_i), the latitude (lat_i), longitude (long_i) and timestamp (t_i).

Then, the trajectory T_x of an individual x will consist of all the observations with identifier x ordered by their timestamps t_i. These can be represented as $T_x = (x_1, x_2, \ldots, x_m)$ if there are m observations for individual x.

We say that *two individuals meet* or their trajectories cross (on points x_i and y_j) if they have been co-located. We denote this by $x_i \approx y_j$. Note that being co-located depends on thresholds for proximity (χ) and time (τ), since the sampling rate of positions is not regular nor constant. Moreover two persons cannot be in the exact same place at the same time.

We define a *matching* as a maximal subset of pairs of elements of a set.

We denote by $Sw(T)$ the resulting trajectory after all swaps have been applied to T. Next, we define the following two primitives for our algorithm: *generate random matching* and *swap*.

1. *Swap:* Given two trajectories $T_x = (x_1, \ldots, x_i, x_{i+1}, \ldots)$ and $T_y = (y_1, \ldots, y_j, y_{j+1}, \ldots)$ that meet in points x_i and y_j, a swap of T_x with T_y at points x_i and y_j results in $Sw(T_x) = (y_1, \ldots, y_j, x_{i+1}, \ldots)$ and $Sw(T_y) = (x_1, \ldots, x_i, y_{j+1}, \ldots)$.
2. *Generate random matching:* Given a set of elements $S = \{s_1, s_2, \ldots, s_m\}$, we generate a random matching by making pairs of the first $m/2$ with the following $m/2$ numbers, followed by a random permutation of all numbers m.

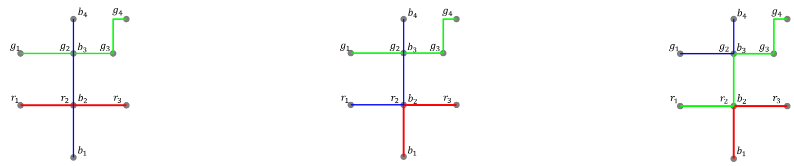
Note that, in case that the number of elements m is odd, to generate a matching we must leave out one element and that all possible random matchings can be generated following our procedure.

Crossing paths and Swapping: We propose a model such that two peers get in contact (meet) if they have been co-located on a similar timestamp depending on parameters of proximity χ and time τ.

Next, we simulate SwapMob protocol by swapping the users IDs when the users have passed close enough. We calculate the set of users that get in contact in a given time interval, and choose a random matching among them when they are even and a matching of all but one, when they are odd. Here, the swapping is carried out in a pairwise manner, but it could be done as a permutation such as in [4].

Note that changing pseudonyms (IDs) is equivalent to swapping the partial trajectories.

In Figure 1, we present an example of three simple trajectories crossing T_r, T_g, T_b. We assume that they are moving from left to right and upwards, $T_r = (r_1, r_2, r_3)$, $T_g = (g_1, g_2, g_3, g_4)$ and $T_b = (b_1, b_2, b_3, b_4)$. Note that we are also assuming that the blue trajectory meets the red trajectory first ($b_2 \approx r_2$) and then the green trajectory ($b_3 \approx g_2$). In this tiny example, we can see how the iterative swaps preserve parts of the trajectory intact, but at the end each trajectory has parts of many others, such as the green one which ends having a segment of the blue trajectory, a segment of the red and a segment of its original trajectory $Sw(T_g) = (r_1, r_2, b_3, g_3, g_4)$.



(a) Original trajectories (b) After first swap (c) After second swap

Fig. 1: Three trajectories before and after swapping

Algorithm 1: Offline algorithm for swapping trajectories

Input: Trajectory Database. Thresholds for time τ and proximity χ.
Output: Swapped trajectories identifiers $Sw(T_i)$.
Partition the timestamps $t = \bigcup \tau_j$ in intervals of length τ
for *each pair of registers* i, j *in interval* τ_j **do**
  if $dist(l_i, l_j) < \chi$ **then**
    add i, j to close records list (possible swaps) S_{τ_j} at the given time interval.
  end
end
generate random matching with possible swaps in S_{τ_j}
order all swaps in $\bigcup S_{\tau_j}$ by timestamp
for *each pair* $i \approx j$ *in* $\bigcup S_{\tau_j}$ **do**
  swap T_i with T_j
end
return *Swapped trajectories* $Sw(T_i)$

4.2 SwapMob sanitizer

We follow a similar architecture to the one in [16] in which a Trusted Third Party (TTP) knows the vehicles' identities but cannot access sensor information (such as position and speed); and a Service Provider (SP) knows the sensor measures but not the identities. Further, the SP calculates which records are close to each other without knowing to which individual they belong and communicates them to the TTP (in this case SwapMob anonymizer) such that it can swap their identities without knowing at which location they were.

This is achieved in the following way (See Figure 2):

1. Users communicate with SwapMob, sending their sensor data (M) encrypted with the public key (K_{SP}) of SP. SwapMob keeps the number of register (i), which user has sent it (u_i), its current pseudonym (ID_i), the timestamp (t_i) and the encrypted sensor data $E(M_i, K_{SP})$, which includes their encrypted location (l_i).
2. SwapMob sends the vector $(i, t_i, E(M_i, K_{SP}))$ to the SP, who decrypts $E(M_i, K_{SP})$ and keeps a buffer of data on interval τ_j that contains all times-

tamps between timestamp t_j and t_{j+1} and has length τ, that is $\tau_j = \{t : t_j < t < t_{j+1}\}$.
3. SP sends the set S_{τ_j} of registers that were at distance less than the predefined threshold χ during the interval of time τ_j back to SwapMob, more formally $S_{\tau_j} = \{i, i' : d(l_i, l_{i'}) < \chi \text{ and } t_i, t_{i'} \in \tau_j\}$. SwapMob calculates the swaps and stores the users and swapped IDs list, that is, for every record i SwapMob keeps the corresponding swapped id $Sw(ID_i)$ and the user (u_i) to which such pseudonym corresponds.
4. Finally, every given period of time which could be daily, weekly or monthly, SwapMob reports the list of $(i, Sw(ID_i))$ to SP.

The authentication data integrity of the communications can be guaranteed with a hash-based message authentication code.

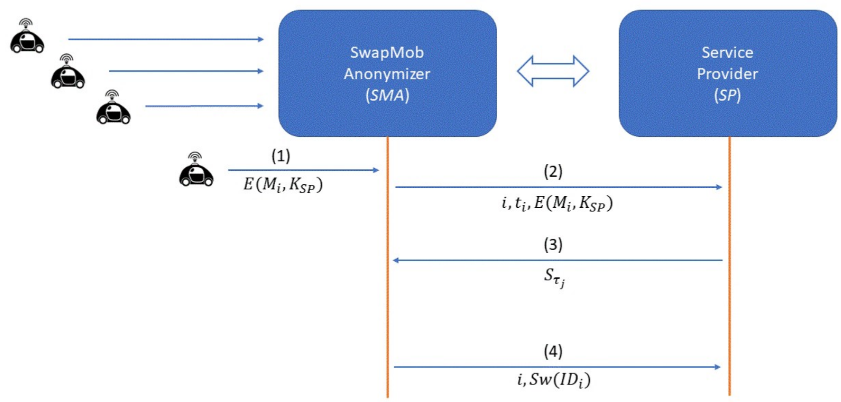


Fig. 2: Architecture of our system

In this way, SP obtains the measures of all sensors M in real-time (Step 2), and at the end of the day also gets the anonymized trajectories of the users that generated them (Step 4). Even, though SP knows which records belong to S_{τ_j} (Step 3), SP does not know to which other record they have been swapped during period τ_j, and by the iterative swaps it gets even harder to associate them to a specific user.

At the same time, SwapMob only knows the users, the timestamps at which they have crossed, and the reported trajectories are already sanitized by SwapMob (Step 4).

Our system, can be applied for the use case proposed in [3], by defining a set of swap zones (similar to the mix zones) and adding the restriction that the swapping cannot be performed outside such places. Then, the spatio-temporal trajectories of users between such swap zones could be monitored in an anonymous and precise way.

However, there will still be some differences. Namely, the swap zone that we consider is the entire application zone, whereas in [3] a user entering a mix zone can be distinguished from another user emerging from the same zone if the size of the mix zone is too large. This same argument justifies that the distance and time parameters, χ and τ must not be too large either in our algorithm, otherwise swapping could not be credible.

4.3 Protecting against reidentification

It is well known that de-identification does not necessarily means anonymization. The same attributes that are used for extracting knowledge, may be used for pointing to a specific individual, and uniquely relating their data to their real identity.

Other notions of privacy are defined depending on the context, which may be of statistical databases [9], networks [40], or geo-located data.

By identifying the POIs of an individual, it is possible to infer their habits (e.g., does sport, travels a lot), the locations that he visits frequently (may be related to political or religious beliefs) or even related to health (clinics, hospitals). This may also be used to infer their schedule, predict their future locations, learn their past locations and possibly even infer their personal relations by observing frequent or periodic co-locations. Moreover, such habits and locations can be easily used to reidentify the individuals behind the data, as it has been shown on previous studies on anonymity of home/work location.

Regarding this topic, Golle and Partridge studied in [15] workers who revealed their home and work location with noise or rounding on the order of a city block, a kilometer or tens of kilometers (census block, census tract, or county) and showed that the sizes of the anonymity set were respectively 1, 21 and 34,980. That is, when the data granularity was on the order of a census block, the individuals were uniquely identifiable, and for granularities on the order of census track or county, they were protected within sets of size 21 or 34,980. In [39], Zang and Bolot inferred the top N locations of a user from call records and correlated such information with publicly-available side information such as census data. Then, they showed that the top 2 locations likely correspond to home and work location and that the anonymity sets are drastically reduced if an attacker infers them.

Therefore, for protecting the individuals against reidentification, it is crucial to protect their home addresses and POIs, to provide them with minimum guarantees of keeping them anonymous. Swapped data may not allow for following a specific individual and his whereabouts, and thus, this will not permit personalization or individual classification, which are ways of protecting their privacy.

A different approach regarding the possibility of reidentification and the (im)possibility of protection, is in [21], where they measure the uniqueness of human mobility traces depending on their resolution and the available outside information, assuming that an adversary knows p random spatio-temporal points. Then, they coarsen such data spatially and temporally to find a formula for uniqueness depending on such parameters. We argue that SwapMob preserves privacy by dissociating the segments of trajectories from the subject that generated them.

4.4 Utility of swapped data as privacy-preserving decisions

In this paper we are assuming that the interest of using data sanitized by SwapMob is for making mobility maps and predictions that may be useful for intelligent transportation systems and for planning in a city. Our main contribution here is to formalize the relationship between statistical decision procedures that are used to extract utility from the data on one hand and anonymizers that attempt to guarantee a particular measure of privacy via anonymity on the other.

Current examples: As Hoh and Gruteser proposed in [17], pre-specified vehicles could periodically send their locations, speeds, road temperatures, windshield wiper status and other information to the traffic monitoring facility. These statistics can provide information on the traffic jams, average travel time or the quality of specific roads, and can be used for traffic light scheduling and road design.

Furthermore, the sensors do not necessarily have to be attached to vehicles, they could be carried on mobile phones, and the utility of using the individuals for sensing is preserved, since all their sensor data, including all their movements and timestamps (in aggregate) are kept intact by SwapMob.

In [5], a real-time urban monitoring platform and its application to the City of Rome was presented; they used a wireless sensor network to acquire real-time traffic noise from different spots, GPS traces of locations from 43 taxis and 7268 buses, and voice and data traffic served by each of the base transceiver stations from a telecom company in the urban area of Rome. These are few examples of sensors that could be carried by individuals, sanitized and transmitted to a service provider via SwapMob.

Another example is the offline mining in [37] representing the knowledge from taxi-drivers as a landmark graph could be done with SwapMob sanitized data. A landmark is defined as a road segment that has been frequently traversed by taxis, and a directed edge connecting two landmarks represents the frequent transition of taxis between the two landmarks. This graph is then used for traffic prediction and for providing a personalized routing service.

SwapMob is a Sufficient Sanitizer: In general, lossless maps of flows, up to a statistical experiment and its sufficient statistics, encoded by *sufficiently sanitized trajectories* can be obtained by using SwapMob at several aggregation levels and time resolutions specified by χ and τ, respectively. Next we show that unlike k-anonymity and ϵ-differential privacy based approaches, SwapMob does indeed preserve the sufficient statistics of counts, transition counts and Origin-Destination matrix (ODM) – the three sufficient statistics with their corresponding statistical experiments described in Section 3.

It is easy to see that the SwapMob anonymizer for a given time interval τ and spatial resolution specified by χ, preserves the sufficient statistics of counts in each cell or state given by the χ-specified spatial partition. First, the swapping operation within each cell only swaps random pairs of trajectories within it and thus leaves the counts invariant. Also, the points of entry and exit for each trajectory for a given spatio-temporal cell is preserved as the swapping operation only happens across random pairs of trajectories inside the cell. Thus, the number of transitions between any two spatio-temporal cells will also be preserved. This actually preserves the sufficient statistics for the time-inhomogeneous Markov chain and not merely that of the time-homogeneous Markov chain. Note that, although we have talked about discrete time Markov chains specified by units of τ, we can just as easily generalize the underlying models to continuous-time Markov chains by appropriate projections and the use of timestamp information in the trajectories.

5 Empirical evaluation

We tested our algorithm on the T-drive dataset [38,37] which contains the GPS trajectories of 10,357 taxis during the period of Feb. 2 to Feb. 8, 2008 within Beijing. The total number of points in this dataset is about 15 million and the total distance of the trajectories reaches nearly 9 million kilometers. It is important to note that not all taxis appear every day and not all report their positions at the same interval. The average sampling interval is about 177 seconds and 623 meters. Each measurement contains the following data: taxi id, date time, longitude, latitude.

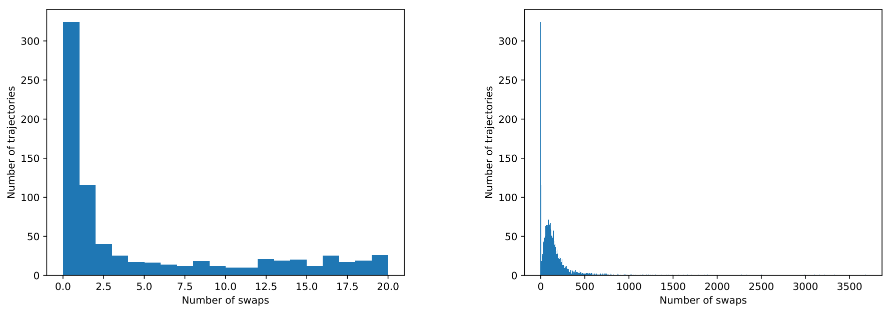
5.1 Applying SwapMob on the data

Before applying SwapMob to the dataset we perform some cleaning of the data. We begin by removing all measurements for which the latitude and longitude is outside the box $[115, 117] \times [39, 41]$, these measurements are far outside Beijing and most of them have both latitude and longitude equal to zero, which indicates that the measurement is most likely not valid. We then remove all trajectories which have no measurements belonging to them at all. This removes 756561 invalid measurements and 77 trajectories that have no measurements in this area, and we end up with 10280 trajectories and 16906423 measurements.

For applying SwapMob we consider two taxis co-located if they are in the same spatio-temporal cell – the spatial cell is given by a square of side-length 0.001 degrees ($\chi = 0.001$), about 111 meters, and the temporal interval is specified by being in the same minute ($\tau = 60$). Note that this is about 6 and 3 times less than the average sampling interval for distance and time, respectively, in the dataset.

With this we get that the number of possible swaps between all the trajectories is 641262. The average number of swaps for each trajectory is 137. Of all the 10280 trajectories 9508, 92%, take part in at least 20 swaps, for the 772 trajectories with less than 20 swaps we have the distribution seen in Figure 3a. We see that 324 trajectories do not participate in any swaps at all, however 265 of these trajectories have less than 10 measurements (compared to an average of more than 1000). In Figure 3b we can also see the distribution for all trajectories, here we can see that most trajectories have less than 500 swaps but a few participate in thousands of swaps.

We can conclude that most of the trajectories participate in several swaps, only a small amount participate in less than 20 swaps and that most of the trajectories that don't participate in any swap have very few measurements.



(a) Frequency histogram of number of swaps for all the 772 trajectories participating in less than 20 swaps.

(b) Frequency histogram of number of swaps for all trajectories.

Fig. 3: Frequency histograms of number of swaps for trajectories.

5.2 Reidentification by linkage

In this section we simulate an adversary who knows finitely many exact locations and timestamps, and tries to reidentify a trajectory in the dataset. In [21], a similar kind of adversary is considered, but in that case, it only knows location and timestamp up to some resolution. In contrast to this, our adversary should be considered to be very well-informed. We discuss the information that the adversary gains, after propagating his knowledge of one data point of the original trajectory in the sanitized one. In most cases, only a small fraction of the full trajectory is disclosed.

Since we assume the adversary knows exact locations and timestamps, it can identify an (unswapped) trajectory using only one such point, assuming no two measurements are exactly the same. After applying SwapMob, the adversary can still identify a trajectory with the measurement, but it does not know exactly which parts of the trajectory have been swapped and thus does not learn the full trajectory. It does however learn part of the trajectory: it can follow the trajectory from the known measurement forward in time until the next swap can occur and also backwards in time until the previous swap that could occur. This part of the trajectory is known to belong to the wanted individual, since no swaps were performed on it, but after the swaps the adversary does not know for certain which path belongs to the original trajectory.

To measure how much the adversary learns, we thus have to look at how long the segments between the swaps are. Since every trajectory participate in an average of 137 swaps and is thus split into an average of 138 segments. Knowing one point the adversary will learn one of these segments. To see how much the adversary learns, we can thus look at how long these segments are. For each trajectory we can look at the longest such segment and compare its length to that of the whole trajectory. We plotted the distribution function of such measure in Figure 4. Here, the length means the number of measurements, but elapsed time and distance traveled would both be other natural choices for length.

Figure 4 shows that for more than 75% of all trajectories, the longest unswapped segment makes up less than 20% of the total trajectory. For 90% of the trajectories the number is less than 40%. For most trajectories, an adversary will thus learn only a small fraction of the original trajectory.

We can also consider the case when the adversary knows several points of the trajectory. If the extra points lie on the same segment of the trajectory as the first one, no more knowledge is gained. However, if the extra points lie on other segments of the trajectory, the adversary learns also these and more of the trajectory is disclosed. If the adversary knows several segments of the trajectory, it can also try to infer which way was taken between them, and thus learning more than just the disclosed segments. Analysing this is however outside the scope of this article and left as further research.

5.3 Privacy when preserving the Origin-Destination Matrix

We now consider the effects on the privacy measures of restricting swapping to preserve the Origin-Destination Matrix (ODM), introduced in Section 3. That is, for two trajectories to swap they have to share the same starting location or origin and ending location or destination (up to some scale). This is in addition to the earlier requirements for allowing a swap.

We define the states or locations used in the ODM by the labelled cells or states in a grid obtained by partitioning the city into equally sized squares (in units of degrees). The resolution of the grid is given by the width or side-length of the squares in degrees of latitude and longitude (1 degree of latitude is about 111000 m in Beijing), a lower width then corresponds to a finer grid. The start location or origin for a trajectory will be given by the square that its first measurement belongs to and the end location or destination by the square that its last measurement belongs to. In general, it might be more appropriate to

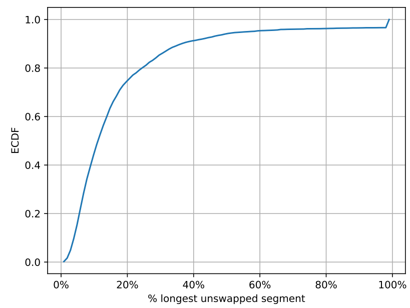
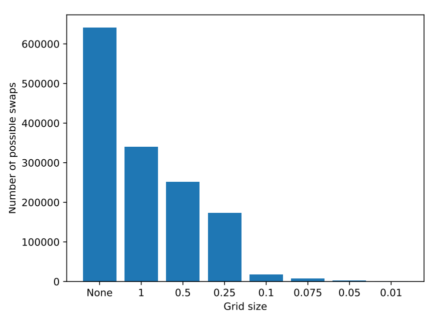


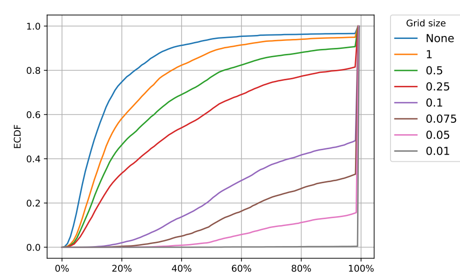
Fig. 4: Length of the longest unswapped segment as percentages of the total length for each trajectory. The length was here given by the number of measurements.

have start and end locations to be determined by the location of the trajectory at a certain time of the day. However, for keeping it simple, we choose to use only the first and last measurement. More generally, our approach allows for an arbitrary set of subsets of the city and arbitrary time-intervals to specify Origins and Destinations in a single ODM, or even a sequence of ODMs, but we use a simple grid-based partition at different spatial resolutions to illustrate the effects on privacy here.

We will analyze how the preserved privacy changes when we go from having no grid to having a very coarse grid and then making it finer and finer.



(a) The number of possible swaps depending on the grid size. Going from having no grid to a very fine grid.



(b) Length of the longest unswapped segment as percentages of the total length for each trajectory for different grid sizes. The length of the trajectory was here given by the number of measurements.

Fig. 5: Preserved privacy when also preserving the ODM

In Figure 5a we see how the number of possible swaps change when we make the grid finer. At first, we have the number of swaps without a grid (same as Figure 4) and then we have the numbers for grids of squares of the given height. The largest height used is 1 degree, about 11100 meters, which can be compared to the distance of 0.001 degrees, about 111 meters, that we used for determining if two trajectories are swappable, i.e. close enough to be swapped. This grid splits the city into four parts, of which two contain most of the measurements. On the other extreme, the finest grid is made up of squares of width 0.01 degrees or about 1110 meters, and this is 10 times the proximity threshold for swappability. We see that the number of possible swaps quickly decreases as the grid gets finer. Even at the coarsest grid, the number of swaps is halved compared to having no grid. When the grid height goes below 0.1 we have very few possible swaps.

Since the preserved privacy heavily depends on the number of possible swaps, we expect it to quickly decrease as the grid becomes finer. We can confirm this by computing the same measurement as in Section 5.2 for each grid size, see Figure 5b. The line corresponding to having no grid is the same as in Figure 4 and we can see that the privacy decreases as the grid becomes finer.

We can conclude that the preserved privacy is greatly influenced by the grid size of the ODM. If the grid is too fine almost no swaps occur and the SwapMob algorithm is not efficient. For very coarse grids the privacy is still reduced but depending on the application it could still be considered acceptable. Furthermore, by defining a sequence of ODMs, say $(M_1, M_2, \ldots, M_m)$, specified by arbitrary subsets of space and intervals of time $[\underline{t}_{i,o}, \overline{t}_{i,o}]$ and $[\underline{t}_{i,d}, \overline{t}_{i,d}]$ for each M_i, one can increase privacy by increasing the number of swappable trajectories. Such a sequence of ODMs should generally be of greater utility for certain decision problems. We defer a thorough investigation of sufficient sanitizers that preserve sufficient statistics for such sequences of ODMs across spatial and temporal resolutions in a principled manner for future research.

6 Conclusions

We have defined and tested a novel algorithm for mobility data sanitization that consists of swapping trajectory segments. In contrast to the k-anonymity or differential privacy models for trajectory sanitization, the proposed method does not modify the data, but its association to specific individuals, and it is performed in real time, without the need of having the entire dataset. The proposed protocol tackles both identity and location privacy, and our data model can be adapted to protect either single trajectory positions, as they lose the relation to the individual who has generated the data, or the whole trajectories, since they are mixed among many different peers.

We show that for the T-drive dataset a high number of swaps occur and most trajectories participate in several swaps. We can see that the original trajectories are split up into many smaller segments and that it makes it hard even for an adversary who knows exact points of the trajectory to infer much of the full trajectory. However, when adding the restriction of preserving the ODM, the number of swaps quickly decreases as the grid is made finer and it becomes much easier for an adversary to infer a big portion of the trajectory of an individual knowing only a few measurements. This is the natural tradeoff between the *societal utility gained* through the preservation of the ODM in decision problems, where ODM is a sufficient statistic, and the *individual privacy lost* by the sufficient sanitizer.

We have simulated our protocol with an offline algorithm. Although, the protocol could be run in real time in which data is transmitted by user devices to our sanitizer that communicates and collaborates with a server. By changing the sanitizer for a group protocol, the protocol could provide security against collusion between the service provider and the anonymizer.

It must be mentioned that swapping cannot be carried out when an individual does not come close to anyone along their path. Hence, the proposed technique will not protect an individual who does not proximally encounter anyone in their daily activity. We consider that it is not very common for an individual to spend too much time without meeting someone or going out from home. Moreover, such individuals can be kept outside the database without compromising its utility, e.g., in the case of T-drive data 265 of these 324 trajectories have less than 10 measurements (compared to an average of more than 1000).

The use case considered is for obtaining aggregate mobility data that preserve sufficient statistics for various statistical decision problems used in traffic engineering and city planning, including exact count queries, transition count queries and ODM queries, which neither k-anonymity nor differential privacy cannot formally guarantee.

As we have shown, there is a clear tradeoff between preserving a particular statistic, such as ODM, and the privacy provided by this algorithm. While swapping without constraints provides the highest level of privacy, it comes at the cost of losing individual trajectory mining utility. Future work directions to solve this issue are to add the restriction of non-swapping streets or non-swapping zones to better preserve entire trajectories inside a given street or zone. A formal privacy-preserving decision-theoretic framework based on probabilistic models and statistical experiments for co-trajectories that can be integrated across multiple spatial and temporal resolutions needs further investigations, especially when the computational setting becomes distributed to handle mobility data at a massive scale.

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