No Place to Hide that Bytes won’t Reveal: 
Sniffing Location-Based Encrypted Traffic to Track User Position

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Abstract. News reports of the last few years indicated that several intelligence agencies are able to monitor large networks or entire portions of the Internet backbone. Such a powerful adversary has only recently been considered by the academic literature.
In this paper, we propose a new adversary model for Location Based Services (LBSs). The model takes into account an unauthorized third party, different from the LBS provider itself, that wants to infer the location and monitor the movements of a LBS user. We show that such an adversary can extrapolate the position of a target user by just analyzing the size and the timing of the encrypted traffic exchanged between that user and the LBS provider. We performed a thorough analysis of a widely deployed location based app that comes pre-installed with many Android devices: GoogleNow. The results are encouraging and highlight the importance of devising more effective countermeasures against powerful adversaries to preserve the privacy of LBS users.

Keywords: Location-Based Services, Network Traffic Analysis, Privacy, GoogleNow, Mobile Devices

1 Introduction

In 1996 the Italian police were intercepting the phone of one of the top Mafia boss of the time (the one responsible for the death of the anti-mafia prosecutor Giovanni Falcone). To locate the boss, the police had a policeman drive a noisy motorcycle around the city of Agrigento (Sicily). The police rider would make substantial noise (by repeatedly accelerating) when instructed to do so by the officers eavesdropping on the calls. The peculiar noise pattern of the motorcycle was picked up from the background noise of the calls and used to locate the boss and ultimately arrest him [2]. Today, surveillance systems that track the movements of cellphone users are stealthier and more sophisticated. Cellular carriers keep very detailed databases of the locations of their customers to deliver calls, messages, and other services [6]. Intelligence agencies can easily locate the
cell tower a target is using and find his location with pinpoint accuracy when combined with other services such as GPS. This tracking technology is available to anyone with enough money [6].

Tracking devices exploit security vulnerabilities of the Signaling System 7 (SS7) network used by carriers around the world to provide services to their traveling customers. According to a Washington Post article [6], it is possible to compromise the SS7 network and collect location data of anyone in the world and learn whether a person is walking down a specific street, driving, or taking a flight. Once the approximate location of a target is known, it is possible to employ stingrays [4] (that work as fake towers and interact with the phone) to redirect calls, monitor Internet traffic, steal phone's data, and even install malware.

All the attacks above are active and (partially) intrusive, i.e., they are not completely stealthy. Indeed, the boss could hear the motorcycle noise in the first example, queries to the SS7 network can be logged and phones could be configured by experts to detect stingrays (e.g., IMSI-Catcher Detector on Android phones). In general, intelligence agencies need the cooperation of vendors, mobile carriers, various companies, ISPs, and possibly a judge for a court order. Often the target is in a foreign country and special permissions or agreements must be in place to be able to track his movements.

In this paper we show that it is possible to locate the position of a cellphone by simply monitoring the traffic of certain phone applications that provide location-based services (LBS). Clearly this is simple if the traffic is in the clear, but our main contribution is to show that it is possible to track users even when the traffic is properly encrypted. We believe our method will have significant implications in the way location-based services are provided. These services are often accessed through apps that will be referred to as Location Based Apps or LBAs. LBAs are used to find friends and restaurants nearby, to locate points of interest, to check public transport timetables and even to search for deals or special offers. Several physical retailers, including Best Buy and Kohls, also deploy location-based promotions to push notifications while the consumer is in or near the store. TripAdvisor, Booking and weather forecasting applications are other examples of LBAs.

It is difficult to protect the privacy of users while at the same time provide useful location-based services. It is possible to obfuscate the exact position of a user but these obfuscation techniques are rarely adopted by vendors (location data is too valuable to them). Moreover, customers appreciate services or information they receive and do not seem concerned about sharing their location data with LBS providers. In addition, traffic from users to LBS providers is encrypted to preserve confidentiality and privacy.

The motivation behind our paper is to show that any third party that has access to the encrypted traffic from the user to the LBS provider can infer the position of the former. This can be performed in a non-intrusive way in the sense that it is enough to have access to the network traffic directed towards the LBS provider anywhere in the world to infer users' exact positions. For instance, an
intelligence organization could monitor routers belonging to some Autonomous System (AS) traversed by LBS’s packets and be able to infer the position of a target in a foreign country without involving that country’s ISPs, mobile carriers, or any other local entities. Encryption or NAT’ed addresses do not help much in this scenario. Indeed, we leverage results of previous works on analysis on encrypted traffic which already highlighted the possibility of identifying apps installed on a device [21], or the presence of a specific user within a network [22].

Another important concern to consider in this context is that current LBAs have started to adopt push technology solutions to send “the right information at the right time” [14]. This is the maxim of the GoogleNow app which comes preinstalled on most Android devices and provides several services that are tied to the user’s position. Several LBAs that come preinstalled on a phone do not even ask permission to use location data. The adoption of push technology implies that the user is continuously tracked by the LBS provider, even when the app runs in the background [7].

**Contributions** In this work we highlight a new privacy problem related to LBSs. We introduce a new adversary model for LBSs, and in this settings we propose a technique that unauthorized third parties may use to infer the position of a target user. Furthermore, we analyze one of the most popular LBAs, GoogleNow, and we show that the analysis of its encrypted network traffic reveals the position of a user with high accuracy. This research is inevitably controversial. The method we developed could be used to undetectably monitor movements of users and abuse their privacy rights. However, it should be considered as a warning to the research community to spur more research in the area and come up with effective countermeasures.

**Organization** The rest of this paper is organized as follows. In Section 2, we introduce the adversary model. In Section 3, we detail the different phases of the attack. In particular, Section 3.1 explains the method used by the adversary to collect the relevant data from the LBS provider. Then, Section 3.2 details the data analysis approach that can be used to infer the user’s location. Section 4 reports on the experiments and the results achieved when analyzing GoogleNow. In Section 5, we review previous work. Finally, in Section 6 we draw the conclusions and discuss some possible future works.

## 2 The Adversary Model

We assume the existence of an adversary $A$ that can sniff the network traffic of a mobile device. The adversary does not need to intercept the entire network traffic but just the packets that are exchanged between the LBA and the LBS provider. The adversary may do so either (i) by compromising one of the network devices of the Internet Service Provider that provides connectivity to the mobile device, or (ii) by compromising one of the network devices of any Autonomous System that routes the information from the mobile device to the LBS. We assume
that the adversary does not want to be detected, and therefore he does not compromise the mobile device nor change the content of network packets. This adversary’s ability is well within the arsenal of powerful intelligence agencies. It is well-known that the NSA can identify users around the world of specific services (such as TOR) by detecting packet “fingerprints” and monitoring large portions of the Internet. NSA accomplishes this by collaborating only with US telecoms firms under various programs [5].

We assume that the adversary is able to identify and isolate the network traffic of the user he is interested in, and, among those packets, he is able to identify and isolate packets that are generated by the LBA. The adversary is able to determine where discrete communications begin and end (such as the download of updated information from the LBS). This is possible, for example, by observing the typical communication patterns of the LBA. Note that if the network traffic is not encrypted, then our adversary may trivially inspect the packet content and determine the location of the mobile device. Therefore, we assume that the network traffic exchanged between the mobile device and the LBS is encrypted via SSL/TLS. Furthermore, we assume that the LBS provider does not use any mechanisms to protect the privacy of its users, such as k-anonymity cloaking, etc. This assumption is based on the fact that current LBS providers do not implement these mechanisms.

To launch the traffic analysis attack that we consider in this paper, the adversary must build a knowledge base that summarizes the network traffic exchanged between the LBA and the LBS when the mobile device is located in certain locations of interest. We assume that the adversary can collect this data by using bogus accounts and virtual mobile devices. More details about the approach are given in Section 3.

2.1 Example Scenario

Figure 1 represents a possible attack scenario. The target $U$ is a user with a mobile device; the adversary is a malicious entity $A$ that is after the geographical location of $U$. In this scenario, $A$ is not allowed to collude neither with the LBS nor with the ISP (the owner of the Base Transceiver Station - BTS) otherwise locating the user would be trivial (but intrusive) or even impossible if the LBS or the ISP refuse to provide private information. The LBS provider will keep sending new and relevant information to the device as the user moves around. This can happen without the user’s intervention via push communication. Several LBAs, more prominently GoogleNow, work this way. In this paper we analyze under which conditions collecting the encrypted traffic between the LBS provider and the device is enough to determine the exact user’s geographical position. Figure 1 depicts possible position in the network where $A$ can sit to intercept the network traffic. This is represented by the router $R_y$ highlighted in red. However, it is worth mentioning that $A$ can be potentially in any router laying in the path from the user’s device toward the LBS. Furthermore, those routers may belong to different ASes. Thus, the adversary may infer the user position from ASs
3 The attack

In this section, we detail the approach used by the adversary to infer the actual position of a target user. The entire approach can be logically divided into two steps: the data collection phase, and the candidate locations selection. The aim of the data collection phase is to collect enough information from the LBS provider to learn how different locations can be distinguished from each other. During this phase, the adversary builds up its knowledge base that will later be used to infer the most probable locations the target can be in. For the sake of simplicity, in this section we will assume that the LBS sends the same information to all users in the same location. However, in the experimental section we will consider a more advanced LBS that sends personalized information to its users.

3.1 Data Collection

Suppose that the adversary is interested in localizing users in a given area. First, the adversary logically divides the entire area in \( n \) subareas, and arbitrarily chooses a point in each subarea as a representative for that location. The size of the subareas is chosen according to the desired accuracy and the granularity of the information provided by the LBS. Hence, the adversary comes with a set of point locations \( \mathcal{L} = \{l_1, l_2, \ldots, l_n\} \).

Then, the adversary collects data from the LBS about all the locations in \( \mathcal{L} \).
Table 1: Example of the adversary knowledge base, user dataset related to a user position during time, and possible guesses

| LocID | Bytes       | Timestamp       |
|-------|-------------|-----------------|
| 1     | 35780       | 1399743000      |
| 2     | 30780       | 1399743000      |
| 3     | 33630       | 1399743000      |
| 4     | 18740       | 1399743000      |
| 1     | 36780       | 1399743060      |
| 2     | 30784       | 1399743060      |
| 3     | 37780       | 1399766340      |
| 4     | 30111       | 1399766340      |

This can be easily accomplished by using the same LBA of regular users and by spoofing the GPS coordinates to pretend to be in locations \( l_i \) for \( 1 \leq i \leq n \). Since the LBS may require a subscription to be used, the adversary may have to register a set of bogus accounts \( a_1, ..., a_m \) with the LBS. The adversary periodically performs the procedure above to learn the traffic pattern of the LBS over time (e.g., data sent by the LBS may change and follows daily or weekly trends).

The network traffic that the adversary collects is used to build its knowledge base. The following steps are performed during this phase:

**Prefiltering:** The network traffic is analyzed with a network protocol analyzer, and only the packets directed towards, or coming from, the network of the LBS are preserved.

**Knowledge Base Record Composition:** For each location \( l_i \) that is monitored, the adversary adds a record in its knowledge base composed of the following fields:

- **Location ID** (LocID for brevity in the following): An identifier of the probed location \( l_i \in L \).
- **Bytes:** The total size in bytes of the transmitted and received encrypted packets that belong to the same TLS/SSL session.
- **Timestamp:** The timestamp of the first packet of the TLS/SSL session.

An example of knowledge base that the adversary would create is reported in Table 1 on the left.

### 3.2 Selection of the Candidate Locations

To track the user position, the adversary relies upon only two fields: the sum of the exchanged bytes of a TLS/SSL session and the timestamp. This information
is derived from the header of the packets, therefore it is not encrypted by the SSL protocol. To learn the position of a given user $U$ at time $t_0$, it is enough for the adversary to collect the communication traffic between the user’s LBA and the LBS between time $t_0 - t$ and $t_0$. For each TLS/SSL session, $A$ calculates the fields described above and creates the user dataset. This is shown in Table 1 on the right.

At any given moment, each location is potentially characterized by a fixed amount of bytes. As such, the adversary selects a small subset of candidate locations by analyzing the locations that have generated an amount of bytes similar to the entries of the user dataset. More specifically, suppose that $A$ wants to know the position of the user $U$ at time $t_0$, then he builds a filtered adversary knowledge base containing only the instances of the knowledge base such that their timestamps fall within the time frame $[t_0 - t, t_0]$. The size of the time frame depends on the specific LBA and LBS taken into consideration, and on the typical behavior of the user. We assume that within the targeted time frame the adversary knows that the user does not move from his location.

The adversary restricts the number of possible locations studying the statistical distribution of the filtered adversary knowledge base and the user dataset. It is worth highlighting that in the experimental section we will consider also the case of time-misalignment between the filtered adversary knowledge base and user dataset. This case is useful when the adversary is not able to collect data during the time frame $[t_0 - t, t_0]$. In such a case, the adversary may use a different time frame $[t_0 - t - \delta, t_0 - \delta]$, for a given $\delta > 0$. The adversary may use a statistical distance measure to quantify the distance between the samples of the user dataset, and the samples of the filtered adversary knowledge base, for each possible location. This will allow $A$ to settle on a list of candidate locations where the user was at time $t_0$.

Several statistical distance measures can be used for this purpose. However, in the experimental section, we will show that our approach is accurate even when using a very simple distance metrics. For the sake of clarity, let us indicate with $\bar{x}$ the user dataset, and with $\bar{y}$ the filtered adversary knowledge base. Furthermore, given the set of all possible locations $\mathcal{L}$, with the notation $\bar{y}[l_i]$ we refer to the subset of the adversary knowledge base $\bar{y}$ related to an individual location $l_i \in \mathcal{L}$.

In other words, $\bar{y}[l_i]$ contains all the instances of the filtered adversary knowledge base such that the field $\text{LocID}$ is equal to $l_i$. Then the adversary will select a candidate location set of size $k$ in the following way:

$$\min_{S \subseteq \mathcal{L}, |S| = k} \sum_{l_i \in S} d(\bar{x}, \bar{y}[l_i])$$  \hspace{1cm} (1)

where $d(\bar{x}, \bar{y}[l_i])$ indicates some statistical distance measure between $\bar{x}$ and $\bar{y}[l_i]$. In the experimental section, we used the following definition of distance: $d(\bar{x}, \bar{y}[l_i]) = |m(\bar{x}) - m(\bar{y}[l_i])|$, where $m(\cdot)$ is the median function. Once the size $k$ is fixed, Equation 1 allows to select a candidate location set of size $k$, composed of the locations $l_i$ that minimize the overall distance between $\bar{x}$ and $\bar{y}[l_i]$. 

4 Experiments and Results

To prove the feasibility and the accuracy of our approach, we performed a thorough analysis of one of the most popular and advanced LBAs: GoogleNow. GoogleNow is an application provided by Google which comes preinstalled with the vast majority of Android devices [14]. It is also available on iOS, Google Glass and even on Android Wear devices. GoogleNow is not only a LBA, but it acts also as a personal assistant by providing personalized information to the user. User-based and location-based information are sent together within the same encrypted traffic. However, we will show that the use of encrypted communications does not prevent the process of identifying the user location as long as some of the GoogleNow user’s preferences are known a priori.

GoogleNow app operates regardless of the interactions with its user, and independently determines when information is downloaded from the server LBS [13] (unless a refresh is forced by the user). We can therefore speculate that GoogleNow app periodically sends the GPS location of the user to the LBS (Google servers). The LBS then responds with the information related to the GPS position sent by the GoogleNow app (e.g., nearby restaurants, bus stops and images of the location). To test this hypothesis, we have installed the GoogleNow app on an Android X86 Virtual Machine (VM), and we analyzed the data exchanged between our VM and Google servers. This experiment confirmed our hypothesis. In particular, the GoogleNow app, in addition to the GPS coordinates of the user, sends to the LBS much more data, including all the information currently displayed by the app on the smartphone.

4.1 Data Collection of GoogleNow Data

We performed a location spoofing attack in order to collect the encrypted network traffic exchanged by the GoogleNow app and the Google servers, and to build the adversary knowledge base as described in Section 3.1. In particular, we send periodically to the Google server a request containing the spoofed GPS user location, where the actual position is modified according to each points that the adversary is interested in monitoring.

We used the mitm-proxy software for this task [1] configured as a transparent proxy on a network of AndroidX86 Virtual Machines run in a Virtualbox hypervisor running on a Linux host. Each VM has been configured with a different user account in order to establish to what extent Google personalizes the data sent to each users. More details on the different settings of the user accounts will be provided in Section 4.3.

Since at this stage we are interested in modifying the GPS location exchanged between the app and the server (that are encrypted with SSL), we performed a man-in-the-middle attack. To this aim, a self-signed certificate was copied into each VM and added to the root certificates of Android. In this way, we have been able to decrypt the SSL traffic and modify the cleartext. Hence, we found out that GoogleNow uses a protocol called Protobuf as data interchange format [3]. This protocol has been designed by Google itself to be smaller and faster than XML.
By analyzing the data structure of the protobuf messages that were intercepted by the mitm-proxy, we have been able to identify the fields that contain the latitude and longitude of the user. These fields are sent to the Google servers in all the HTTPS requests that contains the following string within the URL: “tg/fe/request”.

We collected data about an area of two square kilometers positioned in the center of a large European city. The adversary simulated the presence of its dummy users in the area by moving them on a grid of $5 \times 10$ points (50 different LocID in total). The location $(i,j)$ of the grid is identified by the label $i_{-}j$. In order to collect a large amount of data in a short time range, rather than changing the user position of the VM through a MockLocationProvider and then wait for a GoogleNow genuine request, the adversary replayed periodically a request containing the “tg/fe/request” string in the URL several times, modifying the actual position with every point of the grid. The network traffic intercepted by the proxy has been used to generate the knowledge base of the adversary.

For the sake of the experiments we had to simulate the target users as well. Therefore, during the same period of three weeks, different VMs have been configured with distinct user accounts. Users moved into the monitored area, and their respective traffic was collected and stored separately. Clearly, this last step will not be performed when tracing real users.

4.2 Exploratory Data Analysis

In this section, we analyze the collected data in order to improve our understanding of the GoogleNow traffic dataset. The exploratory data analysis presented in the current section is performed over the data collected for an individual user profile. All the remaining user profiles show a very similar behavior. Figure 2 reports on the probability distribution of the bytes per SSL session exchanged between the GoogleNow app and the Google servers during the entire monitored period. On average, 32,604 bytes have been exchanged per session, with a standard deviation of 7,518. The minimum recorded value is equal to 80, while the maximum is equal to 83,831 bytes. The median is 31,804 bytes, while lower and upper quartiles are equal to 27,791 and 36,520, respectively.
To determine whether the bytes exchanged between the GoogleNow app and the Google servers might be useful to identify the actual location of the user, we analyzed the statistical distribution of the bytes exchanged in each monitored location. Figure 3 shows the boxplots diagram for all the 50 locations of the adversary knowledge base. The boxes extend from the lower to the upper quartile values of the data, with a line at the median. The whiskers extend from the boxes indicating variability outside the lower and upper quartiles. Figure 3a shows the statistical distribution of the bytes received in all the locations during the entire period of collection (3 weeks). Figure 3b has been obtained while analyzing only one hour of traffic randomly selected among the three weeks. Note that in Figure 3a, all the locations show a similar behavior. They have a mean value that rarely is greater than 40,000 and lesser than 20,000. The variance is very high, and lower and upper quartiles are quite far from the median value. With statistical distributions so much similar to each other, it might be difficult to guess the actual location of a user. Since we noticed that the time of the day has a great influence on the information provided by GoogleNow, we limited the analysis to a period of time one hour long, randomly selected among the three
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Fig. 4: Daily pattern of the amount of Bytes exchanged between GoogleNow and the Google servers for a specific location. The vertical line indicates the midnight.

weeks period. Figure 3b shows the boxplot diagram related to this subset of data. It can be observed that almost all the locations have a very tight variance. First and third quartile are very close to each other. Furthermore, once a particular size is selected, only a few locations may have produce it. This is the main reason that lead us to consider the time as an important parameter in our analysis process.

Figure 4 shows the amount of bytes exchanged per TCP session between GoogleNow and the Google servers for a specific location during a period of around two weeks. A daily pattern can be noticed. In particular, during night hours the amount of bytes exchanged drops significantly, and falls down in the interval between 22,000 and 24,000 bytes. During daily hours it falls between 26,000 and 32,000 bytes. The cyclic behavior depicted in the figure is repeated for all the locations that we monitored. It suggests that it may be more effective to create specific classifiers for a given hour in a day rather than building a classifier for the entire day.

4.3 Accuracy results

In the following, we will report on the results of the tests that we performed on the collected dataset. All the experiments presented next represent the average of 10,000 tests. In each test, the adversary tries to guess the position of a user. The $k$-identifiability of a tested user position is defined as 1 if the actual position of the user is within the $k$ candidate locations selected with the approach described in Section 3.2, otherwise $k$-identifiability is defined as 0. Thus, the $k$-accuracy is the average of the $k$-identifiability values of each tested instance [17].

In Figure 5, we show the $k$-accuracy of a user location when varying $k$ and $t$, that is the size of time frame used to filter the adversary knowledge base. Observe that for $k = 8$, we reach a value close to 95% with a time frame of only 20 minutes. The behavior of the $k$-accuracy is asymptotic, and for each $k$ it reaches a value close to the maximum around $t = 20$. In other words, the
Fig. 5: Accuracy of Locations Sets: effect upon accuracy of varying $k$ (size of the candidate locations set) and $t$ (size of the time frame).

adversary has to analyze only 20 minutes of traffic to reach the best accuracy performance, independently of the value $k$ selected.

In Figure 6, we show the effect of varying $\delta$, that is the difference of time between the filtered adversary knowledge base and the user dataset. In general, larger delays result in lower accuracy. However, the figure shows a cyclic behavior that respects the daily activity highlighted in Figure 4. Thus, if the adversary does not have in its knowledge base instances that fall in the same time frame of the user dataset, than it is better to use a filtered knowledge base that is one day older (1440 minutes) than one that is only 12 hours older (720 minutes). Indeed, in the former case the accuracy is slightly below 60%, while in the latter case it is around 12% only. The figure also shows a decrease of the peaks that are in correspondence of every 24 hours. This is mainly due to the fact that the information provided by the app are constantly updated, and they become old after a few days.

Profiles influence The information received by the GoogleNow app might vary when considering users with different settings enabled. In GoogleNow, the user can set his home location, work location, and favorite sport team. He can request automatic road traffic information, activate “cards” about the stock market, etc. Based on these settings, different information might be sent to different users that are in the same location. This may cause a change on the overall amount of bytes exchanged between LBA and LBS, hindering our approach. In the previous experiments, the same user settings were used by both the adversary and the targets. As such, we assumed that the adversary knew the exact settings of the
Fig. 6: Accuracy of Locations Sets: Effect upon accuracy of varying $\delta$ (time delay between the filtered adversary knowledge base and the user dataset). ($k = 4$, $t = 60$)

Table 2: Configuration of the GoogleNow Accounts

| Profile | Home | Lang (Cust.) | Transport | Driving | Commute | Sport | Stock |
|---------|------|--------------|-----------|---------|---------|-------|-------|
| 0       | ✓    | ✓            | ✓         | ✓       | ✓       | ✓     | ✓     |
| 1       | ✓    | ×            | ✓         | ×       | ✓       | ✓     | ×     |
| 2       | ✓    | ×            | ✓         | ×       | ✓       | ✓     | ×     |
| 3       | ✓    | ×            | ✓         | ×       | ✓       | ✓     | ✓     |
| 4       | ✓    | ×            | ✓         | ×       | ×       | ×     | ×     |
| 5       | ✓    | ×            | ✓         | ✓       | ×       | ×     | ×     |

targets. The objective of this experiment is to evaluate the impact of user settings on the accuracy of the selection of the set of candidate locations. To such aim, six different profiles were created with different settings. Table 2 summarizes the settings enabled on each profile. The first column reports the profile id. The remaining columns are the settings of the profile. The symbol ✓ in the cell $(i,j)$ means that the profile $i$ has the feature $j$ activated. Otherwise the cell contains the symbol ×. Every profile has the home location set. On profile 0, we changed the default language of the application. On profile 1, we activated the commute location feature (a feature that allows GoogleNow to share the position of the user with his friends). On profile 2 and 3, the favorite team and the stock market monitoring were respectively activated. Profile 4 and 5 receive information respectively on public transportation and driving conditions (road traffic status).
Fig. 7: Performance matrix of the Candidate Locations Set selection over different profiles. If the adversary used profile $x$ to collect the data, and then he tried to find the location of a user with profile $y$, then the matrix reports the achieved $k$-accuracy in cell $(x,y)$. ($k = 4$)

For each pair of profiles, we report in Figure 7 the $k$-accuracy, for $k = 4$. The figure depicts the full comparison for each pair of profiles. As expected, the best performance appears on the diagonal of the matrix that goes from $(0,0)$ up to $(5,5)$, that is when the adversary uses exactly the same settings of the victim to populate its knowledge base. Nonetheless, several settings have a low impact on the accuracy. This is the case, for instance, of the language setting. Indeed, profiles $(0,1)$ and $(1,0)$ use different languages but still, the algorithm is able to successfully recognize the actual location of the user in most of the cases. Also, Figure 7 shows that some profiles are easier to track than others. For example, adversary profiles number 1, 2 and 3 reach an accuracy around 90% on the diagonal, while profile 4 reaches only 70%. Furthermore, notice that when the Public Transport and Driving settings are activated on the profile, the adversary must somehow infer the actual profile of the user, otherwise the accuracy is too low to allow for effective tracing (e.g., by using profile 2 to track profile 5 the adversary obtains an accuracy of just 0.211).

5 Related Work

The closest research areas to this work, are traffic analysis and location obfuscation. In the following, both of them will be briefly described.

Traffic Analysis is devoted to exploiting observable features in an encrypted traffic to infer information about the content of the communication. In [10, 20]
the authors leverage observables such as the timing and the exchanged bytes to discover communication patterns that can be used to break the anonymity or the confidentiality of the communication. Liberatore et al. [17] propose two traffic analysis techniques based on the Naïve Bayes classifiers and on the Jaccard’s coefficient. They are able to determine which website over a set of 2000 has been contacted by the victim user even though the real destination has been hidden through a VPN. Such an attack was improved in [16] where the authors presented a method that applies common text mining techniques to the normalized frequency distribution of observable IP packet sizes obtaining a classifier that correctly identifies up to 97% of requests directed towards 775 sites. The technique was further refined through support vector machine classifier in [19] allowing to identify webpages even if the victim uses both encryption and anonymization networks such as Tor. Even though the related work described so far focused on HTTP, other protocols such as VoIP have been analyzed as well [23] showing that the lengths of encrypted VoIP packets can be used to identify spoken phrases of a variable bit rate encoded call.

Apart from the attacks, several countermeasures have been developed as well [18, 17, 24]. Such countermeasures manipulate packet size, web object size, flow size, and the timing of the packets to hinder the traffic analysis. Unfortunately, some of them [17] have significant performance drawbacks. Furthermore, in [12], the authors showed that nine known countermeasures are vulnerable to simple attacks that exploit coarse features of traffic (e.g., total time and bandwidth). They showed that one can use even only total upstream and downstream bandwidth to identify which of two websites was visited.

Location Obfuscation is aimed at not revealing the exact users’ geographical position to LBSs. In [9] different obfuscation operators are used to protect the privacy of the location information of users. The authors consider both location information accuracy and privacy, introducing the concept of relevance.

In [15] the authors propose to adjust the resolution of location information along spatial or temporal dimensions to meet specified anonymity constraints. In [11] a peer-to-peer method is proposed where users cooperate to hide their real location to the the LBS. Another approach has been proposed in [8] where the authors suggest to add a controlled noise to the users location in order to obtain an approximate version of it, and then sending only the approximate location to the LBS.

6 Conclusions and Future Works

In this paper, we introduced a new adversary model for Location Based Services. The model takes into account an unauthorized third party, different from the LBS provider itself, that wants to infer the position of a LBS user. We analyzed one of the most popular location based apps available on Android, that is GoogleNow, and we shown that our adversary can guess the position of a user with an accuracy of almost 90% through a statistical analysis of the user’s encrypted network traffic.
It is worth pointing out that GoogleNow seems to be a worst case scenario. Indeed, the information that the app provides to each user is not only related to his location, but also to his preferences and habits. We reported the results of our approach for different user settings and analyzed how they affect the accuracy of our results. A more comprehensive study on measuring the effects of user settings and preferences is left as a future work.

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