I Know Where You Live: Inferring Details of People’s Lives by Visualizing Publicly Shared Location Data

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ABSTRACT
This research measures human performance in inferring the functional types (i.e., home, work, leisure and transport) of locations in geo-location data using different visual representations of the data (textual, static and animated visualizations) along with different amounts of data (1, 3 or 5 day(s)).

We first collected real life geo-location data from tweets. We then asked the data owners to tag their location points, resulting in ground truth data. Using this dataset we conducted an empirical study involving 45 participants to analyze how accurately they could infer the functional location of the original data owners under different conditions, i.e., three data representations, three data densities and four location types.

The study results indicate that while visual techniques perform better than textual ones, the functional locations of human activities can be inferred with a relatively high accuracy even using only textual representations and a low density of location points. Workplace was more easily inferred than home while transport was the functional location with the highest accuracy. Our results also showed that it was easier to infer functional locations from data exhibiting more stable and consistent mobility patterns, which are thus more vulnerable to privacy disclosures.

We discuss the implications of our findings in the context of privacy preservation and provide guidelines to users and companies to help preserve and safeguard people’s privacy.

Author Keywords
Location data; data representations; empirical study; privacy.

ACM Classification Keywords
K.4.1 Computers and Society: Privacy

INTRODUCTION
People’s location data is collected seamlessly [28] every day on a large scale, often without users’ knowledge (i.e., silently through background processes) [20], [34].

Many people use social networking sites to share thoughts (tweets, status updates, etc.), pictures, videos, or interesting articles with friends, family and/or the public. Often, location data (geo-tags) is shared along with the timestamp – either as part of the information meant to be shared (secondary) or as the information itself (primary). Often emotions and feelings are attached to the information (Figure 1). Secondary sharing can sometimes be unintentional, since location sharing can be turned on as part of the tool and users can be unaware of it. Social networks such as Twitter, Facebook and Instagram allow location information to be shared either as a primary (Figure 1 (a), (c), (d)) or as a secondary (Figure 1 (b), (e), (f)) piece of information1.

Figure 1. Examples of posts from social media sites with location data displayed as primary ((a), (c), (d)) and secondary ((b), (e), (f)) forms.

It is feasible to discover someone’s identity by using only three location points [11]. Websites like PleaseRobMe2 have in the past alerted Twitter users of the dangers of sharing geolocation data publicly. When Twitter users broadcast where they live, any subsequent tweets with a different geo-location publicly reveal that they are not at home, making their home

1Google+ does not allow sharing of geo-location data, although in Hangouts, the user can share their current location as a map.
2http://pleaserobme.com/
address more vulnerable to crimes. Foursquare is another application that presents similar risks [29], since it allows users to publicly share (to review) their current location when reaching a place (restaurant, bar, museum etc.) [22].

Even though online service providers and their users might be aware of the risks [12] of sharing location data, the practice of capturing and broadcasting this information has not stopped or decreased, but rather has increased. Companies such as data brokers, social networking providers and advertisers use such data to profile their users to provide better targeted advertising [40]. GPS location is the most requested permission in Android apps [21] and it is almost always associated with targeting advertising due to its commercial value [23].

How easy is it to discover locational information that is private to people? Does one need a large dataset to do so? Can anyone infer these locations just by looking at data? How much data is required to get the right answer? In this paper we want to address these questions by conducting an empirical study in which we examine different ways of presenting location data, using different techniques (visual or textual), examining different people’s routines, and different densities of location points (1 to 5 days). We will look at how these different factors might affect the ability to infer someone’s location type, by anyone without any specialized tools, technical expertise and/or detailed knowledge of the area.

**RELATED RESEARCH**

With the widespread use of mobile devices, highly accurate location data is being collected [21] and often shared without users’ knowledge [5]. The accurate and realistic nature of location data makes it one of the most valuable and personal types of information [35], [32]. Tracking users’ locations has been shown to enable the inference of their behaviors [25], activity patterns [24], [37], the structure of their friendship networks [13], [32], semantic information about places [4] and personal associations [41] and even people’s own identities [11]. It was also shown that only four spatio-temporal data points are needed to uniquely identify individuals in a set of de-identified data [11].

People generally know about these privacy issues, but nonetheless many still share their locations for their own rewards and benefits [38]. Individuals often share their locations to connect and coordinate with their social friends [26], and to recommend (and be recommended) nearby social and interesting events [30]. Location sharing has not only proven to benefit individuals but also society in general. In fact large datasets of people’s locations have provided invaluable insights into the quality of urban services [18], [19] and socio-dynamics of neighborhoods [31]. These urban insights can lead to improvements in current and public structures and ultimately improve the quality of the geographical area itself. Location sharing can also benefit health services in preventing sickness [33] and tracking the spread of a disease [14].

Visualizing geo-referenced information has become increasingly popular. Numerous tools [2], [3], [8], [9], [10], [16], [17], [18], techniques [7], [27], [39], and apps are available that provide simple and intuitive interfaces to view and plot large amounts of location data [4-5][1].

These analytic tools have used social location data and have been created to discover significant and common patterns, to understand the significance of locations [3], [17], and to identify people with common and related interests [2], [16]. Other tools have been created to help disaster responders [10] and/or police to focus and efficiently navigate and coordinate their efforts in emergency situations by identifying common [9] and/or anomalous [8] movements, and crowded places [3].

In order to improve the visualization of large location datasets, various new techniques have been designed and implemented to represent the directionality and routes of people’s movements. Examples are flow maps [27] (origin to destination), as well as heat maps [39] in order to avoid occlusions. Boyandin et al. [7] describe Flowstrates that use heatmaps to represent changes from origin to destination taking into account time and space.

However, it is commonly assumed that extrapolating and inferring the above mentioned information requires specialized knowledge, technical expertise and sizable location datasets of large numbers of individuals. The aim of this research was to design a study to evaluate these assumptions.

**AIMS & CHALLENGES**

The aim of this research is to investigate how easy it is for a person (casual observer without specialized skills) to infer the type and/or relative function (home, work, leisure or transport) of a given geo-location point (shared as part of a tweet) by visualizing location data in a simple and easily replicable manner (either on paper or using tools that require little to no technical abilities). This will highlight possible privacy risks related to the leak of this data (e.g., robbery).

We want to understand how accurately the type of a given geo-location point can be inferred based on different ways the data is visualized – visual (map-based) or textual (table-based) – and the number of location points (density) presented. We are also interested in understanding if certain location types can be more easily discovered than others and if the accuracy has any relation to the user’s mobility patterns.

This research presented several challenges:

1. **Real-life tagged location dataset**: A dataset of people’s real life locations needed to be created. This dataset needed to include accurate and realistic tags for each location point describing its type and/or function, classified into home, work, leisure or transport. This dataset also needed to include realistic mobility patterns based on people’s routines. Routines could prove to have an effect when identifying the type and/or function of the location type. Different densities of location points to be presented needed to

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5 [https://cartodb.com](https://cartodb.com)

6 Twitter was selected based on the availability of the social network itself. In Twitter we were able to collect users’ tweets and geo-locations in addition to being able to ask permission and availability to be part of this research.
be included in this dataset. However, since we wanted to
test different densities we needed to ensure that repetition
of the same dataset would not affect responses.

2. Data representations: Data representations need to be de-
signed to be easily replicated with online/offline tools with-
out demanding advanced technical abilities, ideally in a
way that could even be presented with only pen and paper.

3. Control variables vs. study length: There are many fac-
tors that may influence location inference. Ideally, a study
should examine all these factors. However the number of
stimuli required increases exponentially in relation to the
number of control variables. In addition, repeated mea-
sures are also desirable, but lengthy studies would suffer
from tiredness and fatigue. We thus have to design a bal-
ance between the number of control variables, the number
of stimuli, the number of repeated measures and the overall
length of study. It was important to test visual representa-
tions alone, hence we needed to remove familiarity since
this could have had an effect on the responses.

4. Learning effect vs. confounding effect: On the one hand,
the same real-life dataset is ideally tested under different
conditions in order to minimize confounding effects. On
the other hand, all real-life datasets are semantically rich
and thereby sensitive to learning effects. After participants
saw a dataset in one condition (e.g., visual), they would be
able to reason about the same dataset in another condition
(e.g., textual) with some ease. This is a common design
challenge with identification tasks.

CREATING A REAL-LIFE LOCATION DATA SET

This part of the research was designed to capture people’s real
location patterns and relative location types, classifying the
locations of people into: where they live (home), where they
work (work), their movements (transport) and where they re-
relax (leisure) resulting in ground truth data.

Procedure

To solicit participation in our study, we identified and direct-
messaged people using Twitter, posted advertisements on
(Boston/Cambridge) Craigslist, and also emailed various uni-
versity mailing lists in the Boston area. In all solicitations
we attached a link with explanations of requirements for this
study. We looked for people located in the Boston or Cam-
bridge, Massachusetts (USA) area. We asked permission to
collect their tweets and the corresponding geo-location data
attached to the tweets (latitude and longitude) over a period
of three weeks. We informed them that we were interested in
capturing their locations and that if they had enough loca-
tion points at the end of the three week period we would
contact them to ask them to participate in a study with the
sole purpose of tagging their location as home, work, leisure
or transport.

We recruited 230 people who were using Twitter and had
location sharing turned on, and collected all of their tweets
over a period of three weeks. At the end of the three week
period we analyzed the location data and identified 87 users
who had location points spanning three weeks. We contacted
these users and asked them to participate in the study to dis-

close their location type. We explained that if they success-
fully tagged their locations we would add them to a random
draw to receive a $20 Amazon gift voucher. Each user an-
swered 12-25 questions depending on the variety of their loca-
tion points. In each question we displayed four data points
(Figure 2) and users had to tag each of the points as either
home, work, leisure, transport, other or unsure. To help users
remember we also showed the tweets associated with the loca-
tion for the day. Tweets could be viewed by clicking the
link next to the location marker (we limited the number of
tweets shown to 15). We created a survey link for each user
tailored to their location patterns and emailed it to them.

Each user also answered four demographic questions (gen-
der, age, occupation, ethnicity) and four additional questions
targeted at understanding their daily routines. In particular
we were interested in understanding if their patterns could
be categorized as regular/repetitive, irregular/non-repetitive
or somewhere in-between these types.

Trustworthiness of the data

In order to ensure that participants tagged each location point
with the appropriate description tag, we created five repeated
questions in each survey designed to check their behavior,
i.e., whether they were randomly clicking or not paying at-
tention to the tagging task. We used location points either
extremely close to one another (based on latitude and longi-
Social Media and Location Data

Results
43 people tagged their locations; of these, 37 participants (22 females, avg. age 29; 15 male, avg. age 27) consistently
tagged their locations. The remaining 6 gave different
types of location tags between repeated questions (designed either
using location points very close to one another or the same
point).

Table 1. The numbers of location points for each of the 27 data subjects
grouped by the type of location for each category of density of location
data: (L) low (1 day); (M) medium (3 days); (H) high (5 days).

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<th>D.S. ID</th>
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We selected data belonging to 30 of these participants (Table
1). 27 participants’ data was used in the study and 3 partici-
pants’ data was used as part of the training. Table 1 shows the
number of location points for each participant (data subject).
The number of points for each type of location is also shown.
Three different location point densities are also shown. They
represent the number of location points within 1 day (low);
3 days (medium); 5 days (high). For each density the same
day of the week was chosen. The low density represented
Monday of week 1, the medium option represented Tuesday,
Wednesday and Thursday of week 2, and the high option rep-
resented Monday to Friday of week 3. The data in different
categories of density is from different weeks to prevent learn-
ing effects.

Participants’ occupations and routines/mobility profiles
Selected participants have various levels of occupation and
interests. We covered occupations such as undergraduate,
masters and graduate students, part-time worker, salesman,
housewives with and without children, engineers working
from home, office or a colocation space, and self-employed
people working from home or a colocation space. We
selected these participants with various occupations to intro-
duce necessary stochasticity in the real-life data.

Interesting observations
From the data we collected we can see that participants tend
to mostly tweet when at home or work (Table 1). They some-
times tweet when moving (transport, car) or when they are out
(transport time). These results show that people tend to publicly
give away their most commonly visited locations (which are often
the most sensitive ones) when tweeting. Using public data repor-
tories, the location information of someone’s work or home
or home can be used to determine the average income of one’s
neighborhood, average housing cost, debt, number and length of
car ownership, demographics, likely political views, etc.

Removing data points
We removed location points where the data owners selected
the tag to be others or unsure, but these only accounted at
most for 10% of their individual data sets.

DATA REPRESENTATIONS: SIMPLE AND REPLICA
BLE
We designed two simple ways of visualizing the gathered
location data, a visual and a textual representation. Location
data has been commonly represented using a map, hence
for for the visual techniques we showed the location data as
points on a map. For the textual representation we used a table
format. These two representations have been shown to
raise awareness on a user’s perception of privacy.

These two data representations can be easily reproduced ei-
erly by hand or by available tools online. By hand a person
could print a map of the area and annotate location points
(visual) or could annotate sequential location points on paper
(table). Several (free) tools exist that allow people to insert
the desired location data (either as geo-tags or addresses) and
automatically visualize the results on a map (e.g. mapsdata10
or CartoDB11).

Visual Representation
The visual technique displays each location point (marker)
on a map (Google Maps was used). At the center of each
marker we showed a number (ID) representing the order of
appearance (captured time was used to order each point). In
order to avoid occlusion as much as possible, each marker

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8Location points marked as others or unsure were removed from
the dataset and were not used in the study.

10http://www.mapsdata.co.uk
11https://cartodb.com
was assigned a transparency of 80% and tilted by 20°. The line from the location point to the marker was alternated in size (from long to short) to reduce occlusion problems. The ID number of each location point was also reported on the side of the map as a table (Figure 3 (b)). The marker of the location to be inferred was set to 3px larger than the other ones. The visual representation was presented in two forms, static and animated visualization:

- **Animated**: In the animated visualization, numbered location points (markers) were shown at one second intervals following the order of the ID table positioned next to the map (Figure 3 (b)). The ID table was also animated. Markers and corresponding ID appeared at the same time. Unlike a traditional memoryless animation [15], once the marker appeared, it remained on the map and within the side table. The table next to the map showed the location point ID and captured time. The table was colored according to the time of day (morning, afternoon or evening). Similarly to the text-only technique, colored lines were used to delimit the day periods and different days.

- **Static**: The static visualization showed all the numbered location points (markers) on a map with corresponding ID table next to it. The static techniques are equivalent to the final state of the animated one.

### Textual Representation

The text-only technique displayed data in a table (Figure 3 (a)). The table was composed of an ID row (as shown in the visual techniques) ordered by capture time, with corresponding geo-location in the form of latitude and longitude. The street address associated with each location was also displayed (Figure 3 (a)) followed by the captured time. Each row (representing a location) was also colored according to the time of day (morning, afternoon or evening). At the end of each day a colored line depicting the end of that period was added. This was included to avoid confusion when the location to be inferred (in red) appeared at the end and the beginning of a period. When multiple days were presented (data densities medium (3 days) and high (5 days)) a yellow line was inserted to show the end and the start of the new day. All this information was documented in the legend below each table and map.

### Privacy & Geo-Tag: Inferring Types of Location

We are interested in measuring the feasibility and accuracy of uncovering the functional types of people’s places (home, work, transport and leisure) by visualizing different amounts of data about real people’s locations using different data representations. In particular we are interested in:

1. How do different data representations impact participants’ ability to infer functional location?
2. Does the accuracy of inference depend on different types of location?
3. Does increasing data density improve or impede the accuracy of inference?

### Apparatus

The study was developed as a web application using Google Maps and D3 [6]. The map was 780px × 585px and any interactions, such as zooming, panning, scaling were disabled, because they were not the focus of the study but could introduce significant confounding effects. All landmarks were also removed to ensure that there were no advantages between the visual or textual techniques. To avoid any cross browser compatibility issues, the study was performed using only the Chrome browser. A progress bar was shown on top of the study to indicate the participant’s progress in the study. Four
optional answers – home, work, transport and leisure – were displayed below the visual or textual data representation. A don’t know option was added in case people could not motivate an answer based on what they saw.

**Visual consistencies between data densities**

We wanted to ensure that the visual representations (static and animated map) were consistent between densities levels (for each data subject). To do this we removed data points that would create a different zooming level between the different data densities. These points are outliers representing one-off “leisure” activities. Table 1 reports the number of locations after this change. We showed zoomed-out versions of the map for the low or medium densities to ensure that the same zooming and visual clues were conveyed at each level.

**Process for choosing target location**

One target location was set to be identified for each data subject. This enabled a comparison between inferring the same location type across different data representations and data densities (Table 1). Only one type of location was targeted for each data subject to avoid skewing assessment. This was done because people might not have visited (hence tagged) all the locations types we are interested in within each collected density. For example a person working part-time could have gone to work on Tuesday but not on Monday. This kind of routine would not allow work to be suitable since it was not present as a location tag in the low density level (low data density uses location points captured on Monday of week 1).

Suitable target locations are the ones where the data subject has visited that location type at a close time within each collection period (density level). If the data owner has not visited a possible target type during a similar or close time in any of the days, the location target was not a suitable choice. This was done to avoid the confounding problems generated by different times throughout the day. This strategy also alleviates would-be confounding effects caused by using different weekdays for stimuli at the same density levels, while preventing showing the same data (e.g., Monday of week 1) in the stimuli for different levels. The day of the week was never shown to participants. Participants were informed that the location data displayed was collected from weekdays. Functional locations of home, leisure and transport were asked to be inferred for seven data subjects, and workplace was asked to be inferred for six data subjects (a total of 27) (Table 1).

**Procedure**

The study was conducted in a computer lab with identical machines in order to avoid any variation of screen size and computer speed and to ensure that participants were not distracted or disturbed during the study execution.

As each of the 27 data subjects yielded 3 non-overlapping datasets (low, medium and high density), there are 81 distinctive datasets. Each participant could encounter each dataset once in the study to prevent learning effects. Meanwhile, each dataset needed to be tested with three data representations (text, static and animated visualizations). In order to achieve this, we adapted a between-group design by dividing participants into three groups. For each of the 81 datasets, one group saw text, another saw static visualizations and the other saw animated visualizations. With a careful planning, we ensured that each dataset was shown only once by one group, and each group saw exactly 9 stimuli in each of the 9 conditions (3 representations and 3 density levels). [Detailed stimuli info for each group is given in the supplementary material.]

Participants in the study answered a total of 90 questions: 9 training questions and 81 study questions. Participants were randomly assigned to one of the three groups.

**Information session**

The information session consisted of a presentation used to familiarize participants with the details about execution, requirements and respective remunerations of the study. Each participant was given a £10 Amazon gift voucher after successfully completing the study. We explained what participants should see, how they could answer, and how they could progress to the next question. We presented the three different representations and explained the day periods and the detailed captured time. We also informed participants that the data to be viewed was captured during the week and that they were going to see data representing 1, 3 and 5 days. Each day was separated by a yellow line (similar to the day periods separation shown in Figure 3).

When discussing remuneration, we explained that if random clicking was detected they would forfeit compensation. As an added incentive, an additional reward (£15 Amazon gift voucher) was also given to the top three participants with the most accurate answers. At the end of the information session, participants could ask questions and seek clarification. Before starting, they signed the consent form. At this point they could start the training session. Participants could leave the study at any time without any penalties.

**Training**

Nine training questions were created to familiarize and train participants for the study. These questions showed all combinations of visualization (static, animated and text only) and location density (low, medium, high).

Prior to each question, participants were shown a page explaining what they would be seeing and details on how to conduct the study. In this page we emphasized again that they should not randomly guess an answer but rather select the don’t know option if they were unsure about the type of location. After the explanation, the question was shown as it would appear in the study. The location data points (corresponding data subjects) used in the training session were not reused in the actual study (Table 1). Questions were not randomized in the training part.

**Study**

After the training session, participants had to answer 81 questions. Questions within the study were randomized. Participants had to provide an answer (choosing from home, work, leisure, transport and don’t know) before they could progress.
to the next question. Participants were allowed to change their answer prior to pressing the “next” button to proceed to the following question.

Survey
At the end of the study we gave participants a paper survey (4 questions) designed to understand their motivations and reasoning behind their answers. We enquired about their preferences among data representations and data densities.

Trustworthiness of the data
Questions in the study were randomized, appearing in a different order for each participant. The order of the questions was saved to account for fatigue effects and random clicking. The accuracy of participants’ answers did not decrease towards the end of the study. We did not detect any random clicking. This suggests that the incentive of the additional reward of £15 appeared to be effective.

RESULTS & ANALYSIS
Participants
We solicited participation in our study using internal mailing lists. 47 people participated. 2 participants did not finish the study. 45 people successfully completed the study (15 in each of the 3 in-between groups).

Of these, 24 were male (avg. age = 33) and 21 female (avg. age 34), 1 gender not disclosed (age 32). Level of education varied from having attended but not completed high school (3), completed high school (2), two-year college degree (5), four-year college degree (3), undergraduate student (6), completed four-year college degree (3), completed master degree (7), being a graduate student (4) to advanced graduate work or completed Ph.D (12). The study took an average of 54 minutes to complete (min = 45; max = 98 minutes). Participants did not live in or have any extensive knowledge of Cambridge/Boston MA13. All participants lived in England, UK. This was done in order to alleviate confounding effects due to significant biases towards those with local knowledge.

Responses
We collected 3,645 responses from 45 participants (Table 2). The responses cover all combinations of the three visualizations (animation, static and text-only) with the three different data densities (low, medium and high (Table 1)) and four location types (home, leisure, transport, workplace).

We gathered 1,215 responses for each of the three visualization conditions: animated, static and table-based. Each condition was shown with the same location variable. For location type of home, leisure and transport, we gathered 945 responses each. For location type of workplace we gathered 810 responses. Table 2 outlines responses for each visualization type and time variable. Questions were evenly distributed between each data representation (Table 2).

Location Types and Data Representations
The level of accuracy to which location can be inferred depends on both the type of location and how it is presented.

Are certain types of location more easily inferred than others? Location types tagged as leisure were more difficult to deduce resulting in the lowest accuracy level overall (μ = 53%).

Table 3. Accuracy level for each type of location, showing the mean of the percentage of accuracy, the standard deviation, the odds ratio and confidence level and the corresponding p-values.

<table>
<thead>
<tr>
<th>TYPE OF LOCATIONS</th>
<th>(%)</th>
<th>(%)</th>
<th>95% CONFIDENCE INTERVAL</th>
<th>ODDS RATIO</th>
<th>MIN</th>
<th>MAX</th>
<th>P-VALUES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>58%</td>
<td>18%</td>
<td>0.757 0.851 0.881 0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leisure</td>
<td>53%</td>
<td>18%</td>
<td>0.367 0.305 0.682 0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transport</td>
<td>72%</td>
<td>14%</td>
<td>1.712 1.46 2.31 0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workplace</td>
<td>69%</td>
<td>17%</td>
<td>1.431 1.21 1.69 0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Home was found to present a lower mean accuracy of discovery than work, with home being discovered μ = 58% while work μ = 69%. Discovering when a person was moving (transport type of location) was found to be the easiest to deduce with μ = 72% (Figure 4, Table 3).

There are statistically significant differences between inferring the different types of locations determined by one-way ANOVA F(3, 176) = 12.235, p < 0.001. A Tukey post-hoc test showed that there were statistically significant differences between discovering home and workplace (p < 0.010), home and transport (p < 0.001), workplace and leisure (p < 0.001) and leisure and transport (p < 0.001).

The odds of identifying the type of location when it is transport or workplace are 1.7 and 1.4 respectively (Table 3) compared to the odds of identifying when the location is home or leisure with odds of 0.881 and 0.68 respectively (Table 3).

However in all cases participants were found to be able to identify the type of location two to three times higher than chance (25%), underlining serious privacy disclosures based on location data.

Do data representations impact accuracy of inferring?
There are statistically significant correlations between accuracy of inferring of functional locations within each data representation. This is determined by one-way ANOVA F(2, 132) = 8.841, p < 0.001 for correct responses.

A Tukey post-hoc test showed that there were statistically significant differences between table-based and static techniques

13The Twitter data used for this study was collected from people living in the Cambridge/Boston MA, area.
(p < 0.001), and between the animated and table-based techniques (p < 0.001), with visual techniques leading to more correct deductions of location type (animation μ = 66.3%; static μ = 66.4%) than the textual (μ = 56.4%) one. There was no statistical significant difference between visual techniques. Textual techniques were shown to present a higher accuracy of inferring when location type was work and data densities were low and high (Figure 7). Visual representations presented a higher accuracy when location type was transport. This is due to the inherent type of locations, transport and the directionality that can be better visualized using a visual representation.

Figure 5 shows the mean of response time for each of the three visualization techniques grouped by type of location. We can see that visual techniques, which lead to more correct answers, do not take a longer time to reach a correct answer (with the exception of transport, where static visualizations give the quickest response). Textual techniques require more time to answer than the two visual techniques. Transport location types, which are the ones with the highest accuracy of inference, also show the lowest response time across all representations in comparison with the other location types.

The number of location points presented was found to have an effect on accuracy in both visual and textual representations of the data. In particular the accuracy of inferring the type of location was affected within each technique.

Does data density affect accuracy of inference?
Different location types - home, work, leisure and transport - were found to present different accuracy levels based on the number of location points presented (Figure 6). The highest level of accuracy across all location types was achieved when the highest number of location points was used (5 days).

While increasing the number of location points improved accuracy when it came to home locations, this was not always the case when it came to other types of location. In fact when the location type was either transport, work or leisure, the accuracy decreased when a medium density (3 days of location data) was presented. This shows that presenting more points of location data does not always improve accuracy, and, it may sometimes decrease accuracy.

Location types and data densities

The density of location points presented and the visual representations used affected the accuracy of inferring the location type. Textual representations performed worse than visual ones for all location types except work where the low and high density of location points were presented, textual representation performed better (Figure 7).

Location types and mobility patterns
Are there routines that are more privacy-vulnerable?
We selected data subjects with different routines in order to be able to present a variety of patterns to participants. Based on data owners’ self reporting and from analysis and motiva-
tion behind this report, we categorized each routine as regular, irregular or semi regular\textsuperscript{15}.

A \textit{regular} routine depicts a stable working and home schedule; \textit{semi-regular} routines encompass routines which can be somewhat irregular, for example a temporary worker who might have a stable routine only 2 or 3 days a week; \textit{irregular} routines are routines with no stable schedule (i.e., going to work and/or coming home at different hours, working from different locations, taking transport at different times, etc.).

The types of location to be inferred were distributed between these different mobility patterns depicting users’ routine types\textsuperscript{16} (Table 4). Participants reported that when looking at the data, they made assumptions about people’s routines based on the clustering and time of the day (Figure 9).

Table 4. Location types to be inferred within each routine/mobile pattern; R = Regular; SR = semi-regular; IR = irregular.

<table>
<thead>
<tr>
<th>LOCATIONS</th>
<th>R</th>
<th>SR</th>
<th>IR</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOME</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>LEISURE</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>WORK</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>TRANSPORT</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 8 shows that the functional locations of people living structured and routine-based lives are highly likely to be inferred correctly compared to less structured or chaotic ones.

In fact, participants found it difficult to answer when several clusters were present in the data or when no clear clusters were shown. This could be related to the fact that participants looked for repetitive patterns. This is also probably the reason why textual techniques performed worse, especially when it came to location types like transport where an animated representation outlines the mobility aspect. Work was the one type that was the easiest to infer using textual techniques, likely due to the fact that clear repetitive patterns can be seen even when in a table\textsuperscript{17}.

Figure 8. Box plot of percentages of correct responses grouped by the data subjects’ routine patterns such as regular; semi-regular; irregular.

Inclinations towards particular data representations

\textbf{Are people visual- or textual-inclined?}

Our results highlight three distinct inclinations among participants: \textit{visually}, \textit{text} and \textit{hybrid} inclined participants.

\textbf{Visually inclined}: These participants (36) were found to be able to deduce location type when the location data was represented using one (or both) of the \textit{visual} visualization techniques (static or animated). The majority of these participants however were more inclined to answer correctly when using the animated (17) rather than the static technique (14), with five participants showing equal accuracy level with either technique. Participants might have been more inclined towards the animated technique because it delivered temporal information more intuitively and participants used more time to answer these questions\textsuperscript{18} (Figure 10).

\textbf{Text inclined}: These participants (6) were found to be able to better recognize the functional type of location when the data was represented using the textual technique (Figure 10).

\textbf{Hybrid}: These participants (3) were found to able to infer the functional type of locations equally well using visual and textual representations (Figure 10).

\textsuperscript{15}Data subjects maintained their routine patterns in between the different weeks i.e., data densities.

\textsuperscript{16}Semi-regular had three more questions than the other two patterns. The is due to the fact that we were using real data and that we had a limited number of participants within the regular and irregular mobility patterns.

\textsuperscript{17}Home presented a lower accuracy level due to the fact that home was often confused with workplace due to the participants’ assumptions that a person would go to work in the morning.

\textsuperscript{18}At the end of the animation, the data was shown as it appeared in the static technique.
Social Media and Location Data

Figure 10. Inclinations of participants towards particular data representations, showing accuracy (%) for textual vs. visual representations: (a) animated vs. textual; (b) static vs. textual. The accuracy (%) for each participant for each data representation is also shown (c). Participants are ordered from most accurate to least accurate. The descriptive statistics of accuracy between the three data representations are also included (d).

CONCLUSION

When we think of collecting personal data, it is commonly framed in the form of big data collection and analysis of mobility patterns over several days. However we have seen that with a small number of data points, people’s locations can be inferred. This kind of information can lead to several privacy disclosures. Using publicly available data, the type of locations can be used to estimate someone’s average income based on one’s neighborhood, average housing cost, debt, and other demographic information, such as political views etc.

We have shown that deducing people’s most frequent and private locations such as work and home can be achieved using only a small sample of location points (1 day worth). Adding a larger sample of location points has the potential to increase accuracy or confusion. We saw that 3 days worth of data led to more confusion and decreased accuracy. Transport was found to be identified more accurately than the rest. Work was discovered more accurately than home, while deducing other types of location like leisure proved to be more complicated even when a larger location dataset was used.

The study showed that most participants benefited from visual techniques and that these have higher response time than textual one. It is interesting to note that private locations can also be inferred without using visual techniques.

Our study showed that using the textual visualization could lead to correct identification over 50% of the time, with 6 participants correctly deducing functional location more accurately than with visual techniques. We showed that three distinct and different affinities for data visualization were present within our study participants. We found participants were either visually or textually inclined (only nine presented hybrid results, having correctly answered the same number of questions in both visual and text-only techniques).

Guidelines

This study has shown the sensitivity of location data and the need to adapt technologies to allow people to be able to specify which personal location should be (or not be) shared.

- Enquiring about sensitive locations: Tools could enquire about a functional location after a certain amount of sharing, and hence either stop sharing this location information or share nearby locations rather than specific ones which could present privacy risks to the users.
- Creating confusion: Adding confusion to the data, e.g., adding fake locations to make regular and semi-regular routines look irregular.
- Adding meaningless clusters of data: Participants in our study described looking for clusters to identify personal locations such as home and work, hence adding more clusters of location points might confuse analysis and help people preserve their privacy and minimize possible risks.
- Tagging sensitive locations: Users could tag their location and decide a priori which locations should be shared or not.

EXPERIMENT LIMITATIONS

We wanted to use real data, however this brings associated problems. Our understanding of users’ locations and functional locations depends on self-tagged data from Twitter users. Due to the nature of real data, it is possible that we have not covered all possible routines. In addition, the privacy risks we have highlighted are associated with leakage of location data specific to Twitter users. People tend to use different social networks for different purposes and this can affect the locations where they share the information. This study is not representative of all social networks. For example data leaked with Instagram might reflect functional locations representing likes, dislikes or hobbies rather than personal locations like home or work. This location leakage could have other risks rather than disclosing personal locations.

ACKNOWLEDGMENTS

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