PRIVÉ: Anonymous Location-Based Queries in Distributed Mobile Systems

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ABSTRACT

Nowadays, mobile users with positioning devices can access Location Based Services (LBS) and query about points of interest in their proximity. For such applications to succeed, privacy and confidentiality are essential. Encryption alone is not adequate; although it safeguards the system against eavesdroppers, the queries themselves may disclose the location and identity of the user. Recently, there have been proposed centralized architectures based on $\mathcal{K}$-anonymity, which utilize an intermediate anonymizer between the mobile users and the LBS. However, the anonymizer must be updated continuously with the current locations of all users. Moreover, the complete knowledge of the entire system poses a security threat, if the anonymizer is compromised.

In this paper we address two issues: *(i)* We show that existing approaches may fail to provide spatial anonymity for some distributions of user locations and describe a novel technique which solves this problem. *(ii)* We propose PRIVÉ, a decentralized architecture for preserving the anonymity of users issuing spatial queries to LBSs. Mobile users self-organize into an overlay network with good fault tolerance and load balancing properties. PRIVÉ avoids the bottleneck caused by centralized techniques both in terms of anonymization and location updates. Moreover, the status is distributed in numerous users, rendering the system resilient to attacks. Extensive experimental studies suggest that PRIVÉ is applicable to real-life scenarios with large populations of mobile users.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Distributed Systems—*Distributed Applications*; H.2.7 [**Database Management**]: Database Administration—*Security, integrity, and protection*

General Terms

Design, Experimentation, Security

Keywords

Privacy, Anonymity, Spatial Databases, Peer-to-Peer

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1. INTRODUCTION

The increased popularity of mobile communication devices with embedded positioning capabilities (e.g., GPS, RFID) has triggered the development of location-based applications. General Motor's OnStar navigation system, for example, combines the vehicle's position with real-time information to avoid traffic jams and automatically alerts the authorities in case of an accident. More applications based on the users' location are expected to emerge with the arrival of the latest gadgets (e.g., iPAQ hw6515, Mio A701) which combine the functionality of a mobile phone, PDA and GPS receiver.

Consider the following scenario: Bob uses his GPS enabled mobile phone to ask the query "Find the nearest hospital to my present location". This query can be answered by a *Location-Based Service* (LBS) in a public server (e.g., Google Maps), which is *not* trusted. To preserve his privacy, Bob does not contact the LBS directly. Instead he submits his query via an intermediate trusted server which hides his ID (services for anonymous web surfing are commonly available nowadays). However, the query still contains the exact coordinates of Bob. One may reveal sensitive data by combining the location with other publicly available information. If, for instance, Bob uses his mobile phone within his residence, the untrustworthy owner of the LBS may infer Bob's identity and speculate that he suffers from a medical condition.

In practice, users are reluctant to access a service that may disclose sensitive information (e.g., corporate, military), or their political/religious affiliations and alternative lifestyle. To preserve privacy in LBSs, recent research focused on adapting the well established $\mathcal{K}$-anonymity technique to the spatial domain. $\mathcal{K}$-anonymity [20, 22] has been used in statistical databases as well as for publishing census, medical and voting registration data. A dataset is said to be $\mathcal{K}$-anonymized, if each record is indistinguishable from at least $\mathcal{K}-1$ other records with respect to certain identifying attributes. In the LBS domain, a similar idea appears in the work of Ref. [10, 11]. Both approaches employ *spatial cloaking* to conceal the location of the user: Instead of reporting the exact coordinates to the LBS, they construct an *Anonymizing Spatial Region* ($\mathcal{K}$-ASR) which encloses the locations of $\mathcal{K}-1$ additional users. Ref. [14, 17] extend this method by proposing a framework for the entire process of query anonymization in LBSs.

Most existing approaches utilize a *centralized* anonymizer. This is a trusted server that acts as an intermediate tier between the users and the LBS. All users subscribe to the anonymizer and continuously report their location while they move. Each user sends his query to the anonymizer, which constructs the appropriate $\mathcal{K}$-ASR and contacts the LBS. The LBS computes the answer based on the $\mathcal{K}$-ASR, instead of the exact user location; thus, the response of the LBS is a superset of the answer. Finally, the anonymizer filters the result from the LBS and returns the exact answer to the user.

Our work is motivated by the following shortcomings of existing anonymization approaches: *(i)* The centralized anonymizer is a bottleneck due to the handling of all query requests and the required post-processing, in addition to the frequent updates of user locations. Moreover, the anonymizer is a single point of failure; the system cannot function without it. *(ii)* The complete knowledge of the locations and queries of all users is a serious security threat, if the anonymizer is compromised. Even if there is no attack, the centralized anonymizer may be subject to governmental control, and may be banned or forced to disclose sensitive user information (similar to the legal case of the Napster file-sharing service). *(iii)* Independent of the centralized architecture, the hierarchical partitioning method for $\mathcal{K}$-ASR construction [11, 17] may fail to provide anonymity under certain conditions (see Section 3).

In this paper we propose PRIVÉ, a distributed architecture for anonymous location-based queries, which solves the problems of existing systems. Our contributions are: *(i)* We develop a superior $\mathcal{K}$-ASR construction mechanism based on the Hilbert space-filling curve, that *guarantees* anonymity even if the attacker knows the locations of all users. *(ii)* We introduce a distributed protocol used by mobile entities to self-organize into a fault-tolerant overlay network. The structure of the network resembles a distributed B$^+$-tree (each mobile user corresponds to a data point), with additional annotation to support efficiently the Hilbert-based $\mathcal{K}$-ASR construction. In PRIVÉ, $\mathcal{K}$-ASRs are built in a decentralized fashion, therefore the bottleneck of the centralized server is avoided. Moreover, since the status of the system is distributed, PRIVÉ is resilient to attacks. *(iii)* We also conduct an extensive experimental evaluation. The results confirm that PRIVÉ achieves efficient anonymization and load balancing with low maintenance overhead, while being fault-tolerant. Therefore, it is scalable to a large number of mobile users.

The rest of the paper is organized as follows: Section 2 discusses the architecture of PRIVÉ. In Section 3, we introduce our Hilbert-based $\mathcal{K}$-ASR construction mechanism, whereas in Section 5 we describe the distributed protocol of the overlay network. Section 6 presents the experimental evaluation of our system. A brief survey of the related work is included in Section 7. Finally, Section 8 concludes the paper and discusses directions for future work.

2. SYSTEM ARCHITECTURE

Fig. 1 depicts the architecture of PRIVÉ. We assume a large number of users who carry mobile devices (e.g., mobile phones, PDAs) with embedded positioning capabilities (e.g., GPS). The devices have processing power and access the network through a wireless protocol such as WiFi, GPRS or 3G. Moreover, each device has a unique network identity (e.g., IP address) and can establish point-to-point communication (e.g., TCP/IP sockets) with any other device in the system through a base station (i.e., the two devices do not need to be within the range of each other). For security reasons, all communication links are encrypted.

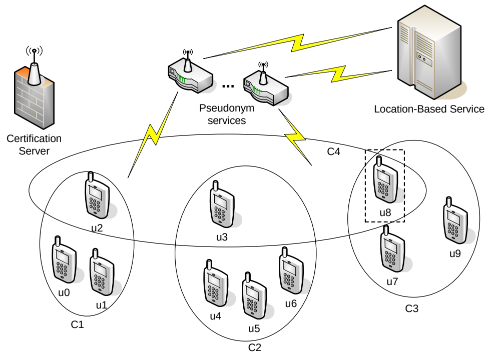


Figure 1: Architecture of Privé

In addition, we assume the existence of a trusted central *Certification Server* (CS), where users are registered. Prior to entering the system, a user u must authenticate against the CS and obtain a certificate. Users having a certificate are trusted by all other users. Typically, a certificate is valid for a few hours; it can be renewed by recontacting the CS. Apart from the certificate, the CS returns to u the IP addresses of some users who are currently in the system. u employs this list to identify an entry point to the distributed network. Note that the CS does not know the locations of the users and does not participate in the anonymization process. Therefore the workload of the CS is low (i.e., no location updates); moreover, even if it is forced, it cannot disclose any sensitive information.

Each user corresponds to a peer. Peers are grouped into clusters, according to their location. Within each cluster, peers elect a cluster head, and the set of heads is grouped recursively to form a tree. To achieve load balancing, the cluster heads change periodically in a round-robin manner. By definition, cluster heads may belong to multiple levels of the tree. In Fig. 1, for instance, there is a two-level hierarchy, where users u_2, u_3, u_8 are the heads of cluster C_1, C_2 and C_3, respectively; also u_8 is the head of the upper layer cluster C_4.

Typically users ask Range or Nearest-Neighbor (NN) queries with respect to their location. For example, user u_1 in Fig. 2, may ask: "Find the nearest hospital to my present location" (the answer is h_2). Such queries reveal the exact location of u_1. To achieve anonymity, PRIVÉ requires users to set a degree of anonymity $\mathcal{K}$ (note that $\mathcal{K}$ is based on individual criteria and may vary among queries). In our example, u_1 chooses $\mathcal{K} = 3$. PRIVÉ identifies an appropriate set of 3 users (i.e., u_1, u_2 and u_3) in a distributed manner and constructs the corresponding $\mathcal{K}$-ASR (i.e., the rectangle which encloses the 3 users). Next, the transformed query must be sent to the LBS. In order to hide his IP address, u_1 uses a pseudonym. To obtain a pseudonym, any existing service for anonymous web surfing can be used[1] (e.g., onion routing [9]). Note that the pseudonym service does not know the location of any user. Moreover, the auxiliary users inside the $\mathcal{K}$-ASR, collaborate only to hide the location but do not know the exact query of u_1; therefore, a single point of attack is avoided.

[1] Since each user can access his preferred pseudonym service, that service is not a bottleneck or a single point of failure.

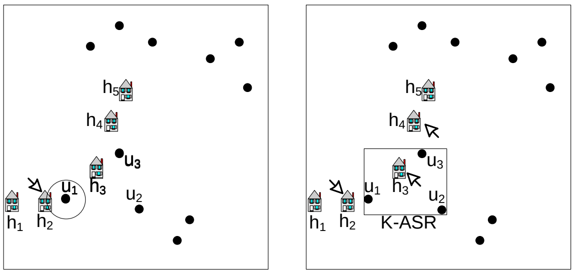


Figure 2: Example: "Find the nearest hospital" (users are shown as black dots).

Privé can collaborate with various *untrustworthy* spatial databases providing LBSs. The only requirement for the LBS is to support NN queries of regions (i.e., $\mathcal{K}$-ASRs) as opposed to points. Intuitively, the nearest neighbors of a region are all the data objects inside the region plus the NNs of every point in the perimeter of the region. In our example (Fig. 2), the NNs of the $\mathcal{K}$-ASR are $\{h_2, h_3, h_4\}$; the set is filtered by u_1 to obtain the actual answer h_2. The cardinality of the NNs set (thus the processing and communication cost) depends on the $\mathcal{K}$-ASR; therefore we aim to minimize the size of the $\mathcal{K}$-ASR. Query processing at the LBS [12, 14, 17] is orthogonal to our work but outside the scope of this paper.

3. SPATIAL $\mathcal{K}$-anonymity

A user u who issues a location-based query is considered to be $\mathcal{K}$-anonymous if his location is indistinguishable from the location of $\mathcal{K}-1$ other users [11]. Formally:

Definition [Spatial $\mathcal{K}$-anonymity] Let H be a set of $\mathcal{K}$ distinct user entities with locations enclosed in an arbitrary spatial region $\mathcal{K}$-ASR. A user $u \in H$ is said to possess $\mathcal{K}$-anonymity with respect to $\mathcal{K}$-ASR if the probability P of distinguishing u among the other users in H does not exceed $1/\mathcal{K}$. We refer to $\mathcal{K}$ as the required degree of anonymity.

Note that: *(i)* The definition assumes a *snapshot* of the users' locations. Although Privé supports user mobility, $\mathcal{K}$-anonymity is undefined across multiple snapshots. *(ii)* Spatial $\mathcal{K}$-anonymity does *not* depend on the size of the $\mathcal{K}$-ASR. In the extreme case, the $\mathcal{K}$-ASR can degenerate to a point, if $\mathcal{K}$ users are at the same location. In general, we prefer small $\mathcal{K}$-ASRs, in order to minimize the processing cost at the LBS and the communication cost between the LBS and the mobile user. Nevertheless, some applications impose a lower bound on the size of the $\mathcal{K}$-ASR [17]. In such a case, the $\mathcal{K}$-ASR can be trivially enlarged to satisfy the lower bound, by been scaled proportionally in all directions. The same procedure can also be used to avoid having users on the perimeter of the $\mathcal{K}$-ASR.

A naïve $\mathcal{K}$-ASR construction algorithm would choose a random $\mathcal{K}$-ASR. However, if the $\mathcal{K}$-ASR is too small it may contain fewer than $\mathcal{K}$ users, whereas if it is larger than necessary, it will affect the query cost. Constructing the $\mathcal{K}$-ASR in the neighborhood of the querying user u (e.g., using the $\mathcal{K}$ nearest neighbors of u) is also inappropriate, because u tends to be closest to the center of the $\mathcal{K}$-ASR, thus easily identified. Moreover, we cannot pick randomly $\mathcal{K}-1$ auxiliary users and send $\mathcal{K}$ independent NN queries to the LBS, because we would disclose the exact locations of $\mathcal{K}$ users; this is undesirable in any anonymization method.

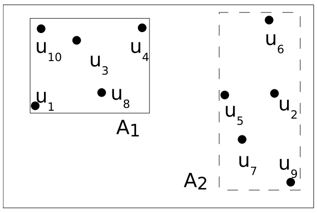


Figure 3: $\mathcal{K}$-ASR Reciprocity Example, $\mathcal{K}$=5

We identify the following property that is sufficient for a $\mathcal{K}$-ASR construction technique in order to preserve user privacy:

Definition [$\mathcal{K}$-ASR Reciprocity] Consider a user u_q issuing a query and its associated $\mathcal{K}$-ASR A_q. A_q satisfies the reciprocity property iff there exists a set of users AS lying in A_q such that *(i)* $|AS| \geq \mathcal{K}$, *(ii)* $u_q \in AS$ and *(iii)* every user $u \in AS$ lies in the $\mathcal{K}$-ASRs of all other users in AS.

Fig. 3 shows an example with 10 users. For $\mathcal{K}$=5, the $\mathcal{K}$-ASR of users $u_1, u_3, u_4, u_8, u_{10}$ is area A_1 an the $\mathcal{K}$-ASR of users u_2, u_5, u_6, u_7, u_9 is area A_2. In this example, $\mathcal{K}$-ASRs of all users satisfy the reciprocity property. For instance, for user u_1, if we set $AS = \{u_1, u_3, u_4, u_8, u_{10}\}$, we may easily verify that AS satisfies all the requirements of the reciprocity property.

Theorem 3.1. *For a given snapshot of user locations, and regardless of the query distribution among users, a $\mathcal{K}$-ASR construction technique* guarantees *$\mathcal{K}$-anonymity of the query source against location-based attacks,* if *every constructed $\mathcal{K}$-ASR satisfies the reciprocity property.*

Proof. We assume the worst case scenario, where an attacker knows the exact location of all users in the system. The attacker possesses a set $\mathbf{A}$ of $\mathcal{K}$-ASRs associated to user queries.

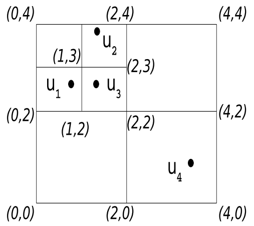
Let us consider a $\mathcal{K}$-ASR, $A_q \in \mathbf{A}$. The attacker attempts to infer the user u_q that constructed A_q. Since A_q satisfies the reciprocity property, there exists a set of users AS (lying in A_q) such that *(i)* $|AS| \geq \mathcal{K}$, *(ii)* $u_q \in AS$ and *(iii)* every user $u \in AS$ lies on the $\mathcal{K}$-ASRs of all other users in AS.

Moreover, since every $\mathcal{K}$-ASR satisfies the reciprocity property, it follows that when the attacker inspects any $\mathcal{K}$-ASR that includes u_q, he will observe the same set of users AS. Therefore, for all users u in AS, the probability P_u of being the query issuer is the same:

$$P_v = P_{u_q} = \frac{1}{|AS|} \leq \frac{1}{\mathcal{K}}$$

Hence, the $\mathcal{K}$-anonymity property is satisfied. □

In view of this property, an optimal $\mathcal{K}$-ASR construction algorithm must partition the user population into $\mathcal{K}$-ASRs that posess the reciprocity property, such that the sizes of the resulting $\mathcal{K}$-ASRs are minimized. However, calculating the optimal partitioning of a set of user locations into anonymizing $\mathcal{K}$-ASRs is an NP-Hard problem [15]. A number of on-the-fly $\mathcal{K}$-ASR construction techniques have been proposed, which attempt to achieve anonymity and reduce the $\mathcal{K}$-ASR size. In the following, we briefly survey these solutions and highlight their drawbacks.



Quadrant	Extent	Users
q1	(0,0),(4,4)	u1,u2,u3,u4
q2	(0,2),(2,4)	u1,u2,u3
q3	(2,0),(4,2)	u4
q4	(0,2),(1,3)	u1
q5	(1,3),(2,4)	u2
q6	(1,2),(2,3)	u3

Figure 4: Limitations of quadASR, $\mathcal{K}$=2

3.1 Drawbacks of Existing Approaches

The anonymization technique of Ref. [11] builds the $\mathcal{K}$-ASR of a given location using the PR-Quad-tree. When a user u issues a query, the Quad-tree is traversed until a quadrant which contains u and less than $\mathcal{K}-1$ other users is found. The parent of that quadrant is returned as the $\mathcal{K}$-ASR. A similar idea is used in Ref. [17]. We refer to this technique as QUADASR.

There are two drawbacks of QUADASR: *(i)* It may fail to achieve anonymity for some user distributions. Consider the example of Fig. 4. Each user resides in his own quadrant identified by its lower-left and upper-right coordinates. When any of the users u_1, u_2 or u_3 issues a query with degree of anonymity $\mathcal{K}$=3, the quadrant $q_2 = ((0,2),(2,4))$ which encloses $u_{1...3}$ will be returned as the $\mathcal{K}$-ASR. On the other hand, when the isolated user u_4 issues a query with $\mathcal{K}$=3, the larger quadrant $q_1 = ((0,0),(4,4))$ is returned. Note that if $1 < \mathcal{K} \leq 3$, the only reason to return quadrant q_1 is that u_4 issued a query. If an attacker knows the locations of the users in the area[2], he will be able to pinpoint u_4 as the query origin. This vulnerability is the result of the fact that QUADASR does not satisfy the reciprocity property (i.e. $u_{1..3}$ belong to the $\mathcal{K}$-ASR associated to u_4, but not the other way around). *(ii)* A second drawback of QUADASR is that due to the non-uniform distribution of user locations, the number of users enclosed by a $\mathcal{K}$-ASR may grow much larger than $\mathcal{K}$ (as for u_4 in the previous example). This corresponds to larger spatial extent of the $\mathcal{K}$-ASR, hence higher processing cost. Both problems also exist if, instead of the Quad-tree, we use data partitioning spatial indices such as R-trees.

Recently, a P2P system has been proposed that performs distributed query anonymization for location-based queries; we refer to it as CLOAKP2P [7]. CLOAKP2P uses a technique similar to iterative deepening [24] to construct $\mathcal{K}$-ASRs. The query source initiates a $\mathcal{K}$-ASR request by contacting all peers within a given physical radius r, which is a fixed system parameter. If the set of peers S_0 found in the initial iteration is larger than $\mathcal{K}$, the nearest $\mathcal{K}$ of them are chosen to form the $\mathcal{K}$-ASR; otherwise, the process continues, and all peers in S_0 issue a request to all peers within radius r. The process stops when $\mathcal{K}$ or more users have been found. Intuitively, CLOAKP2P determines a query $\mathcal{K}$-ASR by finding the $\mathcal{K}$ -1 users nearest to the query source. Unfortunately, this simple heuristic fails to achieve anonymity in many cases, since the query issuer tends to be near the center of the $\mathcal{K}$-ASR. In Section 6, we show experimentally the vulnerability of CLOAKP2P.

None of the existing methods satisfies the reciprocity propoerty. Next, we describe our HILBASR algorithm, which overcomes the aforementioned drawbacks.

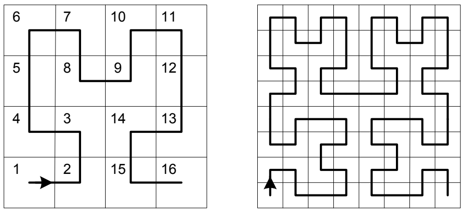
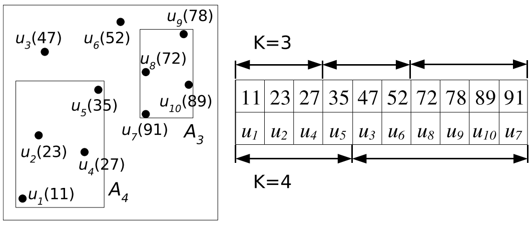


Figure 5: Hilbert curve (Left: 4×4; Right: 8×8).



11	23	27	35	47	52	72	78	89	91
u_1	u_2	u_4	u_5	u_3	u_6	u_8	u_9	u_{10}	u_7

Figure 6: hilbASR, $\mathcal{K}$=3 and $\mathcal{K}$=4

4. THE HILB-ASR ALGORITHM

Our HILBASR algorithm *guarantees* that the probability of identifying the query initiator is always bounded by $1/\mathcal{K}$, even if the attacker knows the locations of all users. HILBASR uses the Hilbert [6] ordering to group users into buckets of $\mathcal{K}$. The Hilbert space-filling curve is a continuous fractal which maps each region of a multi-dimensional space to an integer. In our case, the 2D coordinates of user locations are mapped to an 1D value. With high probability, if two points are close in the 2D space, they will also be close in the Hilbert transformation [18]. Fig. 5, for instance, shows the curve for a 4×4 and 8×8 space partitioning; the granularity of the regions can be arbitrary small.

To compute the $\mathcal{K}$-ASR, HILBASR employs an appropriate partitioning scheme that supports users' mobility and varying $\mathcal{K}$ with minimal overhead. Intuitively, HILBASR computes and sorts the Hilbert values of all users. Then, the algorithm conceptually groups the sorted Hilbert values into $\mathcal{K}$*-buckets* that contain $\mathcal{K}$ users, except from the last one which may contain up to $2{\cdot}\mathcal{K}-1$ users. Let us consider a user u posing a query with anonymity degree $\mathcal{K}$. To compute the $\mathcal{K}$-ASR of user u, HILBASR computes the Hilbert value $\mathcal{H}(u)$ of u and finds the $\mathcal{K}$-bucket that $\mathcal{H}(u)$ belongs to. The minimum bounding rectangle (*MBR*) of all the users in the $\mathcal{K}$-bucket corresponds to the $\mathcal{K}$-ASR.

For example, in Fig. 6, we illustrate the position of 10 users and their sorted Hilbert values. To compute the 3-ASR of user u_9, HILBASR first finds the $\mathcal{K}$-bucket which $\mathcal{H}(u_9)$ belongs to. In our case, this consists of four users, u_8, u_9, u_{10} and u_7. Then, HILBASR returns the MBR of these users. Thus, the 3-ASR of user u_9 is area A_3. Similarly, the 4-ASR of user u_5 is area A_4.

Note that for a given snapshot, HILBASR returns the same $\mathcal{K}$-ASR for all users in the $\mathcal{K}$-bucket. This makes the $\mathcal{K}$ users of the $\mathcal{K}$-bucket indistinguishable from each other. Thus, the probability of identifying the query initiator is bounded by $1/\mathcal{K}$.

LEMMA 4.1. *For a given snapshot of user locations* HILBASR *guarantees query source anonymity against location-based attacks.*

[2] By triangulation, phone companies can estimate the location of a user within 50-300 meters, as required by the US authorities (E911).

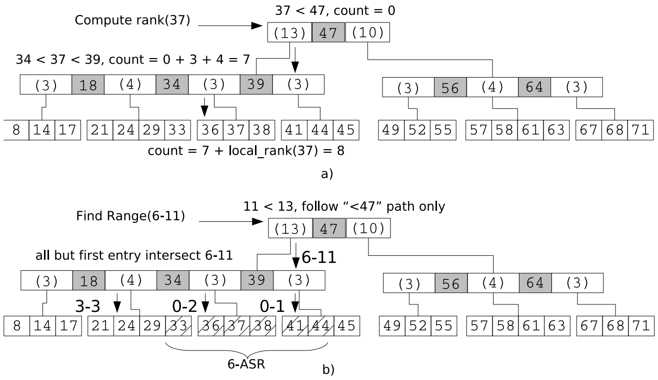


Figure 7: hilbASR with Annotated B$^+$-tree

Proof. hilbASR satisfies the reciprocity property, so from Theorem 3.1 immediately results that hilbASR guarantees $\mathcal{K}$-anonymity. □

In general, techniques that use fixed buckets suffer from lack of flexibility in accommodating queries with varying $\mathcal{K}$. Our method overcomes this limitation by avoiding to materialize the $\mathcal{K}$-buckets. Instead, it maintains a balanced sorting tree, which indexes the Hilbert values of users' locations. Let a user u initiate a query with anonymization degree $\mathcal{K}_u$. Our algorithm performs a search for $\mathcal{H}(u)$ in the index and computes $rank_u$, which corresponds to the position of $\mathcal{H}(u)$ in the in-order traversal of the tree. From $rank_u$, we calculate the *start* and *end* positions defining the $\mathcal{K}$-bucket which includes $\mathcal{H}(u)$, as:

$$\begin{aligned} start = &\quad rank_u - (rank_u \mod \mathcal{K}_u) \\ end = &\quad start + \mathcal{K}_u - 1 \end{aligned} \tag{1}$$

The complexity of the in-order tree traversal is $O(N)$, where N is the number of users; this is too high for our application. To compute $rank_u$ efficiently, we use an annotated B$^+$-tree (similar to the aR-tree [19]), where each tree node stores the number of leaf nodes in each of its subtrees. Consider the example in Fig. 7. For each internal node entry e, we store the number of leaf entries that are rooted at e; annotation counters are shown in parenthesis. Assume we want to determine a $\mathcal{K}$-ASR for entry 37, with $\mathcal{K}$=6. First, we compute the rank of entry 37 (Fig. 7a): we follow the path in the tree from root to the leaf that contains 37, and at each internal node we add to the rank value the sum of all counters in the node situated at the left of the followed pointer. At the leaf layer, we add to the rank the local rank value of key 37 in its leaf, and obtain rank 8 (ranks start from 0). Then, we calculate the bucket delimiters using Eq. (1), and obtain the interval [6..11]. Next (Fig. 7b), we perform a range search to locate the entries with ranks [6..11]. Observe that this operation uses the annotation, rather that the B$^+$-tree keys. Sub-ranges at each level are determined by splitting the initial range based on subtree sizes; the offset for the recursive call at entry e is determined as the initial start value minus the sum of counters of all entries in the node preceding e. The resulting $\mathcal{K}$-ASR is highlighted in the diagram.

The data structure is scalable, since the complexity of constructing the $\mathcal{K}$-ASR is $O(\log N+ \mathcal{K})$, whereas search, insert and delete cost is $O(\log N)$. Therefore, hilbASR is applicable to large numbers of mobile users who update their position frequently and have varying requirements for the degree of anonymity $\mathcal{K}$.

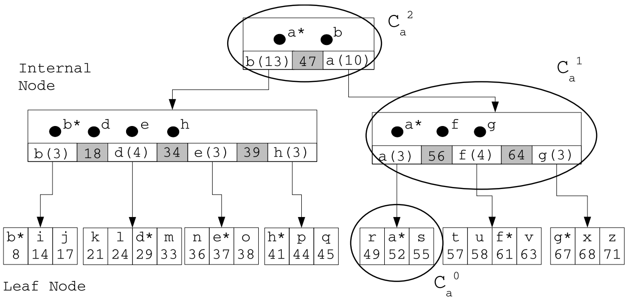


Figure 8: Distributed Index Structure, α=2

5. ANONYMIZATION IN Privé

In this section, we introduce Privé, a distributed protocol which supports decentralized query anonymization using the hilbASR algorithm. Privé mimics the functionality of a B$^+$-tree in a distributed setting. Each mobile user u has an associated index entry consisting of an ID (e.g., IP address), and the Hilbert value $\mathcal{H}(u)$ of his location as index key. A node (leaf or internal) in the B$^+$-tree, corresponds to a *cluster* of users, with size bounded between α and 3α, where α is a fixed system parameter. We use the terms *cluster* and *index node* interchangeably. The maximum cluster size is 3α, instead of the usual 2α for B$^+$-trees, to prevent cascading splits and merges (i.e., a split followed by a user departure), which are costly in the distributed environment.

Every user belongs to a leaf level cluster (level 0), and the contents of each cluster are disjoint (see Fig. 8). The users of each cluster C elect a leader called *head*(C). The head (marked with an asterisk) handles all index operations on behalf of the users in the cluster. Cluster heads are recursively grouped to form a tree; therefore, they belong to multiple levels of the tree. We denote by C_u^i, the level i cluster which includes user u. In our example, user u_a is the head of cluster C_a^0 at level 0. The same user is also the head of cluster C_a^1 and C_a^2; therefore, it belongs to every level of the tree. There is a single cluster at the top of the hierarchy, which we refer to as *top*. The cluster head of *top* is denoted by *root* (u_a in the example). In our protocol description, we use remote procedure call convention to specify interactions between users. The notation $u.func(params)$ denotes the invocation of subroutine $func$ with parameters $params$ at user u.

Each cluster is associated with its *state* information. The state of a leaf level cluster consists of an ordered list of (IP address, $\mathcal{H}(u)$) pairs (the user coordinates can be derived by the $\mathcal{H}(u)$ value). The state of an upper layer cluster with m elements consists of a list of m user addresses, separated by $m-1$ key values used to direct the search; the process is similar to a B$^+$-tree, with the role of memory pointers fulfilled by the IP addresses of users. Each internal node entry is annotated with a counter (depicted in parenthesis) representing the total number of users at the subtree under the entry. Only the head needs to know the state of the cluster. However, in our implementation, we replicate the state to every user within the cluster, in order to improve fault tolerance (in Section 6, we discuss the tradeoff between fault tolerance and maintenance cost). The Privé hierarchy has at most $\log_\alpha N$ layers, where N is the total number of

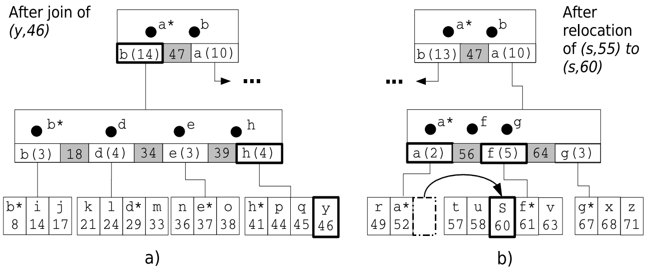


Figure 9: User Join and Relocation, α=2

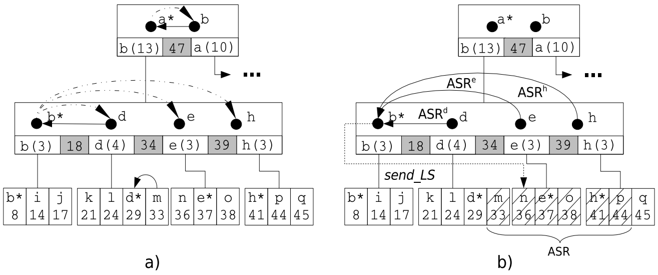


Figure 11: $\mathcal{K}$-request, α=2, $\mathcal{K}$=6

```
u.RelocateMyself() /*executed by moving user*/
  determine new key value $\mathcal{H}_u$ = Hilbert($u.x, u.y$)
  call $head(C_u^0)$.Relocate($u, \mathcal{H}_u$,0)
u.Relocate($relocated\_user$,$\mathcal{H}$,$l$)
  if ($\mathcal{H}$ in indexed key range at level $l$ )
    if ($l = 0$)
      add $relocated\_user$ to leaf user list; return
    else
      let $n$ be the next hop for $\mathcal{H}$
      call n.Relocate($relocated\_user$, $\mathcal{H}$,$l - 1$)
  else
    call $head(parent(C_u^l))$.Relocate($relocated\_user$, $\mathcal{H}$,$l + 1$)
```

Figure 10: User Relocation

users. Since the cluster size is bounded and a user may belong to at most one cluster at each level, there is an upper bound of $O(\alpha \log_\alpha N)$ on the membership state stored at a user.

5.1 Index Operations

The index supports four operations: *join*, *departure*, *relocation* and *$\mathcal{K}$-request* (i.e., a request for a $\mathcal{K}$-ASR with anonymization degree $\mathcal{K}$). We establish two performance metrics for Privé: *(i) latency*: the number of hops an index operation requires to complete. The latency is equal to the longest tree path followed as a result of the operation. Multiple paths may be followed in parallel during an operation. *(ii) communication cost*: the number of messages triggered by an index operation.

Join. User join corresponds to a B$^+$-tree insertion operation. Newly joining users authenticate at the certification server and receive the address of a user already inside the system. Without loss of generality, we assume that joining users know the root, since the root can be reached from any user in $O(\log_\alpha N)$ cost. We stress that since we require an index structure with annotation (in order to determine the absolute ranks of users), all joins must occur through the root. To avoid overloading the root, we devise a load-balancing mechanism (Section 5.2). User join has $O(\log_\alpha N)$ complexity in terms of latency and $O(\log_\alpha N + \alpha)$ communication cost; the second term is for updating the cluster state in all the users of the affected cluster.

Consider user u_y with Hilbert value $\mathcal{H}(u_y) = 46$ that joins the index of Fig. 8: u_y contacts u_a (at the root level) who forwards the join request to u_b and updates u_b's annotation counter in C_a^2 to 14. u_b then forwards the request to u_h, whose annotation counter in C_b^1 is updated to 4. Fig. 9(a) shows the join outcome. User join may trigger a cluster split, handled similarly to a B$^+$-tree node split; the head initiating the split leads one of the resulting clusters, and appoints a random initial cluster node to lead the other.

Departure (informed). User departure is similar to a B$^+$-tree deletion. The effect of deletion must be propagated to *root* to update the annotation counters. Deletion has $O(\log_\alpha N)$ latency and $O(\log_\alpha N + \alpha)$ communication cost. If the cluster size decreases below α, the head triggers a merge operation with the neighbor leaf-level cluster that has fewer members (to avoid a cascaded split). The head of the resulting cluster can be any of the initial heads, except if one of them (e.g., v) is also head at the higher level. If so, v will be chosen as cluster leader, to minimize membership changes.

Relocation. User mobility is treated as an entry update, which in a B$^+$-tree translates into a deletion and an insertion. Since users are likely to change location often, we optimize this process by performing local reassignment of users to nearby clusters. Due to the good locality properties of Hilbert ordering, the number of clusters involved in relocation is likely to be small. Annotation counter updates are only performed by affected clusters; this way, updates are not propagated all the way to the root. The upper bound on relocation latency is $O(\log_\alpha N)$, but in most cases relocation only involves a few clusters, at the low layers of the index. The pseudocode for user relocation is given in Fig. 10.

Consider user u_s from the Fig. 8 that relocates to a new position with Hilbert value 60. He forwards the request to $u_a = head(C_s^0)$. u_a cannot keep u_s within the same leaf entry, since the new value is outside the interval [49..55]. Since $u_a = head(C_a^1)$, with no additional message, u_a decides that u_s can be relocated to C_f^0, forwards the request to u_f and updates the annotation counters of u_a and u_f accordingly. Fig. 9(b) illustrates the relocation outcome.

$\mathcal{K}$-request. A $\mathcal{K}$-request operation corresponds to the hilbASR algorithm described in Section 3. Consider the example in Fig. 11, where user u_m issues a $\mathcal{K}$-request with $\mathcal{K}$=6. The request follows the path: $u_m \rightarrow u_d \rightarrow u_b \rightarrow u_a$ (solid arrows in Fig. 11(a)). The root u_a determines the $\mathcal{K}$-bucket (i.e., *start* = 6, *end* = 11) and sends a $\mathcal{K}$-ASR request to u_b (dotted arrows in Fig. 11(a)). u_b sends in parallel requests for partial $\mathcal{K}$-ASRs with ranges [6..6], [7..9] and [10..11] to u_d, u_e and u_h, respectively. u_b, which is the head of the lowest-layer cluster that completely covers the $\mathcal{K}$-bucket (shown hashed in Fig. 11(b)) collects the partial $\mathcal{K}$-ASRs, assembles the final query $\mathcal{K}$-ASR and sends it back to the query issuer on the reverse path of the request. Note that, the cluster head that covers the $\mathcal{K}$-bucket sustains the highest load among all other users involved in the query. This potential load imbalance issue is addressed in Section 5.2. A $\mathcal{K}$-request has $O(\log_\alpha N) + O(\log_\alpha \mathcal{K})$ latency and $O(\log_\alpha N) + O(\mathcal{K}/\alpha)$ communication cost. The pseudocode for $\mathcal{K}$-request is shown in Fig. 12. Once the $\mathcal{K}$-ASR is constructed, the query issuer (i.e., u_m) can send the anonymized query to the LBS through a pseudonym service, as explained in Section 2.

```
u.𝒦-request() /*executed by query source*/
  determine key value $\mathcal{H}_u$ = Hilbert($u.x, u.y$)
  call $head(C_u^0)$.ForwardRequest($\mathcal{H}_u, 0, 0$)
u.ForwardRequest($\mathcal{H}, count, l$)
  if ($l = 0$) $count = rank_{\mathcal{H}}$ in leaf entry
  else $count+ =$ sum of annotation counters of keys $< \mathcal{H}$
  if ($u$ is $root$)
    compute $start$ and $end$ using eq (1)
    $\mathcal{K}$-ASR = $root.findMBR(start, end, root\_height)$
  else call $head(C_u^{level+1})$.ForwardRequest($\mathcal{H}, count, l+1$)
u.findMBR($start$,$end$,$l$)
  if ($l = 0$) /*leaf level*/
    return MBR of members with local rank in [$start$,$end$]
  find set of next hops $U$ for range [$start$,$end$]
  $MBR = \emptyset$
  for $u' \in U$
    $MBR = MBR \cup u'$.findMBR($start_{u'}, end_{u'}, l-1$)
  return $MBR$
```

Figure 12: $\mathcal{K}$-request

5.2 Fault Tolerance and Load Balancing

Privé implements a soft-state based mechanism to deal with user failures or disconnections without notification. Each cluster leader sends periodically (i.e., every δt seconds) a *membership_update* message to all cluster members. The message contains the membership list of the current cluster C and that of $parent(C)$. Cluster members respond to these messages; if a cluster member does not respond to two consecutive messages, it is considered disconnected and removed from the cluster. The change is broadcast by the cluster head to the remaining cluster members.

If a non-head cluster member u does not receive a *membership_update* from its head for a $2\delta t$ period, it initiates a *leader election* process. Alternatively, when u attempts to initiate a operation, such as query or relocation, but cannot contact the cluster head for two consecutive attempts, it triggers the leader election protocol without waiting for the timer to expire. u checks the membership it had at the last update, and chooses as leader (i.e., *new_head*) the user with the smallest identifier. It then sends a *transfer_head* message to *new_head*, which in turn sends a membership update message to all cluster users and also contacts $head(parent(C))$ to notify for the change in leadership. *new_head* will replace the old head in all layers where the latter was leader before disconnection.

The hierarchical structure can cause significant differences between the load sustained by cluster heads and ordinary cluster members, as well as among cluster heads at different layers of the hierarchy. To alleviate the inherent imbalance, we propose a cluster head *rotation* mechanism, where users take turn in fulfilling the cluster head role. Since the promotion to cluster head translates into presence at a higher layer of the hierarchy, the rotation also ensures that users equally share the load at different layers.

Rotation is triggered when a node reaches a certain load threshold, denoted by *load unit.* In wireless devices the communication cost is dominant. It is also important from the user's perspective, since mobile phone operators charge by the amount of transferred data. Therefore, in Privé the load is best represented by the number of messages sent and received by the user.

When a user u reaches one load unit, it triggers a head rotation in all the clusters it currently heads, starting with its highest layer. For each node along the path to its level 0 cluster, the member with the least load is appointed as new head. Note that, since u stores the membership state about all clusters it belongs to at different layers, the appointment of a new leader can be done directly by u, without the need for a complex protocol or additional messages. Choosing the cluster member with the lowest load prevents the newly appointed head to start a fresh rotation soon after promotion.

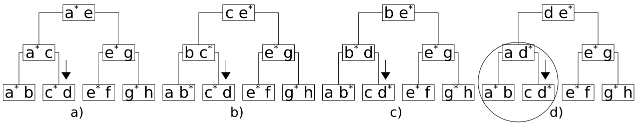


Figure 13: Load balancing mechanism

Fig. 13 illustrates the rotation mechanism. For simplicity, all clusters have size 2; cluster heads are marked with an asterisk. Assume all queries originate at user u_d (marked with an arrow) with $\mathcal{K}$=4. After user u_a reaches one load unit, it hands over the root role to user u_e (at layer 2) from the right-hand subtree. Also, at layer 1, user u_c becomes the head and is automatically promoted to layer 2. Similarly, at layer 0, user u_b becomes the head and is promoted to layer 1; the result is shown in Fig. 13(b). Next, node u_c reaches its load unit, because more requests pass through it (it must inject queries and collect partial $\mathcal{K}$-ASRs). User u_c triggers a rotation at level 1 and appoints u_b as cluster head (see Fig. 13(c)). Subsequently, user u_b may be the next one to reach the load threshold, and start a new rotation in the left subtree. Observe that at step (d), the left subtree has already performed a complete rotation round, whereas the right subtree has only performed one change. Hence, our rotation mechanism alleviates hotspots (an entire subtree shares the load generated by user u_d) and at the same time provides a degree of *fairness*, not allowing a localized hotspot to affect a large partition of the index.

The granularity of load unit choice is important in practice, in order to achieve a good tradeoff between load balancing and communication cost, since a rotation may incur a number of messages as large as $O(\alpha \log_\alpha N)$. We further discuss this issue in Section 6.

6. EXPERIMENTAL EVALUATION

To evaluate Privé, we implemented an event-driven packet-level simulator in C++. Since we are mostly interested in the overlay-layer performance, we consider a full mesh topology with lossless 500ms round-trip time links between any pair of users. Our workload consists of user locations and movement patterns, and is generated using *IAPG* [5], which models user movement on public roads. For user movement, we consider velocities ranging from 18 to 68km/h. We present our results for a data set consisting of the San Francisco bay area (Fig. 16(a)), with number of users N varying from 1000 to 10000. We varied the anonymization degree $\mathcal{K}$ from 10 to 160. We considered both uniform and Zipfian distributions of queries over the users.

Anonymity Strength. In Section 4, we proved that hilbASR guarantees anonymity against location-based attacks, under any query distribution. We now illustrate this property in comparison with the cloakP2P distributed anonymization algorithm [7]. We consider a 10000 users' scenario where 10000 queries are issued. Let u_c be the user who is nearest to the center of the $\mathcal{K}$-ASR. In Fig. 14 we plot the probability of u_c being the query source, for various values of $\mathcal{K}$. The dotted line represents the value 1/ $\mathcal{K}$; ideally, the performance of the algorithm should be *under* that line. In the case of cloakP2P, for $\mathcal{K}$=40, the probability of u_c being

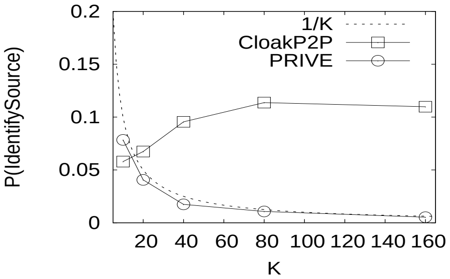
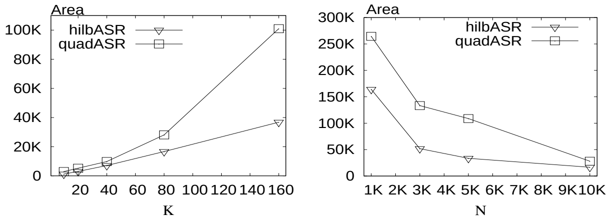


Figure 14: cloakP2P and Privé anonymity strength



(a) Varying K, 10k users (b) $\mathcal{K}$=80, varying N

Figure 15: $\mathcal{K}$-ASR area

the query source is 10%, four times the $1/\mathcal{K}$=2.5% maximum allowed bound. For larger values of $\mathcal{K}$, the situation gets worse, as the number of users included in the $\mathcal{K}$-ASR increases. The users are likely to come uniformly from all directions; hence, u_c is disclosed as the query source. On the other hand, hilbASR achieves the required anonymity degree $\mathcal{K}$ at all times. Due to its poor anonymization strength, we omit cloakP2P from our further discussion.

$\mathcal{K}$-ASR Size. In this experiment, we compare hilbASR against quadASR in terms of spatial extent (i.e., area) of the generated $\mathcal{K}$-ASR. We consider a snapshot of user locations and generate a number of queries equal to the population size N. Each query is initiated by a random user. Fig. 15(a) shows the results for varying $\mathcal{K}$ and 10K users. hilbASR is better in all cases. In Fig. 15(b) we set $\mathcal{K}$=80 and vary the number of users. The decrease in $\mathcal{K}$-ASR size with increasing N is explained by the higher user density in the same dataspace (i.e., $\mathcal{K}$ users can be located in a smaller region). hilbASR again outperforms quadASR in terms of $\mathcal{K}$-ASR extent. Recall that smaller $\mathcal{K}$-ASR translates into reduced execution cost at the LBS and communication cost between the LBS and the user.

Note that quadASR has been proposed only for centralized anonymization. Still, the size of the resulting $\mathcal{K}$-ASR is independent of whether it is constructed in a centralized or distributed setting. Nevertheless, hilbASR outperforms quadASR in terms of both $\mathcal{K}$-ASR size and anonymity strength (recall from Section 3.1 that quadASR may fail for certain user distributions). The only other system that considers anonymization in a decentralized setting is cloakP2P, but we shown that it fails to provide anonymity by a large margin. Hence, Privé is the only distributed anonymization protocol that guarantees anonymity and outperforms existing methods in terms of $\mathcal{K}$-ASR size.

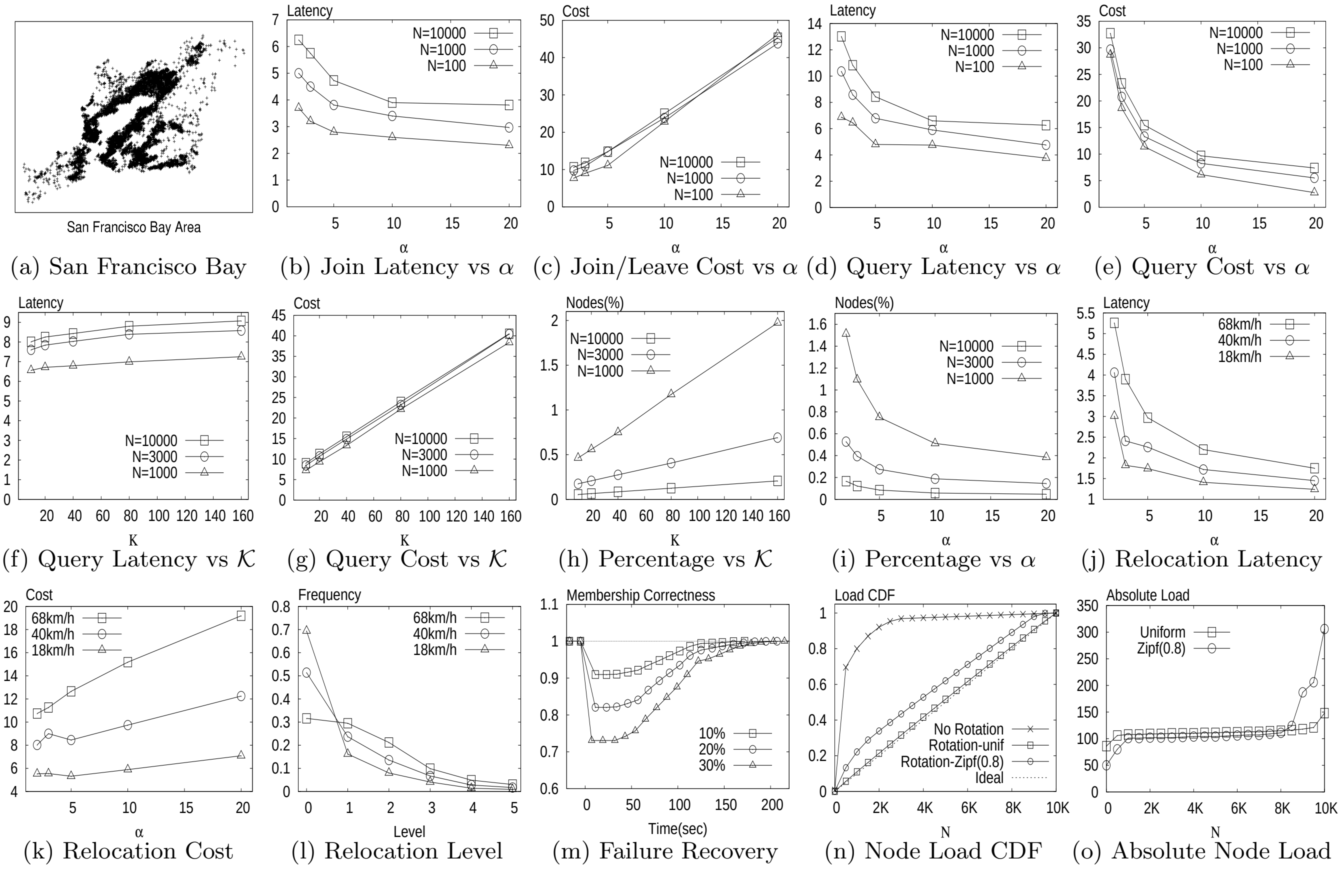
Join and Departure. In a system with N users, we perform $0.1N$ random user joins, followed by $0.1N$ random user departures. Fig. 16(b) shows the join latency measured as hop count from the time a user issues a join request until it receives a join response message from its leaf-level head. We observe that the latency is lower than the theoretical $1 + \log_\alpha N$, as a user may appear in multiple levels and can avoid sending redundant messages to himself. The communication cost (i.e., total messages) per join and departure operation (Fig. 16(c)) varies linearly with α, since every join/departure translates into a *membership_update* broadcast message within one leaf-level cluster. Note the role of α in the latency-cost tradeoff: an increase of α decreases latency as $\log_\alpha N$, but triggers a linear cost increase in membership notification. A larger α also increases the cost of periodic cluster membership maintenance.

$\mathcal{K}$-request. Fig. 16(d) and 16(e) show the $\mathcal{K}$-request latency and communication cost for varying α, where $\mathcal{K}$=40. Larger α decreases the latency as the height of the index decreases. The communication cost also decreases, as fewer leaf-level cluster heads need to be contacted to build the $\mathcal{K}$-ASR. However, α cannot grow very large from index maintenance considerations. Fig. 16(f) and 16(g) show the latency and communication cost variation with anonymization degree $\mathcal{K}$, $\alpha = 5$. Latency is only marginally affected by $\mathcal{K}$ (the dominant factor in latency is $\log_\alpha N$, since in practice $\mathcal{K} \ll N$), while the communication cost grows linearly with $\mathcal{K}$. The percentage of the user population involved in answering a single $\mathcal{K}$-request operation is shown in Fig. 16(h) and 16(i). For small N values, at most 2% of all users are needed to answer a $\mathcal{K}$-request, while for larger N, less than 0.5% of the users are required.

Relocation. Privé addresses user mobility by using an index update algorithm that attempts to resolve relocation at the lowest levels of the hierarchy, in order to reduce both latency and communication cost. In our simulated scenario, we consider 10000 users across 20 consecutive time frames, with half of the indexed users moving at each time frame according to a pattern generated by IAPG [5]. We consider three velocities: 68, 40 and 18km/h. Fig. 16(j) and 16(k) show that relocation is efficiently handled: for the moderate $\alpha = 10$ value, the relocation is done on average in 2.5 hops for fast-moving users and 1.5 hops for slow-moving users. The dominant communication cost is that of the membership change propagation; for $\alpha = 10$ this cost is roughly a quarter that of an index deletion followed by insertion for the $68km/h$ case, and 1/8 for $18km/h$. Fig 16(l) shows the frequency of relocations completed at various levels of the hierarchy for a 6-level, $\alpha = 3$, 10000 users system. Most relocations are solved at the low levels of the hierarchy: for slow movement, 70% are solved at the leaf level and 86% at levels 0 and 1; for fast movement, 32% of relocations are completed at the leaf level, 63% at levels 0 and 1, and 86% at levels 0, 1 or 2.

Fault-tolerance. Starting with a system having correct cluster membership system, we fail simultaneously 10, 20 or 30% of the nodes. We use maintenance timer values of 30 seconds for refreshing cluster membership and 60 seconds for purging a failed member. Fig. 16(m) shows the evolution of membership state correctness over time (1 represents completely correct state). The system recovers to a correct state within 3 purge cycles (138 sec) for 10% failure and 4 purge cycles (197 sec) for 30% failure.

Load-balancing. We measured the load incurred by each user for a 10000 users system, $\alpha = 5$, $\mathcal{K}$=80, *load unit* = 200 messages and a simulated time of 1 hour, during which an average of 8 queries/user were generated. We considered both uniform and skewed (Zipf 0.8) query source distribution. Fig. 16(n) shows the cumulative distribution function (CDF) of *sorted* user loads. The load is highly unbalanced



(a) San Francisco Bay (b) Join Latency vs α (c) Join/Leave Cost vs α (d) Query Latency vs α (e) Query Cost vs α

(f) Query Latency vs $\mathcal{K}$ (g) Query Cost vs $\mathcal{K}$ (h) Percentage vs $\mathcal{K}$ (i) Percentage vs α (j) Relocation Latency

(k) Relocation Cost (l) Relocation Level (m) Failure Recovery (n) Node Load CDF (o) Absolute Node Load

Figure 16: Privé Experimental Evaluation

if no rotation is performed, with 10% of users sustaining more than 80% of the load. With rotation, for uniform query distribution, the load is close to the ideal one (i.e., diagonal line). For skewed query distribution, most of the users share equal load, while part of the users (roughly 10%) share a slightly higher load, as dictated by the fairness requirement discussed in Section 5.2. This is illustrated better in Fig. 16(o) which shows the absolute load of each user.

7. RELATED WORK

$\mathcal{K}$-anonymity was first discussed in relational databases where published statistical data (e.g., census, medical) should not be linked to specific persons. Samarati and Sweeney [20, 22] proposed the following definition: A relation satisfies $\mathcal{K}$-anonymity if every tuple in the relation is indistinguishable from at least $\mathcal{K}-1$ other tuples with respect to every set of quasi-identifier attributes. Quasi-identifiers are sets of attributes (e.g., date of birth, gender, zip code) which can be linked to publicly available data to uniquely identify individuals. Two techniques are used to transform a relation to a $\mathcal{K}$-anonymized one: *Suppression*, where some of the attributes or tuples are removed and *generalization*, which involves replacing specific values (e.g., phone number) with more general ones (e.g., only area code). Both techniques result to information loss. Ref. [4] and Ref. [15] discuss efficient algorithms for anonymizing an entire relation while preserving as much information as possible. In Ref. [23] the authors consider the case where each individual requires a different degree $\mathcal{K}$ of anonymity, while Aggarwal [1] shows that anonymizing a high-dimensional relation results to unacceptable loss of information due to the dimensionality curse. Finally, Machanavajjhala et al. [16] propose ℓ-diversity, an anonymization method which considers the values of the sensitive attribute.

$\mathcal{K}$-anonymity has also been adopted in the LBS domain: in Ref. [10, 11], the location of the user is concealed by constructing an *Anonymizing Spatial Region* ($\mathcal{K}$-ASR) which encloses the locations of the query source and $\mathcal{K}-1$ additional users. However, their methods of $\mathcal{K}$-ASR construction are inefficient, and anonymization may fail for some data distributions. Ref. [14, 17] extend further these ideas and present a framework for the entire process of anonymization and query processing at the LBS. Nevertheless, the aforementioned methods assume a centralized anonymizer, which may become a bottleneck or a security threat. Prior to our work, the only decentralized solution was a P2P-based system, presented in Ref. [7]. However, that system fails to achieve anonymity in most cases (see Section 6).

Key and range search has been studied extensively in distributed environments. Several structured Peer-to-Peer systems (e.g, Chord [21]) support distributed key search with $O(\log N)$ complexity. The drawback of such systems is that they cannot support efficiently node annotation. Without node annotation, the communication cost for satisfying the reciprocity property (which guarantees $\mathcal{K}$-anonymity) is $O(N)$; this cost is too high for large scale systems (recall that PRIVÉ needs only $O(log_a N)$ messages). Closer to our work is the P-tree [8], which supports range queries by embedding a B$^+$-tree on top of an overlay network. No global index is maintained; instead each node maintains its own B$^+$-tree-like structure. BATON [13] also addresses range queries, by embedding a balanced tree onto an overlay network. It uses additional cross-links to prevent hotspots, and achieves $O(\log N)$ complexity for search and maintenance. Similar to Chord, these systems cannot support efficiently node annotation.

Hierarchical clustering in distributed environments has been an active research topic in recent years. In Ref. [3], a hierarchical-clustering routing protocol for wireless networks is presented. The NICE project [2] proposes a scalable application-layer multicast protocol, based on delivery trees built on top of a hierarchically connected control topology. Nodes participating in a multicast group are organized into a multi-layer hierarchy of clusters with bounded size. NICE trees obtain delays in the order of $O(\log N)$, where N is the size of the multicast group, and there is an upper bound of $O(\log N)$ in terms of control state maintained per node. PRIVÉ also uses hierarchical clustering of mobile users, but the requirements of total ordering and annotation impose particular challenges that have not been addressed by existing research.

8. CONCLUSIONS

In this paper we introduced PRIVÉ, a distributed system for query anonymization in LBSs. In PRIVÉ, mobile users wishing to issue location-based queries, organize themselves into a hierarchical overlay network and anonymize queries in a fully decentralized fashion. PRIVÉ supports our HILBASR anonymization technique, which guarantees anonymity under any user distribution. We show experimentally that our system is efficient, scalable, fault tolerant and achieves load balancing.

LBSs for mobile users are already a reality in some places (e.g., Japan), where new mobile phones are equipped with a positioning device, and high-speed wireless networks are common. As such applications gain popularity, privacy and confidentiality concerns are expected to rise. In the future, we plan to address anonymity of continuous spatial queries, and extend our algorithm to trajectories, as opposed to points. We also plan to deploy PRIVÉ in infrastructureless environments, such as ad-hoc wireless networks (Wi-Fi, Bluetooth), without point-to-point links between all users.

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