On the anonymizability of mobile traffic datasets

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ABSTRACT
Preserving user privacy is paramount when it comes to publicly disclosed datasets that contain fine-grained data about large populations. The problem is especially critical in the case of mobile traffic datasets collected by cellular operators, as they are prone to subscriber re-identifiability and they are resistant to anonymization through spatiotemporal generalization. In this work, we investigate the anonymizability of two large-scale mobile traffic datasets, by means of a novel dedicated measure. Our results are in agreement with those of previous analyses, and provide additional insights on the reasons behind the poor anonymizability of mobile traffic datasets. As such, our study is a step forward in the direction of better dataset anonymization.

1. INTRODUCTION
Public disclosure of datasets containing micro-data, i.e., information on precise individuals, is an increasingly frequent practice. Such datasets are collected in a number of different ways, including surveys, transaction recorders, positioning data loggers, mobile applications, and communication network probes. They yield fine-grained data about large populations that has proven critical to seminal studies in a number of research fields.

However, preserving user privacy in publicly accessible micro-data datasets is currently an open problem. Publishing an incorrectly anonymized dataset may disclose sensible information about specific users. This has been repeatedly proven in the past. One of the first and best known attempts at re-identification of badly anonymized datasets was carried out by then MIT graduate student Latanya Sweeney [1, 2] in 1996. By using a database of medical records released by an insurance company and the voter roll for the city of Cambridge (MA), purchased for 20 US dollars, Dr. Sweeney could successfully re-identify the full medical history of the then governor of Massachusetts, William Weld. She even sent the governor full health records, including diagnoses and prescriptions, to his office. A later, yet equally famous experiment was performed by Narayanan et al. [3] on a dataset released by Netflix for a data-mining contest, which was cross-correlated with a web scraping of the popular IMDB website. The authors were able to match two users from both datasets revealing, e.g., their political views.

Recently, severe concerns have been raised by privacy breaches in mobile traffic datasets. These datasets are collected at different locations of the cellular network infrastructure, and contain information about movements and traffic generated by millions of subscribers, typically for long timespans in the order of months. Mobile traffic datasets have become a paramount instrument in large-scale analyses across disciplines such as sociology, demography, epidemiology, or computer science. Unfortunately, they are also extremely prone to attacks on individual privacy. Namely, mobile traffic datasets suffer from the following issues:

1. Elevate re-identifiability. Mobile subscribers have very distinctive patterns that make them easily identifiable even within a very large population. Zang and Bolot [4] showed that 50% of the mobile subscribers in a 25 million-strong dataset could be uniquely detected with minimal knowledge about their movement patterns, namely the three locations they visit the most frequently. The result was corroborated by de Montjoye et al. [5], who demonstrated how an individual can be pinpointed among 1.5 million other mobile customers with a probability almost equal to one, by just knowing five random spatiotemporal points contained in his mobile traffic data.

2. Low anonymizability. The legacy solution to re-identifiability is generalization and suppression of data. However, both studies above proved that blurring users in the crowd, by reducing the spatial and temporal granularity of data, is hardly a solution in the case of mobile traffic datasets. Zang and Bolot [4] found that reliable anonymization is attained only under very coarse spatial aggregation, namely when the mobile subscriber location granularity is reduced to the city level. Similarly, de Montjoye et al. [5] explained that a power-law relationship exists between re-identifiability and spatiotemporal aggregation of mobile traffic. This
Table 1: Standard micro-data database format.

| Pseudo-id | Gender | Age | ZIP | Degree | Income |
|-----------|--------|-----|-----|--------|--------|
| 00013701  | Male   | 21  | 77005 | Bachelor | 13,000 |
| 08936402  | Male   | 37  | 77005 | Master’s | 90,000 |
| 42309327  | Female | 60  | 89123 | High School | 46,000 |
|           |        |     |      |        |        |

Table 2: Mobile traffic database format.

| Pseudo-id | Spatiotemporal samples (fingerprint) |
|-----------|--------------------------------------|
| a         | c1,8, c2,14, c3,17                   |
| b         | c4,8, c5,15, c6,19, c13,15, c14,16, c15,17 |
| c         | c16,7, c17,20                       |
| ...       | ...                                 |

implies that privacy is increasingly hard to ensure as the resolution of a dataset is reduced. In conclusion, not only mobile traffic datasets are easily re-identifiable, but they are also hard to anonymize. Ensuring individual privacy risks to lower the level of detail of such datasets to the point that they are not informative anymore.

In this work, we aim at better investigating the reasons behind such inconvenient properties of mobile traffic datasets. We focus on anonymizability, since it is a more revealing feature: multiple datasets that are all re-identifiable may be more or less difficult to anonymize. Attaining our objective brings along the following contributions: (i) we define a measure of the level of anonymizability of mobile traffic datasets, in Sec.2(ii) we provide a first assessment of the anonymizability of two large-scale mobile traffic datasets, in Sec.3(iii) we unveil the cause of naive re-identifiability and poor anonymizability in such datasets, i.e., the heavy tail of the temporal diversity among subscriber mobility patterns, in Sec.4. Finally, Sec.4 concludes the paper.

2. HOW ANONYMIZABLE IS YOUR MOBILE TRAFFIC FINGERPRINT?  

In this section, we first define in a formal way the problem of user re-identification in mobile traffic datasets, in Sec.2.1. Then, we introduce the proposed measure of anonymizability, in Sec.2.2.

2.1 Our problem

In order to properly define the problem we target, we need to introduce the notion of mobile traffic fingerprint that is at the base of the mobile traffic dataset format. We also need to specify the type of anonymity we consider – in our case, k-anonymity. Next, we discuss these aspects of the problem.

2.1.1 Mobile traffic fingerprint and dataset

Traditional micro-data databases are structured into matrices where each row maps to one individual, and each column to an attribute. An example is provided in Tab.1. Individuals are associated to one identifier, i.e., a value that uniquely pinpoints the user across datasets (e.g., his complete name, social number, or passport number). Since identifiers allow immediate cross-database correlation, they are never disclosed. Instead, they are replaced by a pseudo-identifier, which is again unique for each individual, but changes across datasets (e.g., a random string substituting the actual identifier). Then, standard re-identification attacks leverage quasi-identifiers, i.e., a sequence of known attributes of one user (e.g., the age, gender, ZIP code, etc.) to recognize the user in the dataset. If successful, the attacker has then access to the complete record of the target user. This knowledge can directly include sensitive attributes, i.e., items that should not be disclosed because they may pertain to the personal sphere of the individual (e.g., diseases, political or religious views, sexual orientation, etc.). It can also be exploited for further cross-database correlation so as to extract additional private information about the user.

The same model directly applies to the case of mobile traffic datasets. However, the database semantics make all the difference here: while mobile users are the obvious individuals whose privacy we want to protect, attributes are now sequences of spatiotemporal samples. Each sample is the result of an event that the cellular network associated to the user. An illustration is provided in Fig.1a, which portrays the trajectories of three mobile customers, denoted with pseudo-identifiers a, b, and c, respectively, across an urban area. User a interacts with the radio access infrastructure at 8 am, while he is in cell c1 along his trajectory. Then, he triggers additional mobile traffic activities at 2 pm, while located in a cell c2 in the city center, and at 5 pm, from a cell c3 in the South-East city outskirts. The same goes for users b and c. All these spatiotemporal samples are recorded by the mobile operator and constitute the mobile traffic fingerprint of the user. The resulting database has a format such as that in Tab.2 where subscriber identifiers are replaced by pseudo-identifiers, and each element of a user’s fingerprint is a cell and hourly timestamp pair.

2.1.2 k-anonymity in mobile traffic

In order to preserve user privacy in micro-data, one

1The actual precision of the information recorded, both in space and in time, can depend significantly on the nature of the probes used by the operator. Typically, probes located closer to the radio access can capture more events at a finer granularity, but require more extensive deployments to attain a similar coverage than lower-precision probes located in the mobile network core. In all cases, our discussion is independent of the mobile traffic data collection technique, and all the analyses performed in this work can be applied to any type of mobile traffic data.
has to ensure that no individual is uniquely identifiable in a dataset. This principle has led to the definition of multiple notions of non-uniqueness, such as $k$-anonymity [1], $l$-diversity [6] and $t$-closeness [7]. Among those, $k$-anonymity is the baseline criterion, to which $l$-diversity or $t$-closeness add further security layers that cope with sensitive attributes or cross-database correlation. More precisely, $k$-anonymity ensures that, for each individual, the set of attributes (or its quasi-identifier subset) is identical to that of at least other $k-1$ users. In other words, each individual is always hidden in a crowd of $k$, and thus he cannot be uniquely identified among such other users.

Granting $k$-anonymity in micro-data databases implies generalizing and suppressing data. As an example, in order to ensure 2-anonymity on the age and ZIP code attributes for the first user in Tab.1, one can aggregate the age in twenty-year ranges, and the ZIP codes in three-number ranges: both the first and second user end up with a (20,40) age and 770** ZIP code, which makes them both 2-anonymous. Clearly, the process is lossy, since the information granularity is reduced. Many efficient algorithms have been proposed that achieve $k$-anonymity in legacy micro-data databases, while minimizing information loss [8].

Also in mobile traffic datasets, $k$-anonymity is regarded as a best practice, and data aggregation is the common approach to achieve it [4, 5]. In this case, one has to ensure that the fingerprint of each subscriber is identical to that of at least other $k-1$ mobile users in the same dataset. We remark that previous works have typically considered a model of attacker who only has partial knowledge of the subscribers’ fingerprints, e.g., most popular locations [4] or random samples [5]. In order to counter such a attack model, a partial $k$-anonymization, targeting the limited information owned by the attacker, would be sufficient. However, we are interested in a general solution, so we do not make any assumption on the precise knowledge of the attacker, which can be diverse and possibly broad. Thus, $k$-anonymizing the whole fingerprint of each subscriber in the mobile traffic dataset is the only way to deterministically ensure mobile user privacy.

Both spatial and temporal aggregations can be leveraged to attain this goal. Examples are provided in Fig.1b and Fig.1c. In Fig.1b cells are aggregated in large sets that roughly map to the nine major neighborhoods of the urban area; also, time is aggregated in two-hour intervals. The reduction of spatiotemporal granularity allows 2-anonymizing mobile users $a$ and $b$: both have now a fingerprint composed by samples (V,8-9), (III,14-15), and (VII,16-17). User $c$ has instead a different footprint, with samples (IV,6-7) and (III,20-21). If we need to 3-anonymize all three mobile customers in the example, then a further generalization is required, as in Fig.1c. There, the metropolitan region is divided in West and East halves, and only two time intervals, before and after noon, are considered. The result is that all subscribers $a$, $b$, and $c$ have identical fingerprints (West,1-12) and (East,13-24). Clearly, this level of anonymization comes at a high cost in terms of information loss, as the location data is very coarse both in space and time.

This is precisely the problem of low anonymizability of mobile traffic datasets unveiled by previous works [4, 5]: even guaranteeing 2-anonymization in a very large population requires severe reductions of the spatiotemporal granularity, which limits the usability of the data.

Figure 1: Example of mobile traffic fingerprints of three subscribers. (a) Initial dataset granularity: user locations are represented at cell level, and the temporal information has a hourly precision. (b) First aggregation level: positions are recorded at each neighborhood, and the time granularity is reduced to two hours. (c) Second aggregation level: location data is limited to Eastern or Western half of the city, and the time information is merged over 12 hours.
2.2 A measure of anonymizability

We intend to devise a measure of anonymizability that is based on the $k$-anonymity criterion. Thus, our proposed measure evaluates the effort, in terms of data aggregation, needed to make a user indistinguishable from $k$-1 other subscribers.

We start by defining the distance between two spatiotemporal samples in the mobile traffic fingerprints of two mobile users. Each sample is composed of a spatial information (e.g., the cell location) and a temporal information (e.g., the timestamp). The distance must keep into account both dimensions. A generic formulation of the distance between the $i$-th sample of $a$'s fingerprint, $(s_i^a, t_i^a)$, and the $j$-th sample of $b$'s fingerprint, $(s_j^b, t_j^b)$, is

$$d_{ab}(i, j) = w_s \delta_s (s_i^a, s_j^b) + w_t \delta_t (t_i^a, t_j^b). \quad (1)$$

Here, $\delta_s$ and $\delta_t$ are functions that determine the distance along the spatial and temporal dimensions, respectively. The former thus operates on the spatial information in the two samples, $s_i^a$ and $s_j^b$, and the latter on the temporal information, $t_i^a$ and $t_j^b$. The factors $w_s$ and $w_t$ weight the spatial and temporal contributions in (1). In the following, we will assume that the two dimensional have the same importance, thus $w_s = w_t = 1/2$.

We shape the $\delta_s$ and $\delta_t$ functions by considering that both spatial and temporal aggregations induce a loss of information that is linear with the decrease of granularity. However, above a given spatial or temporal threshold, the information loss is so severe that the data is not usable anymore. As a result, the functions can be expressed as

$$\delta_s (s_i^a, s_j^b) = \begin{cases} \text{dist} (s_i^a, s_j^b) & \text{if dist} (s_i^a, s_j^b) \leq \delta_s^{\text{max}} \\ 1 & \text{otherwise}, \end{cases} \quad (2)$$

and

$$\delta_t (t_i^a, t_j^b) = \begin{cases} \frac{|t_i^a - t_j^b|}{\delta_t^{\text{max}}} & \text{if } |t_i^a - t_j^b| \leq \delta_t^{\text{max}} \\ 1 & \text{otherwise}. \end{cases} \quad (3)$$

In (2), dist $(s_i^a, s_j^b) = |s_i^a.x - s_j^b.x| + |s_i^a.y - s_j^b.y|$ is the Taxicab distance between the spatial components of the samples, whose coordinates are denoted as $x$ and $y$ in a valid map projection system. Both functions fulfill the properties of distances, i.e., are positive definite, symmetric, and satisfy the triangle inequality. They range from 0 (samples are identical from a spatial or temporal viewpoint) to 1 (samples are at or beyond the maximum meaningful aggregation threshold). Concerning the values of the thresholds, in the following we will consider that the aggregation limits beyond which the information deprivation is excessive are 20 km for the spatial dimension (i.e., the size of a city, beyond which all intra-urban movements are lost) and 8 hours (beyond which the night, working hours, and evening periods are merged together).

The sample distance in (1) can be used to define the distance among the whole fingerprints of two mobile subscribers $a$ and $b$, as

$$\Delta_{ab} = \begin{cases} \frac{1}{n_a} \sum_{h=1}^{n_a} \min_{k=1, \ldots, n_b} d_{ab}(h, k) & \text{if } n_a \geq n_b \\ \frac{1}{n_b} \sum_{h=1}^{n_b} \min_{k=1, \ldots, n_a} d_{ab}(k, h) & \text{otherwise}. \end{cases} \quad (4)$$

Here, $n_a$ and $n_b$ are the cardinalities of the fingerprints of $a$ and $b$, respectively. The expression in (4) takes the longer fingerprint between the two, and finds, for each sample, the sample at minimum distance in the shorter fingerprint. The resulting $\Delta_{ab}$ is the average among all such sample distances, and $\Delta_{ab} = \Delta_{ba}$, $\forall a, b$.

The measure of anonymizability of a generic mobile user $a$ can be mapped, under the $k$-anonymity criterion, to the average distance of his fingerprint from those of the nearest $k$-1 other users. Formally

$$\Delta_k^a = \frac{1}{k-1} \sum_{b \in \mathbb{N}^{k-1}} \Delta_{ab}, \quad (5)$$

where $\mathbb{N}^{k-1}$ is the set of $k-1$ users $b$ with the smallest fingerprint distances to that of $a$.

The expression in (5) returns a measure $\Delta_k^a \in [0, 1]$ that indicates how hard it is to hide subscriber $a$ in a the crowd of $k$ users. If $\Delta_k^a = 0$, then the user is already $k$-anonymized in the dataset. If $\Delta_k^a = 1$, the user is completely isolated, i.e., no sample in the fingerprints of all other subscribers is within the spatial and temporal thresholds, $\delta_s^{\text{max}}$ and $\delta_t^{\text{max}}$, from any samples of $a$'s fingerprint.

3. TWO MOBILE TRAFFIC USE CASES

We employ the proposed measure to assess the level of anonymizability of fingerprints present in two mobile traffic datasets released by Orange in the framework of the Data for Development Challenge. In order to allow for a fair comparison, we preprocessed the datasets so as to make them more homogeneous.

- **Ivory Coast.** Released for the 2012 Challenge, this dataset describes five months of Call Detail Records (CDR) over the whole the African nation of Ivory Coast. We used the high spatial resolution dataset, containing the complete spatio temporal trajectories for a subset of 50,000 randomly selected users that are changed every two weeks. Thus, the dataset contains information about 10 2-weeks periods overall. We performed
a preliminary screening, discarding the most disperse trajectories, keeping the users that have at least one spatio-temporal point per day. Then, we merged all the user that met this criteria in a single dataset, so as to achieve a meaningful size of around 82,000 users. This dataset is indicated as \( \text{d4d-civ} \) in the following.

- **Senegal.** The 2014 Challenge dataset is derived from CDR collected over the whole Senegal for one year. We used the fine-grained mobility dataset, containing a randomly selected subset of around 300,000 users over a rolling 2-week period, for a total of 25 periods. We did not filter out subscribers, since the dataset is already limited to users that are active for more than 75\% of the 2-week time span. In our study, we consider one representative 2-week period among those available. This dataset is referred to as \( \text{d4d-sen} \) in the following.

In both the mobile traffic datasets, the information about the user position\(^2\) is provided as a latitude and longitude pair. We projected the latter in a two-dimensional coordinate system using the Lambert azimuthal equal-area projection. We then discretize the resulting positions on a 100-m regular grid, which represents the maximum spatial granularity we consider\(^3\). As far as the temporal dimension is concerned, the maximum precision granted by both datasets is one minute, and this is also our finest time granularity.

### 4. RESULTS

The measure of anonymizability in \( [3] \) can be intended as a dissimilarity measure, and employed in legacy definitions used to understand micro-data database sparsity, e.g., \( (\varepsilon, \delta) \)-sparsity \( [3] \). However, these definitions are less informative than the complete distribution of the anonymizability measure. Thus, in this section, we employ Cumulative Distribution Functions (CDF) of the measure in \( [4] \) in order to assess the anonymizability of the two datasets presented before.

#### 4.1 The good: anonymity is close to reach

Our basic result is shown in Fig.2. The plot portrays the CDF of the anonymizability measure computed on all users in the two reference mobile traffic datasets, \( \text{d4d-civ} \) and \( \text{d4d-sen} \), when considering 2-anonymity as the privacy criterion.

We observe that the two curves are quite similar, and both are at zero in the x-axis origin. This means that no single mobile subscriber is 2-anonymous in either of the original datasets, which confirms previous findings on the elevate re-identifiability of mobile traffic datasets \( [4, 5] \). However, the probability mass gathered in both cases in the 0-1 range, i.e., it is quite close to the origin. This is good news, since it implies that the average aggregation effort needed to achieve 2-anonymity is not elevate.

As an example, 50\% of the users in the \( \text{d4d-civ} \) dataset have a measure 0.09 or less, which maps, on average, to a combined spatiotemporal aggregation of less than one km and little more than 20 minutes. In other words, the result seems to suggest that half of the individuals in the dataset can be 2-anonymized if the spatial granularity is decreased to 1 km, and the temporal precision is reduced to around 20 minutes. Similar considerations hold in the \( \text{d4d-sen} \) case, where, e.g., 80\% of the dataset population has a measure 0.17 or less. Such a measure is the result of average spatial and temporal distances of 1.7 km and 41 minutes from 2-anonymity.

One may wonder how more stringent privacy requirements affect these results. Fig.3 shows the evolution of the anonymizability of the two datasets when \( k \) varies from 2 to 100. As expected, higher values of \( k \) require that a user is hidden in a larger crowd, and thus shift

\[\text{CDF of the anonymizability measure, under the 2-anonymity criterion, in the } \text{d4d-civ} \text{ and } \text{d4d-sen} \text{ mobile traffic datasets.}\]

\[\text{CDF of the anonymizability measure, for varying } k \text{ of the } k \text{-anonymity criterion, in the } \text{d4d-civ} \text{ and } \text{d4d-sen} \text{ mobile traffic datasets.}\]
the distributions towards the right, implying the need for a more coarse aggregation. However, quite surprisingly, the shift is not dramatic: 100-anonymity does not appear much more difficult to reach than 2-anonymity.

4.2 The bad: aggregation does not work

Unfortunately, the easy anonymizability suggested by the distributions is only apparent. Fig. 4 depicts the impact of spatiotemporal generalization on anonymizability: each curve maps to a different level of aggregation, from 100 meters and 1 minute (the finer granularity) to 20 km and 8 hours. As one could expect, the curves are pushed towards smaller values of the anonymizability measure. However, the reduction of spatiotemporal precision does not have the desired magnitude, and even a coarse-grained citywide, 8-hour aggregation cannot 2-anonymize but 30% of the mobile users.

This result is again in agreement with previous studies [4, 5], and confirms that mobile traffic datasets are difficult to anonymize.

4.3 The why: long-tailed temporal diversity

We are interested in understanding the reasons behind the incongruity above, i.e., the fact that spatiotemporal aggregation yields such poor performance, even if the average effort needed to attain k-anonymity is in theory not elevate.

To attain our goal, we proceed along two directions. First, we separate the spatial and temporal dimensions of the measure in (4), so as to understand their precise contribution to the dataset anonymizability. Second, we measure the statistical dispersion of the fingerprint distances along the two dimensions: the rationale is that we observed the average distance among fingerprints to be quite small, thus the reason of the low anonymizability must lie in the deviation of sample distances around that mean.

4.3.1 Impact of space and time dimensions

Formally, we consider, for each user a in the dataset, the set \( N_{a}^{k-1} \) of k−1 other subscribers whose fingerprints are the closest to that of a, according to (4). Then, we disaggregate all the fingerprint distances \( \Delta_{ab} \) between a and the users b ∈ \( N_{a}^{k-1} \) into sample distances \( d_{ab} \), as per (4). Finally, we separately collect the spatial and temporal components of all such sample distances, in \( \Omega_{a} \), into ordered sets \( S_{a}^{w} = \{ w_{i} \delta_{t} \} \) and \( T_{a}^{w} = \{ w_{i} \delta_{t} \} \). The resulting sets can be treated as disjoint distributions of the distances, along the spatial and temporal dimensions, between the fingerprint of a generic individual a and those of the k−1 other users that show the most similar patterns to his.

Examples of the spatial and temporal distance distributions we obtain in the case of 2-anonymity are shown in Fig. 4a,4b. Each plot refers to one random user in the d4d-civ or d4d-sen dataset, and portrays the CDF of the spatial (\( w_{i} \delta_{t} \)) and temporal (\( w_{i} \delta_{t} \)) component distance, as well as that of the total sample distance (\( d \)). We can remark that temporal components typically bring a significantly larger contribution to the total fingerprint distance than spatial ones. In fact, a significant portion of the spatial components is at zero distance, i.e., is immediately 2-anonymous in the original dataset. The same is not true for the temporal components.

A rigorous confirmation is provided in Fig. 5 which shows the distribution of the temporal-to-spatial component ratios, i.e., \( \sum T_{a}^{w} w_{i} \delta_{t} / \sum S_{a}^{w} w_{i} \delta_{t} \), for all subscribers a in the two reference datasets. The CDF is skewed towards high values, and for half of mobile subscribers in both d4d-civ or d4d-sen datasets temporal components contribute to 80% or more of the total sample distance. We conclude that the temporal component of a mobile traffic fingerprint is much harder to anonymize than the spatial one. In other words, where an individual generates mobile traffic activity is easily masked, but hiding when he carries out such activity it is not so.

4.3.2 Dispersion of fingerprint sample distances

Not only temporal components weight much more than spatial ones in the fingerprint distance, but they also seem to show longer tails in Fig. 6a,6b. Longer tails imply the presence of more samples with a large distance: this, in turn, significantly increases the level of aggregation needed to achieve k-anonymity, as the latter is only granted once all samples in the fingerprint have zero distance from those in the second fingerprint.

We rigorously evaluate the presence of a long tail of hard-to-anonymize samples by means of two complementary metrics, still separating their spatial and temporal components. The first metric is the Gini coefficient, which measures the dispersion of a distribution around its mean. Considering an ordered set \( S = \{ s_{i}, \} \),
The former show cases where no dispersion at all is for the spatial (mean). However, two opposite behaviors are observed around 0 distances and spatial component distances.

temporal components to the total sample distance, expressed as the ratio between the sums of temporal component distances and spatial component distances.

The coefficient is computed as

\[ G(S) = 1 - \frac{2 \sum_{i=1}^{N} i s_i + \sum_{i=1}^{N} s_i}{N \sum_{i=1}^{N} s_i}, \]

where \( N \) is the cardinality of \( S \). We compute the Gini coefficient on the sets \( S_k^s \) and \( T_k^t \), for all users \( a \).

The second metric is the Tail weight index \[\text{T}_\text{F}\], which quantifies the weight of the tail of a distribution with empirical CDF \( F \) as

\[ T_F = \frac{F^{-1}(0.99) - F^{-1}(0.5)}{F^{-1}(0.75) - F^{-1}(0.5)} \Phi^{-1}(0.75) - \Phi^{-1}(0.5). \]

In the expression above, \( F^{-1}(\cdot) \) is the inverse function of the empirical CDF and \( \Phi^{-1}(\cdot) \) is the inverse function of a standard normal CDF. We compute again the Tail weight index on the distributions obtained from both \( S_k^s \) and \( T_k^t \), for all \( a \).

Fig. 5 shows the results returned by the two metrics in the d4d-civ or d4d-sen datasets. No significant differences emerge among the two mobile traffic datasets. In both cases, the Gini coefficient, in Fig. 5c and Fig. 5d, has, for all mobile user fingerprints (d), high values around 0.5 that denote significant dispersion around the mean. However, two opposite behaviors are observed for the spatial \( (w, \delta_s) \) and temporal \( (w, \delta_t) \) components. The former show cases where no dispersion at all is recorded (coefficient close to zero), and cases where the distribution is very sparse. The latter has the same behavior as the overall distance, with values clustered around 0.5. The result (i) corroborates the observation that the overall anonymizability is driven by distances along the temporal dimension, and (ii) imparts the latter to the complete absence of easy-to-anonymize short tails in the distribution of temporal distances.

Fig. 6a and Fig. 6d show instead the CDF of Tail weight indices. Here, the result is even more clear: the tail of temporal component distances is typically much longer than that of spatial ones, and in between those of exponential and heavy-tailed distribution.\(^4\) Once more, the temporal component tail fundamentally shapes that of the overall fingerprint distance.

5. DISCUSSION AND CONCLUSIONS

At the light of all previous observations, we confirm the findings of previous works on user privacy preservation in mobile traffic datasets. Namely, the two datasets we analysed do not grant \( k \)-anonymity, not even for the minimum \( k = 2 \). Moreover, our reference datasets show poor anonymizability, i.e., require important spatial and temporal generalization in order to slightly im-

\(^4\)As a reference, an exponential distribution with mean equal to 1 has a Tail weight index of 1.6, and a Pareto distribution with shape 1 has a Tail weight index of 14.
prove user privacy. The fact that these properties have been independently verified across diverse datasets of mobile traffic suggests that the elevated re-identifiability and low anonymizability are intrinsic properties of this type of datasets.

In our case, even a citywide, 8-hour aggregation is not sufficient to ensure complete 2-anonymity to all subscribers. The result is even worse than that observed in previous studies: the difference is due to the fact that we consider the anonymization of complete subscriber fingerprints, whereas past works focus on simpler obfuscation of summaries [4] or subsets [5] of the fingerprints.

Our analysis also unveiled the reasons behind the poor anonymizability of the mobile traffic datasets we consider.

On the one hand, the typical mobile user fingerprint in such datasets is composed of many spatiotemporal samples that are easily hidden among those of other users in the dataset. This leads to fingerprints that appear easily anonymizable, since their samples can be matched, on average, with minimal spatial and temporal aggregation.

On the other hand, mobile traffic fingerprints tend to have a non-negligible number of elements that are much more difficult to anonymize than the average sample. These elements, which determine a characteristic dispersion and long-tail behavior in the distribution of fingerprint sample distances, are mainly due to a significant diversity along the temporal dimension. In other words, mobile users may have similar spatial fingerprints, but their temporal patterns typically contain a non-negligible number of dissimilar points.

It is the presence of these hard-to-anonymize elements in the fingerprint that makes spatiotemporal aggregation scarcely effective in attaining anonymity. Indeed, in order to anonymize a user, one needs to aggregate over space and time, until all his long-tail samples are hidden within the fingerprints of other subscribers. As a result, even significant reductions of granularity (and consequent information losses) may not be sufficient to ensure individual privacy in mobile traffic datasets.

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