Quantifying Surveillance in the Networked Age: Node-based Intrusions and Group Privacy

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ABSTRACT
From the "right to be left alone" to the "right to selective disclosure", privacy has long been thought as the control individuals have over the information they share and reveal about themselves. However, in a world that is more connected than ever, the choices of the people we interact with increasingly affect our privacy. This forces us to rethink our definition of privacy. We here formalize and study, as local and global node- and edge-observability, Bloustein’s concept of group privacy. We prove edge-observability to be independent of the graph structure, while node-observability depends only on the degree distribution of the graph. We show on synthetic datasets that, for attacks spanning several hops such as those implemented by social networks and current US laws, the presence of hubs increases node-observability while a high clustering coefficient decreases it, at fixed density. We then study the edge-observability of a large real-world mobile phone dataset over a month and show that, even under the restricted two-hops rule, compromising as little as 1% of the nodes leads to observing up to 46% of all communications in the network. More worrisome, we also show that on average 36% of each person’s communications would be locally edge-observable under the same rule. Finally, we use real sensing data to show how people living in cities are vulnerable to distributed node-observability attacks. Using a smartphone app to compromise 1% of the population, an attacker could monitor the location of more than half of London’s population. Taken together, our results show that the current individual-centric approach to privacy and data protection does not encompass the realities of modern life. This makes us—as a society—vulnerable to large-scale surveillance attacks which we need to develop protections against.

1 INTRODUCTION
For reasons ranging from urbanization and rural exodus to the democratization of communication technologies, we are more connected than ever. For instance, this is particularly visible when considering the average worldwide degree of separation, i.e. "how many friend-of-my-friend introductions do I need to get to know another person". Proposed in 1929, first measured in 1969, and popularized by the 1990 play "Six degrees of separation" by John Guare, the average degree of separation has been dramatically shrinking in the past 50 years, going from 6 steps in 1969 to 3.5 steps today [2, 11, 33, 34].

Many benefits arise from such connectiveness. Network effects are believed to be fundamental for the scaling laws emerging in cities [25] such as the relationship between size of a city and the average GDP of its inhabitants [4, 5] or number of patents produced per capita [8]. Increased connectiveness allows us to transfer and share information at unprecedented speed [15, 27].

This increased connectiveness, however, challenges the notion of privacy as relating solely to an individual and the control she has over her data. From its first definition as the “right to be left alone” in Warren and Brandeis’ seminal 1890 article [36] to the more modern “right to selective disclosure” [9], our definitions of privacy have been centered on the individual controlling information about herself. This individual-centric view is built into many legal frameworks, including the new European legislation (GDPR) that states: “personal data means any information relating to an identified or identifiable natural person (‘data subject’)” [26].

In the modern world, our privacy increasingly depends on other people. Our Facebook friends, people we call or encounter on the street impact our privacy. Bloustein [6] theorized this in an article in 1978 introducing, in contrast with the individual right to privacy, the concept of group privacy. His definition was a first attempt to recognize that the people surrounding us — our family, friends, colleagues, but also strangers we share the public space with — and the decisions they make impact our privacy. When we interact or are linked with someone, we share private information with one another. The loss of privacy by one person will therefore impact the privacy of individuals she’s related to.

Modern day researchers have, however, only investigated group privacy as the right of individuals to keep their affiliation with a
group private [13, 21]. The common property of the group can be a
religion, sexual orientation, disease or self-determined [16]. More
technically-inclined researchers have then developed technical so-
lutions to protect this affiliation (e.g. t-closeness [17], group-based
obfuscation [22]). We argue here that this “group membership” def-
inition of group privacy is a departure from Bloustein’s concept
which he specifically defines as the “attribute of individuals in asso-
ciation with one another within a group, rather than an attribute of
the group itself”.

In this paper, we propose a framework to study group privacy
through the lens of the relationships an individual establishes with
others, and to quantify the impact of people’s relationships on their
privacy. We define two attack models (local and global) for measur-
ing the loss of privacy, based on node and edge observability in a
network. We study these models from a theoretical and empirical
point of view, proving theoretical properties of the metrics and
showing the impact of the graph structure on group privacy. We
then use our metrics to study group privacy in two real-world cases:
surveillance on a mobile phone network and sensing people’s loca-
tion through a distributed rogue Wi-Fi attack. Firstly, we show that
surveillance on a mobile phone network and sensing people’s loca-
tion through a distributed rogue Wi-Fi attack is curbed by the network’s high clustering, contrarily to previous
work [19]. Secondly, we use real-world sensing data to show that
a distributed rogue Wi-Fi attack scales well. Compromising a small
number of devices in a large city, e.g. through an app, allows an
attacker to monitor the location of a large fraction of its popu-
lation. For example, in London, compromising 1% of the devices
allows an attacker to monitor the location of over half of the city’s
population.

Short Summary of Results.

(1) We propose two models of observability (node- and edge-
observability) that can be used to measure group privacy in
a networked environment.

(2) We study these models from a theoretical perspective and
show that edge-observability is independent of the graph
structure while node-observability only depends on the de-
gree distribution of the graph.

(3) We simulate observability on synthetic networks and show
that attacks spanning several hops severely increase the
observability of the graph especially in the presence of hubs.

(4) We study the observability of communications in a real-
world phone dataset and show that compromising a small
fraction of the nodes leads to a large fraction of the commu-
nications in the network to be observable.

(5) We derive an observability function to estimate the location
privacy risk in contained urban areas and apply it to estimate
the risk of location privacy exposure in large American cities,
showing that large cities are vulnerable to mass surveillance
attacks by compromising only a small number of devices.

2 MODELING GROUP PRIVACY THROUGH
GRAPH OBSERVABILITY

2.1 Threat model

Our framework models group privacy losses in a networked en-
vironment as some of the nodes in a network are compromised
(e.g., they installed a malicious app, they have loose permissions
on Facebook, a judge has ordered mobile phone operators to hand
over their data to the authorities, they have been hacked). We call
these scenarios node-based intrusions. If a node v is compromised,
we consider that the attacker gains access to the communication be-
tween v and its neighbors in the network, as well as any attributes
about v’s neighbors that are available to v. In the k-hops version
of this attack, an adversary can also observe nodes and edges located
at most k hops away from the compromised node (see Figure 1). In
short, an attacker exploits a compromised node to observe and
collect information about its edges and neighboring nodes.

Formally, we consider an undirected graph \( G = (V, E) \), where V
is the set of nodes and E is the set of undirected edges, i.e. unordered
pairs \((i, j) \in E \) with \(i, j \in V \). A set of nodes \( V_c \subset V \) is compromised,
allowing an attacker to observe all their connected edges and nodes
up to some number of hops; conversely, \( \bar{V}_c \triangleq V \setminus V_c \) is the set of
non-compromised nodes which induces a set of observed edges \( E_\sigma \)
and a set of observed nodes \( V_\sigma \), defined below.

Definition 2.1 (Observed Nodes). The set of observed nodes after
\( k \) hops, \( V_\sigma^k \), contains all nodes that are at a distance at most \( k \) from
one compromised node:

\[
V_\sigma^k = \{u \in V \setminus V_c : \exists v \in V_c, d(u, v) \leq k\}
\]

For simplicity, we define:

\[
V_\sigma = V_\sigma^1 \triangleq \{u \in V \setminus V_c : \exists v \in \text{neigh}(u), v \in V_c\}
\]

We choose \( V_\sigma \) to contain only non-compromised nodes, allowing
us to look at \( |V_\sigma| \) as the “information gain” for the attacker from
having access to \( |V_c| \) compromised nodes.

Definition 2.2 (Observed Edges). The set of observed edges after
\( k \) hops \( E_\sigma^k \) contains all edges that are connected to at least one node
within distance \( k − 1 \) of one compromised node:

\[
E_\sigma^k = \{(u, v) \in E : \exists w \in V_c, d(u, w) \leq k − 1 \land d(v, w) \leq k − 1\}
\]

For simplicity, we define:

\[
E_\sigma = E_\sigma^1 = \{(u, v) \in E : u \in V_c \lor v \in V_c\}
\]

Definition 2.3 (Edge-set of a Node). We define the set of all edges
incident to a node \( v \in V \):

\[
E[v] = \{(v, u) \in E\}.
\]

We finally define two models of observability, edge-based and
node-based observability, both assuming an attacker has access to
a random set of nodes \( V_c \). In the edge-observability model, the
attacker is interested in learning information that is transmitted
between nodes; while in the node-observability model, the attacker
is interested in learning attributes of nodes. Note that we here focus
on non-targeted node-based intrusions and their impact on global
and local observability. Indeed, in many real-world scenarios including the one we present here, these attacks are fairly opportunistic: people who installed an app, who clicked on a phishing link and entered their password, etc. We therefore model nodes as having a uniform probability of being compromised. Our model is applicable to more advanced, targeted, attacks e.g. targeting highly connected nodes or actively trying to infect neighboring nodes but we do not study them here.

In each of these two models, we will differentiate between two different risks: the global and local surveillance. Global observability measures the privacy risk over the entire population, while local observability describes the risk for a random individual.

2.2 Edge-Observability

The edge-observability of a graph pertains to the attacker’s ability to obtain knowledge about connections happening in the network (i.e. the edges of the graph). For instance, if someone’s e-mail account is compromised, all her communications with her contacts are visible to an attacker. A fixed number \( n_c = |V_c| \) of random nodes in the network \( (V_c) \) are compromised resulting in a fraction of all the edges in the network to be observable to an attacker.

**Definition 2.4. Global Edge-Observability.** The global edge-observability of a graph \( \rho^*_e \) is defined as the average fraction of the edges that the attacker can observe:

\[
\rho^*_e = \mathbb{E}\left[ \frac{|E_o|}{|E|} \right]
\]

However, in some scenarios, one might be more interested in the fraction of the communication of a non-compromised individual in the network that are compromised. We call this local edge-observability.

**Definition 2.5. Local Edge-Observability.** The local edge-observability \( \rho_e \) of a node \( u \) is defined as the expected fraction of the edge-set of a node \( u \) that the attacker can observe:

\[
\rho_e(u) = \mathbb{E}\left[ \frac{|E_o[u] \cap E_o|}{|E[u]|} \right] = \mathbb{E}\left[ \frac{|E_o[u]|}{|E[u]|} \right]
\]

**Definition 2.6. Local Edge-Observability of a Graph.** The local edge-observability of the graph \( \overline{\rho}_e \) is defined as the expected average (over the nodes) local edge-observability among non-compromised nodes:

\[
\overline{\rho}_e = \mathbb{E}\left[ \frac{1}{|V_c|} \sum_{u \in V_c} \frac{|E_o[u]|}{|E[u]|} \right]
\]

2.3 Node-Observability

The node-observability of a graph quantifies an attacker’s ability to obtain knowledge about the attributes of an individual (i.e. a node of the graph) using their relationship with compromised nodes. This could happen, for instance, in a social network where users reveal some information about themselves to their friends or to the friends of their friends. An app installed by some users with loose permissions could observe their friends’ profiles, leading to observation of a much larger fraction of the network than just the app’s users. One node is observable if (at least) one of its neighbors in the graph (1-hop) or a neighbor of its neighbors (2-hop) is compromised.

**Definition 2.7. Global Node-Observability.** The global node-observability of a graph \( \rho^*_n \) is defined as the average fraction of nodes an attacker can observe:

\[
\rho^*_n = \mathbb{E}\left[ \frac{|V_o| + |V_c|}{|V|} \right]
\]

**Definition 2.8. Local Node-Observability.** The local node-observability of a node \( u \) is defined as the probability that \( u \) is observed:

\[
\rho_n(u) = \mathbb{P}[u \in V_o | u \notin V_c]
\]

**Definition 2.9. Local Node-Observability of a Graph.** The local node-observability of a graph \( \overline{\rho}_n \) is defined as the expected average (over all nodes) local node-observability among all the non-compromised nodes in the graph.

\[
\overline{\rho}_n = \mathbb{E}\left[ \frac{1}{|V_c|} \sum_{u \in V_c} \mathbb{P}[u \in V_o | u \notin V_c] \right]
\]

All of our metrics are functions of \( n_c = |V_c| \) to [0, 1]. Hence, for one particular graph \( G \) with \( |V| = n \) and any metric \( m_G(n_c) \), one can draw the observability curve as \( \{ \frac{n_c}{n}, m_G(n_c) \} \) for \( n_c = 0, 1, \ldots, n \) to represent the evolution of the privacy risk with the number of compromised nodes. The Area under Observability Curve (AUOC) summarizes the information given by this curve, and is defined as

\[
\int_0^1 m_G(x) \, dx
\]

This metric, between 0.5 and 1, quantifies how much the observability deviates from the curve \( m_G(x) = x \), which is the baseline for privacy risk (i.e. compromising a fraction \( x \) of the population yields to observation of a fraction \( x \) of the edges — nodes, nodes considered).

3 THEORETICAL AND EMPIRICAL RESULTS

In this section, we prove theoretical properties of node- and edge-observability and empirically study their behaviour over various synthetic networks.

3.1 Theoretical Properties of Observability

In the previous section, we introduced four metrics to describe the privacy impact of node-based intrusions. We hereafter derive closed-form expressions for these metrics, which allow us to prove several propositions for the 1-hop case.

3.1.1 Edge-observability.

**Proposition 3.1.** The global edge-observability of a graph \( G \) grows quadratically with \( n_c \), and depends only on the number of nodes \( n = |V| \) and the number of compromised nodes \( n_c \). Furthermore, for any graph family, the AUOC tends to \( \frac{1}{2} \) as \( n \) grows.

**Proof.** This is obtained by developing the definition:

\[
\rho^*_e = \mathbb{E}\left[ \frac{|E_o|}{|E|} \right] = \frac{1}{|E|} \mathbb{E}[|E_o|]
\]
One can write $|E_0|$ as the sum over all edges of whether this edge is in $E_0$:

$$E[|E_0|] = \mathbb{E} \left[ \sum_{e \in E} I(e \in E_0) \right] = \sum_{e \in E} \mathbb{E}[I(e \in E_0)]$$

$E[I(e \in E_0)] = \mathbb{P}[e \in E_0]$ and, by definition, $e = (u, v) \in E_0$ if and only if $u \in V_e$ or $v \in V_e$. Hence:

$$\mathbb{P}[\{u, v\} \in E_0] = \mathbb{P}[u \in V_e \lor v \in V_e]$$

$$= 1 - \mathbb{P}[u \notin V_e \land v \notin V_e]$$

$$= 1 - \mathbb{P}[u \notin V_e] \cdot \mathbb{P}[v \notin V_e | u \notin V_e]$$

$$= 1 - \frac{n-n_c}{n} \cdot \frac{n-1-n_c}{n-1}$$

As this is independent from the actual edge considered, we can conclude that:

$$\rho^*_e = \frac{1}{|E|} E[|E_0|] = 1 - \left( \frac{n-n_c}{n} \cdot \frac{n-1-n_c}{n-1} \right)$$

then,

$$AUOC = \frac{2n-2}{n-1}$$

And therefore, $\lim_{n \to \infty} AUOC(n) = \frac{2}{3}$. \(\square\)

**Proposition 3.2.** The local edge-observability of a graph $G$ is a linear function of $n_c$ and depends only on the number of nodes $n$ and the number of compromised nodes $n_c$. Furthermore, for any graph family, the AUOC tends to $\frac{2}{3}$ as $n$ grows.

**Proof.** Firstly, we redevelop the expression:

$$\bar{\rho}_e = \frac{1}{n} \mathbb{E} \left[ \sum_{u \in V} \left[ E_0[u] \right] \cdot I(u \notin V_e) \right]$$

Introducing the notation $\text{deg}(u)$ for the degree of node $u$, we can rewrite it as:

$$\bar{\rho}_e = \frac{1}{n-n_c} \sum_{u \in V} \frac{1}{\text{deg}(u)} \cdot \mathbb{E} \left[ |E_0[u]| \cdot I(u \notin V_e) \right]$$

Observing that:

$$E[|E_0[u]| \cdot I(u \notin V_e)] = E[|E_0[u]| | u \notin V_e] \cdot \mathbb{P}[u \notin V_e]$$

We can write:

$$E[|E_0[u]| | u \notin V_e] = \sum_{v \in \text{neigh}(u)} \mathbb{P}[v \in V_e | u \notin V_e]$$

$$= \text{deg}(u) \cdot \frac{n_c}{n-1}$$

$$\bar{\rho}_e = \frac{1}{n-n_c} \sum_{u \in V} \frac{1}{\text{deg}(u)} \cdot \text{deg}(u) \cdot \frac{n_c}{n-1} \cdot \frac{n-n_c}{n}$$

$$= \frac{n_c}{n-1} \cdot \frac{n-n_c}{n}$$

Hence, $\bar{\rho}_e = \frac{n_c}{n-1} \cdot AUOC(n) = \frac{n}{2(n-1)}$ and $\lim_{n \to \infty} AUOC(n) = \frac{1}{2}$. \(\square\)

Propositions 3.1 and 3.2 show that both global and local edge-observability will tend to constant AUOC values (respectively $\frac{2}{3}$ and $\frac{1}{2}$), and are independent of the number of edges and the structure of the graph. However, as we will see in the subsection 3.2, this is not true when considering multiple hops.

### 3.1.2 Node-observability.

**Proposition 3.3.** The global node-observability of a graph depends only on its number of nodes $n$, number of compromised nodes $n_c$, and its degree distribution $(\text{deg}(u))_{u \in V}$.

**Proof.** $\rho^*_v = \frac{n_c + E[|V_e|]}{n}$, with $E[|V_e|] = E[|\bigcup_{u \in V} I(u \in V_e)] = \sum_{u \in V} \mathbb{P}[u \in V]$. Which can be developed as:

$$\mathbb{P}[u \in V] = \mathbb{P}[u \notin V_e \land \exists v \in \text{neigh}(u), v \in V_e]$$

$$= \mathbb{P}[u \notin V_e | \exists v \in \text{neigh}(u), v \in V_e | u \notin V_e]$$

$$= \frac{n_c - n}{n} \cdot (1 - \mathbb{P}[\forall v \in \text{neigh}(u), v \in V_e | u \notin V_e])$$

As $V_e$ is an arbitrary selection of $n_c$ nodes among $n$ (all selections being equiprobable), $u \notin V_e$ makes this a selection of $n_c$ nodes among $n - 1$. $(\forall v \in \text{neigh}(u), v \notin V_e)$ happens if and only if this selection is made exclusively from nodes in $V \setminus \text{neigh}(u)$, hence among $n - 1 - \text{deg}(u)$ nodes. If $n_c > n - 1 - \text{deg}(u)$, no selection is possible, and thus $u \in V_e$ with probability 1. For simplicity of notations, denote $D(n_c) = \{u \in V | \text{deg}(u) > n - n_c - 1\}$, the set of nodes that will be observed with probability 1. Otherwise, with $C^k_n$ the number of subsets of size $k$ of a set of size $n$:

$$\mathbb{P} \{u \in V_e | v \in \text{neigh}(u), v \notin V_e\} = \frac{C^{n-1-\text{deg}(u)}_n}{C^n_{n_c}}$$

Yielding, when combining the elements:

$$\rho^*_v = \frac{n_c}{n} + \frac{n-n_c}{n} \cdot \left( |D(n_c)| + \sum_{u \in V \setminus D(n_c)} \left( 1 - \frac{C^{n-1-\text{deg}(u)}_n}{C^n_{n_c}} \right) \right)$$

Which is indeed a function of $n$, $n_c$ and the degree distribution $(\text{deg}(u))_{u \in V}$.

**Proposition 3.4.** The local node-observability of a graph depends only on its number of nodes $n$, number of compromised nodes $n_c$ and its degree distribution $(\text{deg}(u))_{u \in V}$.

**Proof.** Using previous results:

$$\bar{\rho}_v = \frac{1}{n-n_c} \sum_{u \in V} \mathbb{E}[|V_e| | u \notin V_e] \cdot I(u \notin V_e)$$

$$= \frac{1}{n-n_c} \cdot \frac{n_c}{n-1} \cdot \frac{n-n_c}{n} \cdot \sum_{u \in V} \mathbb{P}[u \in V | u \notin V_e]$$

$$= \frac{1}{n-n_c} \cdot \frac{n_c}{n-1} \cdot \frac{n-n_c}{n} \cdot \sum_{u \in V} \mathbb{P}[u \in V | u \notin V_e]$$

In the proof of 3.3, we found a value for $\mathbb{E}[|V_e| | u \in V | u \notin V_e]$ that depends only on $n_c$, $n$, and the degree distribution of the graph. Hence, $\bar{\rho}_v = \frac{1}{n-n_c} \cdot \frac{n_c}{n-1} \cdot \frac{n-n_c}{n}$.

Proposition 3.5. **(Relationship between local and global node-observability)** Local and global node-observability obey the following relationship:

$$\rho^*_v = \frac{n_c}{n} + \frac{n-n_c}{n} \cdot \bar{\rho}_v$$

**Proof.** This is a consequence of the expressions found in the proofs of propositions 3.3 and 3.4.

Computing node-observability however requires knowing the full degree distribution of the graph. Degree distributions have been extensively studied in network science, see e.g. [3, 37].
3.2 Empirical study of observability

In this section, we study edge- and node-observability on different families of synthetic networks. We verify empirically the propositions developed previously and study the impact of the network structure on edge and node-observability.

We study graphs generated from four models: a complete graph and three graphs with an average density of 0.015; a Erdős-Rényi graph (with \( p = 0.015 \) - a random graph), Barabási-Albert graph (with \( m = 2 \) - a graph whose degree distribution follows a power law), and a Watts-Strogatz graphs (with \( k = 5 \) and \( p = 0.2 \) - a graph designed to have a large number of triangles), each with 250 nodes. We estimate the node- and edge-observability for each graph type graph size and number of compromised nodes \( n_c \), by repeating the experiment 500 times and reporting the average curves.

Additionally, to model the interplay between graph density and observability, we repeat the entire procedure described above while varying the density from 0.01 to 0.3. To do so, we vary the probability of link creation \( p \) in the Erdős-Rényi graph, the value of the \( m \) parameter in Barabási-Albert, and the value of the \( k \) parameter in Watts-Strogatz graphs in order to obtain comparable densities.

First, Figure 2 and Figure 3 match our theoretical results: the global (resp. local) edge-observability has an AUOC of 2/3 (resp. 1/2) independently of the number of edges in the graph. Furthermore, as expected, being able to observe 2-hops or 3-hops away from compromised nodes greatly increases all the metrics considered.

Second, Figure 2 shows that global and local node-observability behave roughly the same way, especially for small values of \( n_c \), which is expected by proposition 3.5.

Finally, while the 1-hop behaviour is roughly the same for all types of graphs (except the complete one), we observe significant
tapping a phone is one of the most common means of surveillance, of suspects—and therefore all the communications they have with it is, however, arguably loosely protected by current regulations. Graphs, which in turn has larger AUOC than Watts-Strogatz graphs. An explanation for this can be found in the structure of these graphs. Indeed, Barabasi-Albert graphs contain very high degree nodes called hubs. This high degree makes them likely to be observed (connected to a compromised node) which in turn allows the adversary to observe all their connections (2-hops) and the connections of their connections (3-hops), strongly increasing the observability of the graph. The impact of hubs on observability and surveillance was first discussed in PNAS [19]. Watts-Strogatz graphs present a lattice-like structure with high clustering coefficient. This means that most nodes are well connected to close neighbors but not to the rest of the graph. Compromising a node will therefore have a very local impact on observability, as opposed to spanning over the entire graph and limit the observability of the graph. Random graphs, which do not exhibit large hubs or local lattice structure, logically have observability in between the two previous “extreme” cases.

4 APPLICATION: GROUP PRIVACY IN PHONE NETWORKS

The list of who we talked to on the phone—the edges of our social graph—is sensitive and considered private by 63% of Americans [30]. It is, however, arguably loosely protected by current regulations. Tapping a phone is one of the most common means of surveillance, with national laws allowing the authorities to surveil the phones of suspects—and therefore all the communications they have with third parties—but often also the people who they communicate with. For example, US regulation allowed intelligence agencies to collect phone records of people up to three hops from suspects. After the Snowden affair in 2013, this number was reduced to two hops [19]. Similarly, in an attempt to curb illegal immigration, the US Border Patrol was allowed to use call logs to confirm the legal status of their potential target as well as to search for other potential illegal immigrants among the target’s contacts [14].

In this section, we use real-world mobile phone data to study the potential of surveillance through node-based intrusions. Our dataset comprises four weeks of domestic intra-company communications phone logs (calls and texts) of 1.4 million customers of a mobile phone provider, resulting in a social graph containing 6 million edges. To the best of our knowledge, the only similar study has been conducted by Mayer et al. [19] and concluded that hubs increase the number of nodes that can be reached through 3 hops. Their analysis, however, relies on a fairly disconnected dataset of less than 1000 users collected through an app. The small size of the dataset and sampling bias prevents them from quantifying the potential of node-based intrusions for mass and targeted surveillance, from comparing their results to graph models, and to show the importance of the graph’s clustering coefficient.

Figure 4 shows that, under the previous 3-hops policy and by compromising 1% of the population (with a seven days time window) e.g. through warrants, one could surveil a striking 84% of all the communications (global edge-observability) and 73% of the communications of a specific person (local edge-observability). While the new 2-hops policy decreases these numbers, we show that under it, one can still surveil 32% of all the communications (global edge-observability) and 24% of the communications of a specific person (local edge-observability). This article is the first one to present such a large-scale study of these numbers.

Figure 5 compares the AUOC for the real phone network built using 7 days of data with the AUOC obtained using the four graph models used before (each with the same number of nodes and density than the phone network). We observe, as before, that the Barabasi-Albert graph has a higher AUOC (both for edge- and node-observability for 2 and 3 hops) than the random one which in turn has a higher AUOC than the Watts-Strogatz graph. Our phone graph then falls similarly between the hubs-powered Barabasi-Albert graph and the triangle-hindered Watts-Strogatz graph for local and global observability.

This is explained by Figure 6 and Table 1. Figure 6 shows that our phone graph has a degree distribution very similar to the one of a Barabasi-Albert graph, including hubs, which will increase observability. Table 1 shows that our phone graph has a clustering coefficient and modularity [23] that are fairly similar to the ones that can be observed in a Watts-Strogatz graph. Both modularity and clustering coefficient will reduce the observability of the graph.

Finally, Figure 4 shows how the AUOC and edge-observability of our phone graph evolves as the time window considered increases. It shows that the number of nodes that can be mass-observed by compromising 1% of the nodes under the 2-hops policy reaches 46% after a month while the local edge-observability, the ability to edge-observe a random node in the network, reaches a striking 36%.
Figure 4: Global (A) and local (B) AUOC edge-observability of the real phone network as the observation window increases. Global (C) and local (D) edge-observability when 1% of the nodes are compromised.

Figure 5: Area under observability curve (AUOC) for the real phone network (observation window of 7 days) and synthetic networks with the same number of nodes and edges.

Taken together, our results show that large-scale mobile phone network are very vulnerable to mass surveillance through node-based intrusions, especially with more than 1 hops and with long enough observation windows. While our results confirm Mayer’s [19] on the impact of hubs on observability using a small dataset, they show that this impact is hindered by the presence of triangles, a fact that had not been considered and quantified so far in the debate on metadata and surveillance. Our results, furthermore, provide a quantification at large-scale of edge-observability using real data. They show that it is easy to monitor a large fraction of all the communications occurring in a graph through node-based intrusions and that even monitoring one individual’s communications is possible by compromising a relatively small fraction of the nodes in the graph. This is particularly true if the observation window is long enough, a fact that has been absent from the surveillance debate so far.

Figure 6: Degree distribution for the mobile phone dataset graph and the random graph models with equal number of nodes and density. The degree distribution of a Barabasi-Albert graph appears to be the closest fit to the empirical distribution.

Table 1: Modularity and average clustering for the phone graph and the three synthetic networks, all with equal number of nodes and density. Watts-Strogatz’s resulting average clustering coefficient is the closest one to the one of our phone network.

| network type       | avg. clustering | modularity |
|--------------------|-----------------|------------|
| Phone              | $1.6 \times 10^{-1}$ | 0.72       |
| Random             | $3.7 \times 10^{-6}$ | 0.43       |
| Barabasi-Albert    | $1.0 \times 10^{-4}$ | 0.36       |
| Watts-Strogatz     | $2.7 \times 10^{-1}$ | 0.81       |

5 APPLICATION: GROUP PRIVACY IN CO-LOCATION NETWORK

Mobility data is considered as some of the most sensitive data currently being collected. The Electronic Frontier Foundation published a list of potentially sensitive professional and personal information that could be inferred about an individual from their mobility information [7]. These include the movements of a competitor sales force, attendance of a particular church, or an individual’s presence in a motel or at an abortion clinic.

We here use our framework and real world sensing data to show that it is possible to observe the location of a large number of people in a city by compromising a small number of devices. In this tracker attack, an attacker would compromise people’s smartphone, e.g. offering a fake “flashlight” app for people to install [10], and use compromised devices’ GPS location and sensing capabilities to track nearby un compromised devices.

Compromised devices can sense uncompromised neighbouring devices through Wi-Fi or Bluetooth. We believe Wi-Fi attacks to
be more likely as they are already widely used by commercial companies, e.g. Transport For London (TFL) [18], to track their users. Wi-Fi attacks could be either passive, where the app simply observes probe requests that mobile phones send to sense nearby Wi-Fi hotspots (as smartphones search for Wi-Fi networks with high frequency and, by default, even if the user disables Wi-Fi [31]), or active, running a fake hotspot with a common SSID (e.g. atwif1, xfinitywifi) to entice nearby phones to connect. While more complex, the latter would bypass MAC address randomization used by some OSes for privacy protection as phones use their real identifier when connecting to a network. We believe such tracking attacks to be likely given the large number of companies with similar access to user devices (e.g. through code embedding in third-party apps) and strong interest in location data [1].

We first estimate the real world effectiveness (node-observability) of a tracker attack using a dataset collected as part of the Copenhagen Networks Study [32]. The dataset contains mobility information of about 600 students at a European university collected over a month (retrieved via GPS, Wi-Fi, or a combination of the two) along with Bluetooth sensing data (every 5 min). Using this data, we build hourly co-location graphs with edges between all the devices that sensed another within that hour (Figure 7). Repeating this analysis for different hours and regions of 1 km² allows us to estimate the node-observability of such tracker attack. Note that Wi-Fi has a larger range than Bluetooth, making our estimates a conservative estimate of the real-world node-observability.

Figure 8 shows how node-observability increases with the number of compromised nodes per km². The probability of a specific node to be sensed by a compromised node (local node-observability) is higher than 60% with as little as 200 compromised devices per km². We approximate local node-observability for n_c compromised nodes per km² using \(LNO_{\text{approx}}(n_c) = 0.13 \log(n_c) - 0.05 \) (\(R^2 = 0.9\)).

Using this approximation and census data [24, 35], we evaluate the feasibility of tracking attacks in four large cities: Chicago, Los Angeles, London, and Singapore (see Algorithm 1). Figure 9 shows that node-observability is high for all cities. For instance, in London, an attacker can observe the location of 56% of individuals (resp. 84% - local node-observability) by compromising only 1% (resp. 10%) of the London population. For instance, the Judy malware [20] for Android was recently estimated to have infected 36 million devices worldwide, a fake flashlight app collected data from tens of millions of users [12], while e.g. UK start-up Tamoco has deals with 1000 android apps to embed their code allowing them to compromise 100 million devices. This makes the node-intrusion tracking attacks in large densely-populated cities a major concern moving forward.

Figure 9 finally shows that the local node-observability in cities can be reasonably well approximated by assuming that the distribution of the population per km² in the city follows an exponential distribution, where the parameter \( \lambda \) is the density of the entire city \( \frac{\text{population}}{\text{area}} \). This allows us to estimate the local node-observability of a city, the vulnerability of a person to be observed, by knowing only the population and area of the city.

**Algorithm 1 Local node-observability of a city**

1. **procedure** LocalNodeObsCity(n_B, B, x)
2. \( \text{pop} \leftarrow \sum_i B_i \)
3. \( \text{obs} \leftarrow 0 \)
4. for \( i = 1, \ldots, n_B \) do
5. \( m_i \leftarrow x \cdot B_i \)
6. \( \text{obs} + = LNO_{\text{approx}}(m_i) \cdot B_i \)
7. end for
8. **return** \( \text{obs/pop} \)
9. **end procedure**

6 CONCLUSION

In this paper, we proposed a framework to study group privacy in the original sense given to it by Blount, i.e. the impact of the people we interact with on our privacy. We discussed two attack models on a graph, where an adversary compromises a random fraction of the nodes, allowing her to observe uncompromised nodes or nodes. Our framework also handles cases in which the attacker can access information several hops away from the compromised nodes, in line with current regulation.
We prove that, for 1 hop, edge-observability is constant and independent of the graph structure, while node-observability requires knowledge of only the graph’s degree distribution. We show empirically on synthetic graphs that adding hops severely increases observability, particularly in the presence of hubs in the graph structure.

![Graph showing estimated observability vs. fraction of compromised devices.](image)

**Figure 9:** Local node-observability in cities using census data ($AUOC_C$) and estimated local node observability ($AUOC_E$). Inset: distribution of the population per block

We then use our framework to evaluate the success of two possible attacks, using real-world datasets. Our first attack showed that over a month of a large-scale phone graph, compromising 1% of nodes leads to monitoring 98% of all communications on the graph using 3-hops policy and still a striking 46% of all communications using the new 2-hops policy. We also show that, while the presence of hubs increases observability [19], this is balanced by the high clustering coefficient and prominence of triangles in real-world phone datasets. This crucial property of human social network has so far been ignored in the debate on surveillance using node-based intrusions.

Our second attack modeled a population-wide location-tracking attack using a rogue smartphone app. We estimate local-node observability using a real-world co-location and sensing dataset. We then use this to show that, by compromising 1% of the London population, an attacker could observe the location of more than half of the city’s population.

These results show that our connectiveness makes us and our societies very vulnerable to group privacy intrusions where only a small number of compromised nodes might impact the privacy of a large fraction of the population. This makes such intrusions potential candidates for massive population-wide surveillance and emphasize the importance of rethinking of definition of privacy beyond the current individual-centric model.

**Limitations.** We believe our framework suffers from two main limitations:

1. The choice of selecting compromised nodes at random, while realistic for our two applications, does not encompass every possible—or even probable—attack. However, most of our mathematical definitions do not rely on this assumption (while propositions 3.1 to 3.5 do), hence the overall framework could be extended to use different compromised nodes distribution or targeting.

2. Differences in lifestyle, geography, type of population might introduce bias in our extrapolation of local node-observability from the CNS dataset to large cities. We argue, however, that the probability for an individual to be observed by a device within 1 km$^2$, as a function of the number of compromised devices, is roughly invariant of the population in the cell. This is, however, the first attempt — to the authors’ knowledge — at estimating the risk of mass surveillance in large cities based on actual co-location data.

**Future directions.** We propose the following directions for future work on group privacy and surveillance:

1. Application of our framework to other datasets and other forms of data, including social networks such as Facebook, to observe how their structure makes them more or less vulnerable to mass surveillance.

2. An analysis on how observability evolves in mobile phone datasets when considering longer periods of time and different countries, as well as the design of a mobile phone graphs model that replicates both properties of the data (hubs, clustering coefficient) while capturing the local and global observability of the graph.

3. Proposition of a theoretical population model for cities, that incorporates the movement of inhabitants within cells and gives us a different estimate of node-observability in cities.

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