

KloakDB: A Data Federation for Analyzing Sensitive Data with K -anonymous Query Processing

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ABSTRACT

A private data federation enables data owners to pool their information for querying without disclosing their secret tuples to one another. Here, a client queries the union of the records of all data owners. The data owners work together to answer the query using privacy-preserving algorithms that prevent them from learning unauthorized information about the inputs of their peers. Only the client, and a federation coordinator, learn the query’s output.

KloakDB is a private data federation that uses trusted hardware to process SQL queries over the inputs of two or more parties. Currently private data federations compute their queries fully-obliviously, guaranteeing that *no information* is revealed about the sensitive inputs of a data owner to their peers by observing the query’s instruction traces and memory access patterns. Oblivious querying almost always exacts multiple orders of magnitude slowdown in query runtimes compared to plaintext execution, making it impractical for many applications. KloakDB offers a semi-oblivious computing framework, *k-anonymous query processing*. We make the query’s observable transcript *k-anonymous* because it is a popular standard for data release in many domains including medicine, educational research, and government data. KloakDB’s queries run such that each data owner may deduce information about no fewer than k individuals in the data of their peers. In addition, stakeholders set k , creating a novel trade-off between privacy and performance. Our results show that KloakDB enjoys speedups of up to 117X using k -anonymous query processing over full-oblivious evaluation.

1. INTRODUCTION

People and organizations are collecting data at an unprecedented rate and many independent parties collect data on the same topic or area of research. For example, consider two hospitals serving a single patient but each keeps their own records on this individual. Data sharing is crucial for enabling people to realize comprehensive insights from these fractured datasets. On the other hand, data owners are often hesitant to release their data to others owing to privacy concerns or regulatory requirements. Some release anonymized versions of their datasets, but this compromises the semantics of the data in unspecified ways and this makes it difficult to join anonymized data with the data of others. In contrast, a *private data federation* makes it possible for data owners to pool their private data so that clients query it and receive precise insights without needing the anyone to

disclose their sensitive records to others in the federation. We consider this challenge in the context of a data federation, wherein multiple autonomous database systems are united to appear as one for querying. A private data federation performs privacy-preserving data analytics either using cryptographic protocols [5, 8, 63] or secure enclaves [10, 30] to combine the sensitive data of multiple parties.

To illustrate this system, consider a group of hospitals that wish to pool their patient records for research in a private data federation. Here, the data owners are the hospitals. The client is an independent researcher who is seeking to form a study on the efficacy of medication X by seeing if there are enough patients who were prescribed the drug in the federation. She sends the coordinator the query `SELECT COUNT(DISTINCT patient_id) FROM medications WHERE medication=X`. The coordinator crafts a query plan that will ensure the patient identifiers that were prescribed X remain private and that the federation coordinator and client only learn the count.

In practice, data owners usually pool their private data with the assistance of a trusted query coordinator, who collects the sensitive tuples of multiple parties, computes on them in plaintext, and sends the results to the client. Hence, the data owners never view one another’s data and the client only accesses the output of the query, not any input tuples or intermediate results. This pattern of relying on a trusted query coordinator arises in many settings including financial regulators auditing banks [60, 21], electronic health record research networks [23, 32], and prescription drug monitoring programs [22]. We simulate this arrangement with a private data federation, and replace the trusted third party with secure query processing among the data owners such that no one sees all of the query’s inputs. This enables data owners to retain exclusive ownership over their raw records while offering high-level insights to clients. The query coordinator and the client may only view the final output of a query. From the client’s perspective, the federation behaves exactly as if it were a conventional one.

Until now, private data federations have combined the sensitive data of multiple parties using *full-oblivious* query processing. Here the parties computing the query learn nothing more about the inputs of others than than they would if all of the data owners uploaded their data to a trusted third party for processing. When queries run obliviously their observable transcript (i.e., network transmissions, instruction traces, and memory access patterns) is independent of the contents of the tuples they process. This

guarantees that the data owners learn nothing about the inputs of their peers, but at a steep performance penalty since their runtime and intermediate result cardinalities is always worst-case. For example, if we perform an oblivious equi-join on two relations of length n , our output will have n^2 tuples to protect the operator’s selectivity. We pad the join’s output with dummy tuples to prevent information leakage. As dummy tuples cascade up operator tree of a query, this creates a dramatic slowdown in query runtime.

At the other end of the spectrum is *encrypted query processing*, where query’s control flow (e.g., how it branches and loops) is available to the party computing it, but we do not reveal the enclave’s input data. This approach is radically more efficient than full-oblivious ones, but it makes no guarantees against access pattern leakage attacks, a well-known vulnerability in database systems [31, 44].

We posit that there are important design points in between these two extremes for querying sensitive data from multiple sources. To this end, we turn to k -anonymity [53] for inspiration. A data release is k -anonymous if the records of an individual are indistinguishable from those of at least $k - 1$ others. We focus on k -anonymity to protect sensitive data while providing high-performance query processing despite its security shortcomings [1, 38, 39, 42, 57]. These shortcomings are modeled in the context of k -anonymous data releases, whereas KloakDB uses k -anonymity to create batches of tuples that are indistinguishable from one another during query processing. Rather than giving an attacker unlimited access to a dataset that is modified to make each individual appear identical to least $k - 1$ others, we let the curious data owner observe the oblivious processing of batches of tuples containing at least k individuals.

We chose k -anonymity as our model for numerous reasons. First, it provides the formal guarantee that all individuals appearing in a private data federation will be accessed in a way that is indistinguishable from at least $k - 1$ others. Second, it offers regulatory compliance in domains where k -anonymity is the standard for data access, including electronic health records [15, 46], educational research [12, 55], government data release guidelines [24, 20], and some energy customer data [17]. Third, it will enable users to tune the efficiency of their query processing to the sensitivity of their query. For example, in medicine, the k needed to query sufferers of common afflictions like heart disease is lower, usually $k = 5 \dots 11$, whereas studying HIV sufferers has a higher threshold, typically $k = 30$. Setting a single k for an entire dataset, as is done in data releases, would leave significant query performance on the table.

We propose *k-anonymous computation*, a semi-oblivious method of program execution that provides an intermediate level of protection for sensitive data when untrusted parties compute on it. In this work we zoom into a subset of this, *k-anonymous query processing*, that provides anonymized data processing for SQL statements by protecting database tuples as they pass through a query’s operator tree. Here, each entity or individual in a dataset has a unique ID and, for a given compute process, individuals are part of an *equivalence class* wherein k or more of them are indistinguishable from one another in their instruction traces for the duration of the program. A set of tuple counts, one per equivalence class, make up a relation’s *frequency set*. Since each batch contains data from multiple parties, we construct our groups such that if we omitted the tuples of one party the

equivalence class still has k or more individuals in it. K -anonymous query processing will speed up query workloads over sensitive data from multiple data owners or a single data owner who outsourced their storage to an untrusted cloud provider.

To give an intuition about the promise for performance improvements with k -anonymous query processing, consider joining two 100-tuple relations with a uniform data distribution and equivalence classes that are partitioned alike. If we joined them obliviously, we would perform 10,000 tuple comparisons. If we computed this k -anonymously, then we join each equivalence class with exactly one other class in the other relation and this results in $O(nk)$ output tuples. In our example, if $k = 5$ then this would result in an output cardinality of roughly $20 * 25 = 500$ tuples. This disrupts the cascading blowup of intermediate result cardinalities in queries with many operators.

With k -anonymous query processing we create a continuum for this performance-privacy trade-off. By adjusting k , users have simple and intuitive “knob” with which they trade privacy for performance and vice versa. If we run a query where $k = 1$, each tuple belongs to its own equivalence class and we offer the guarantees of encrypted query processing. On the other hand, with a $k > \frac{n}{2}$, we compute on a single equivalence class and the query runs obliviously. By selecting a k between these two extremes we offer novel semi-oblivious query processing for data of varying sensitivity. Section 4.5 details this opportunity and its connection to real-world data sharing regulations.

KloakDB implements k -anonymous query processing by constructing a *k-anonymous processing view* over the tuples of its member databases. This builds on the concept of k -anonymous data releases. This view is k -anonymous with regard to the attributes that inform the control flow of the query. This view breaks the data into equivalence classes such that each one contains k or more individuals. Like full-oblivious query processing, k -anonymous query processing uses dummy tuples to mask the true distribution of values in the underlying data. Although the k -anonymous processing view alters how we execute a query, the client receives precise query results. If we wish to protect the role of an individual in the query’s output, we may add differentially private noise to the query’s output as in [6].

The main contributions of this paper are:

- Designing and implementing KloakDB, a data federation that protects sensitive data by anonymizing its query execution;
- Formalizing and integrating k -anonymous query processing into a relational data federation;
- Evaluating the utility of k -anonymous query processing, and focusing on the trade-off it provides between privacy and performance.

The remainder of this paper is organized as follows. Section 2 has background on areas upon which this system builds. In Section 3, we reveal the architecture and security guarantees of KloakDB. Section 4 formalizes the guarantees of k -anonymous query processing and details how the query operators uphold them. Section 4.2 introduces k -anonymous processing views and how KloakDB constructs one for a given query. Section 5 describes the KloakDB query executor. Section 6 presents our experimental results. We then survey the related work and conclude.

2. BACKGROUND

In this section we first describe the architecture of a private data federation. We then provide an introduction to this system’s building blocks, namely k -anonymity and secure enclaves. Lastly, we show a running example.

2.1 Private Data Federations

A private data federation enables multiple, autonomous database systems to pool their sensitive data for analysis while keeping their input records private. It starts with a common set of table definitions against which the client queries. The tables may correspond to data on a single host or they may be horizontally partitioned among multiple data owners. We focus on the latter scenario in this work, although the system’s core architecture will support both.

This schema is annotated with a security policy. Each attribute in a federation’s shared schema has a security policy that determines the information data owners are permitted to learn when processing a KloakDB query. A column may be *public*, or viewable by other data owners. Otherwise it is *k-anonymous* and data owners running queries over these columns learn about no fewer than k individuals at a time from participating in a KloakDB query evaluation over them. The k parameter may be set once per query or attribute-by-attribute. We evaluate the former approach in this work.

Before the federation accepts its first query, it does a two-stage setup. First, the data owners and other federation stakeholders work together to create a security policy based on the best practices of their domain and any applicable regulations and they initialize the common data model with this. Second, the coordinator works with the data owners to perform private record linkage [27] over individuals or entities that have records spanning two or more databases so that each one resolves to a single identifier.

Each data owner wishes to keep their sensitive tuples private, but they are willing to reveal the results of queries over the union of their data with that of other federation members. The query coordinator plans and orchestrates the execution of private data federation queries. The coordinator ensures that queries uphold the security policy in the federation schema while running efficiently. Each data owner and the query coordinator has hardware for running secure enclaves during query evaluation.

2.2 K-anonymity

A dataset is k -anonymous if each individual in it is indistinguishable from at least $k - 1$ others. A *quasi-identifier* is the minimal set of attributes in a database that can be joined with external information to re-identify individual records with high probability [53].

There is an abundance of research on how to anonymize a dataset to minimize the differences between the revealed data and its private, original values [7, 16, 35, 36, 52]. These algorithms preserve the semantics of their source data to make analysis on them as accurate as possible. In contrast, our goal with k -anonymous query processing is to speed up query runtimes. Hence, we assign the records to small, indistinguishable equivalence classes to minimize the overhead of k -anonymous query processing while upholding its security guarantees as tuples pass through the query tree. We create k -anonymous processing views using a generalization of freeform k -anonymization [14] to minimize the size of a view’s equivalence classes rather than grouping together

True Relations		2-anon Processing View		K -anonymous Query Processing	
demographic	diagnosis	demographic	diagnosis	demographic	diagnosis
ID Sex	ID Diag	ID Sex	ID Diag	ID Sex	ID Diag
1 M	2 flu	0* M	0* flu	0* F	0* flu
2 F	4 flu	0* F	0* flu	0* F	0* flu
3 M	4 infection	0* M	0* infection	0* F	0* infection
4 F	6 infection	0* F	0* infection	0* F	0* infection
10 F	12 migraine	1* F	1* migraine	0* F	0* migraine
11 F	13 migraine	1* F	1* migraine	0* F	0* migraine

Client Query:

```
SELECT diag, COUNT(*)
FROM demographic de, diagnosis di
WHERE de.id = di.id AND sex=F
GROUP BY diag;
```

Aggregate: diag, COUNT(*) FROM d_{join} :

KPV: (flu, 2)(inf, 1)

True vals: (flu, 2)(inf, 1)

Figure 1: K -anonymous query processing example. True (non-dummy) tuples are underlined.

similar values. Freeform k -anonymous processing views have the added benefit of not leaking information about the semantics of their original data. Since standard anonymization algorithms coalesce tuples that are close to one another in value into a single equivalence class, they may reveal additional information about the data’s true distribution.

2.3 Secure Enclaves

KloakDB runs k -anonymous query processing over tuples from multiple sources in secure enclaves distributed among the data owners. The query coordinator also uses a secure enclave to privately construct k -anonymous processing views over sensitive data. Trusted execution environments such as Intel SGX [10] and AMD Memory Encryption [30] are available on most new commodity systems. They may only execute trusted code provided by the coordinator. The code and data associated with an enclave is *sealed*; the system in which it is executing may not view or change its contents.

This hardware uses remote attestation to prove to an authority, such as the coordinator, that the code and data it is running has not been tampered with and that the code executes on trusted hardware alone. Once an enclave has attested its code, this opens up a secure communication channel for the data owners to send their sensitive data to it.

Secure enclaves have a protected region of memory, the encrypted page cache (EPC), that is not accessible by the host operating system or hypervisor. Hence, KloakDB delegates the protection of memory access patterns to the secure enclave for data stored in its EPC. As we will describe shortly, the federation’s query planner partitions its query’s work into independent, fine-grained pieces to fit into trusted memory. We fall back to full-oblivious query processing if this is not possible.

2.4 Running Example

Consider the query in Figure 1. It counts the times a woman is diagnosed with a given ailment. It first filters the demographic table for women, joins the selected tuples with the diagnosis table, and counts the times each condition appears in the join result. Sex and diagnosis have a k -anonymous security policy where $k = 2$. We demonstrate this in the single database setting such as that of outsourced operations in the cloud.

The query planner first creates a 2-anonymous processing view. To illustrate this, we use generalization—omitting the least significant digit of the IDs—instead of KloakDB’s freeform k -anonymization here. The view must have at least two individuals (IDs) in each equivalence class. All of the tuples in an equivalence class are indistinguishable from one

another during query processing. We divide the ID column by 10 in both relations to suppress the least significant digit. Each relation has three equivalence classes, and for demographic they are: (0*, F) (0*, M), and (1*, F). Each equivalence class has a bitmask with a bit or dummy tag for each tuple denoting if it is a placeholder to mask the role of individual tuples in the group. When we run the query, the filter first examines each equivalence class and either 1) outputs it in its entirety if it contains at least one match—obviously marking a dummy tag on each tuple to denote if it met the selection criteria; or 2) produces an empty set. The filter outputs two of the three demographic equivalence classes.

Next, we join the filtered demographics tuples with the diagnoses using the same all-or nothing logic to uphold tuple indistinguishability over an equivalence class. When the join compares two equivalence classes its output is either size of their cross-product of its inputs or an empty set. This join outputs two equivalence classes: (0*, flu) and (0*, infection) and three true tuple matches. If we ran this obliviously the join would output the cross-product or 36 tuples, instead of the 8 shown here. Clearly, k -anonymous query processing has an opportunity to substantially boost the performance of private data federation queries.

After the join, the aggregate iterates on its results one equivalence class at a time to count up the diagnoses for each ailment. For a given group-by bin, an aggregate outputs either: 1) a single tuple if $\geq k$ individuals contributed to it; or 2) a dummy-padded set of tuples equal in length to the source equivalence class. An observer can learn about no fewer than k individuals at a time by observing these outcomes because they either learn that all of the tuples in the class had the same group-by value or that we processed the equivalence class obliviously. At first glance, it may appear that the group-by of (0*, infection) would be processed obliviously. As we will see in the coming sections, the anonymity of an equivalence class is transitive as it passes through a k -anonymous operator. Because the join compares all tuples in an equivalence class to its potential matches in the joining relation, its output is fully padded. Hence, the join did not reveal its selectivity over this equivalence class and the groups with which it was paired. Then the count operator visits all four tuples in the infection group and emits a single tuple with the true count.

3. SYSTEM OVERVIEW

In this section, we describe the security model and the architecture of KloakDB. We first present the k -anonymous guarantees of the query processing engine. After that, we describe the workflow of a query in this system.

3.1 Security Guarantees

We now introduce the anonymity guarantee KloakDB offers data owners during query execution. These queries have instruction traces that have the same distribution as they would if the query were executing over a view of the dataset that is k -anonymous with respect to attributes that alter its control flow. *Control flow attributes* contain values that change the observable instruction traces of query operators running inside an enclave, e.g., how it branches, loops, and their result sizes. We formally them them in Section 4.1. With this in mind, KloakDB guarantees:

DEFINITION 1. K -anonymous Query Processing Consider a query Q that accesses relations specified by the schema \mathcal{T} . Q has control flow attributes C where $C \subseteq \mathcal{T}$. When the system evaluates Q on a dataset, \mathcal{D} , there exists a function \mathcal{V}_C for creating a k -anonymous view of \mathcal{D} with respect to C . A semi-oblivious algorithm for running the query, Q' , satisfies the requirements of k -anonymous query processing iff its instruction traces are computationally indistinguishable from those of a simulator running Q over $\mathcal{V}_C(\mathcal{D})$ for a probabilistic polynomial time adversary. Therefore:

$$\text{Trace}(Q(\mathcal{V}_C(\mathcal{D}))) \stackrel{c}{=} \text{Trace}(Q'(\mathcal{D}))$$

We do not trust the data owners in KloakDB to faithfully execute query operators over the sensitive data of others. We use trusted hardware to ensure that queries over the data of others are completed with integrity and without unauthorized access to their values using the enclave features described in Section 2.3. Thus even if the data owner’s operating system is compromised, or they attempt to act maliciously they will not succeed in compromising the security policy of a private data federation. We trust the data owners to run the SQL statements from the query coordinator to provide accurate inputs for query processing within the secure enclaves of the data owners. On the other hand, each party will attempt to learn as much as they can from observing the query’s execution. Likewise, the query coordinator is trusted to only admit queries that meet the security policy of the private data federation and to construct query plans that will uphold those policies. A client’s SQL statement is visible to all parties including the data owners.

Limitations In this work, we focus on designing and implementing a private data federation that delivers provable adherence to a k -anonymous security policy for the duration of a query’s execution. For k -anonymous query processing, we partition the data into independent equivalence classes that run in an enclave’s protected memory. If a given equivalence class is too large to fit into the EPC, then KloakDB will use the scalable oblivious query processing algorithms offered by Opaque [67].

Intel SGX’s memory protection has received substantial interest from the security community, with side channel attacks being discovered [10, 34, 62, 64] and fixed [11, 56, 54] on a regular basis. We trust the computation over data that fits into the enclave’s EPC. Addressing the shortfalls of present-day secure enclave implementations is beyond the scope of this work.

We do not address the question of access control for client queries, i.e., determining what queries are admitted to the federation for processing. Many existing systems [41, 61] tackle this challenge. In addition, our system is memoryless. Hence, we do not model the effects of information accruing on the client side from serving multiple queries that access overlapping data nor the effects of colluding data owners and clients. If desired, we may address this by adding differentially-private noise to the query results while they are inside the secure enclaves using the techniques in [6].

3.2 Query Processing Workflow and Roadmap

We examine the lifecycle of a KloakDB query in Figure 2. It begins when a client sends a SQL statement to the query coordinator. The coordinator parses the statement into a directed acyclic graph of database operators, its query tree.

ences to it. The client seeks to run a query Q over the private data federation. In our running example, the *demographic* relation is R_{ID} . Each individual in the medical database has just one entry in this table. Every column in \mathcal{T} is assigned a security policy using the mechanism in Section 2.1.

View Anonymization Once the coordinator identifies a query’s control flow attributes, it creates a view definition with which to anonymize query Q ’s execution. We now examine the properties of a k -anonymous processing view in the single-host setting. We call this k -anonymous processing view, V_C for a given query Q with control flow attributes C . This view creates a mapping of values in the domain of C —or $C_R \subseteq C$ for relation R —to equivalence classes. We say that a view, $V_C(R)$ satisfies the requirements of k -anonymous query processing if it meets the following definition:

DEFINITION 2. K -anonymous Processing View Consider a query Q with control flow attributes C that accesses relation R with a subset of the control flow attributes, $C_R \subseteq C$. The relation anonymized as $R' = V_{C_R}(R)$, is suitable for k -anonymous query processing iff the following properties hold for all R' referenced in Q , and over all views $v(R')$:

1. **Anonymized data** $\pi_A(v(R'))$, where $A \subseteq C$ produces either $\geq k$ tuples or an empty set. Its output admits duplicate rows.
2. **Anonymized individuals** For each equivalence class E in R' and each ID column or composite thereof, $id \in ID$, $|\pi_{id}(v(E))| \geq k$. Its tuples reference data from at least k individuals in \mathcal{R}_{ID} .

When we evaluate a k -anonymous operator, its observable behavior reveals a k -anonymous view of C or a subset thereof. In this definition we first check that any projection on the control flow attributes or subset thereof, such as applying an expression, either produces k or more tuples or an empty set. Hence, any operator execution over an equivalence class will either produce a k -anonymous output cardinality or an empty set. We then verify that if we project the IDs associated with each equivalence class, we will produce k or more distinct identifiers.

We now generalize Definition 2 to private data federations to support the partial view of each data owner that evaluates one or more equivalence classes in query Q . This unified view ensures that each host participating in query processing learns about no fewer than k individuals at a time when they run operators over an anonymized view.

DEFINITION 3. Federated K -anonymous Processing View Relation R is horizontally partitioned over n hosts, $R = \{R_1, \dots, R_n\}$. We say that $R'_i = V_C(R_i)$. To ensure that no data owner learns about fewer than k individuals at a time, for all R' referenced in Q , and over all views $v(R')$, for all data owners $i \in \{1 \dots n\}$:

1. For all $A \subseteq C$, $\pi_A(v(R' - R'_i))$, produces either $\geq k$ tuples or an empty set. Its output rows may include duplicates.
2. For each equivalence class j , $E_{i,j}$ is the tuples of E_j owned by host i , $\Pi_{id}(v(E_j - E_{i,j}))$ references data from at least k individuals in \mathcal{R}_{ID} .

Algorithm 1 Single Host K -anonymous Processing View Generator

```

1: Input: Histogram  $\mathcal{H} = \{h_1, \dots, h_n\}$ 
2:  $h_i = (v_i, id_i)$ ,  $v_i \in \text{domain}(C)$ ,  $\forall I \in id_i, \exists I \in R_{ID}$ .
3:  $\mathcal{H}$ ’s entries sorted in descending order by  $|id_i|$ 
4: Output: Equivalence classes  $\mathbb{E} = \{E_1, \dots, E_m\}$ , all  $E_i \in \mathbb{E}$  have  $\geq k$  IDs.
5: Initialize  $E_{now} \leftarrow \emptyset$ 
6: for each  $h_i \in \mathcal{H}$  do
7:    $id_{now} = E_{now}(id) \cup h_i(id)$ 
8:    $v_{now} = E_{now}(v) \cup v_i$ 
9:    $E_{now} = (v_{now}, id_{now})$ 
10:
11:   if  $|id_{now}| \geq k$  then
12:     append  $E_{now}$  to  $\mathbb{E}$ 
13:      $E_{now} \leftarrow \emptyset$ 
14:   end if
15: end for
16: if  $E_{now} \neq \emptyset$  then // incomplete  $E_{now}$ 
17:   Set  $E_{\cup}$  to the union of  $E_{now}$  and the last entry in  $\mathbb{E}$ .
18:   Replace the last entry in  $\mathbb{E}$  with  $E_{\cup}$ 
19: end if
20: Return  $\mathbb{E}$ 

```

If a k -anonymous processing view satisfies Definition 3, then it will also uphold the guarantees of k -anonymous query processing regardless of the host that processes a given equivalence class for each operator. This is because even if the host “subtracts out” his or her tuples from the equivalence class, it will not expose data about fewer than k individuals.

K -anonymous View Generation and Setup Now that we’ve defined the requirements for a k -anonymous processing view, we now introduce algorithm with which we generate a k -anonymous processing view for a given query and dataset. Algorithm 1 shows the logic of our k -anonymous processing view generator for the single host, single relation setting. Before the algorithm begins, we order the histogram in descending order by the number of IDs associated with each control flow value. It then iterates over the histogram entries, greedily filling up equivalence classes when they have k or more individuals. This approach needs minimal extensions for adding more hosts and relations. The algorithm is optimized to minimize the size of our equivalence classes. The output of the algorithm is within 2X of the optimal view, we omit the proof of this approximation for brevity.

In the multi-relation setting, we construct the control flow attributes C with the unioning process in Section 4.1. We then collect statistics from each relation and sort by the composite values, v_i in Algorithm 1. In the multiple relation, single host setting, we canonicalize the control flow attributes to provide a global total ordering across relations and hosts. Canonicalization means that we map control flow attributes to single integer value. This allows us to reduce the multi-relation algorithm to running multiple single relation algorithms. We run the loop which fills a single equivalence class for each relation, and then take the maximum sized equivalence class over all relations. Since we have canonicalized the input, this ensures that join keys are mapped to the same anonymized value.

In the multiple host, federated, setting, we extend Algorithm 1 and the multiple relation, single host algorithm. The crucial detail is that instead of checking each equiv-

alence class has more than k tuples, we ensure that each equivalence class satisfies Definition 3. Hence, if we removed the contribution of any one data provider from the equivalence classes, the view will remain k -anonymous.

We use this algorithm as part of a larger framework of preparing a query for execution in a private data federation. This setup phase adds three steps to the query processing pipeline: statistics collection, view generation, and redistribution. When the coordinator prepares a query for k -anonymous execution, it first performs *statistics collection* once per relation per host. For each value in the control flow attributes C , or C_R for relation R , each host sends the identifiers associated with it to the coordinator’s enclave. Next the query does *view generation*, and this creates a set of equivalence classes that satisfy Definition 2 for the single data owner setting, or Definition 3 for private data federations. After determining the equivalence classes for a query, the coordinator ships the view definition to the data owners over a secure channel. This includes an assignment of equivalence classes to hosts. We partition the query’s work randomly such that it will be approximately evenly distributed over all hosts by hashing each control flow value using SHA-256 and taking the modulus of the hash value with regard to the number of hosts. Lastly, the data owners use this view specification to *redistribute* the data so that tuples in the same equivalence class are collocated.

4.3 Principles of K-anonymous Querying

Each database operator i that evaluates k -anonymously does so over the control flow attributes $C_i \subseteq C$. As tuples pass up the query tree, each operator upholds the guarantees in Definition 1 and Definition 3 owing to the following property:

Subset Property: Let R be a relation, and let C be the set of attributes that alter Q ’s control flow. If R is k -anonymous with respect to C , then R is k -anonymous with respect to any set of attributes P such that $P \subseteq C$.

Proof: Consider the frequency set of R with respect to C . If we remove any attribute C_i from C , then each of these equivalence classes will remain the same, or it will coalesce with another one. Thus each frequency set will be greater than or equal to its previous size. \square

In other words, an operator with a control flow that is a subset of C will merge equivalence classes from the initial k -anonymous processing view and thus still be k -anonymous in its query processing. In addition, we need to ensure that as we sequentially run operators in the query tree that composing them will also uphold the requirements of k -anonymous query processing:

Transitivity Property: Given a relation R that is k -anonymous with respect to C , the execution and output cardinalities of any transformations predicated on C or $P \subseteq C$ are themselves k -anonymous.

Proof: In the k -anonymous processing view, any equivalence class is associated with at least k individuals and the tuples associated with these individuals are indistinguishable from one another during query evaluation. Thus any transformations, including selections and joins will treat the individuals in a given equivalence class identically. The observable transcript of transformations on a k -anonymous relation cannot reveal information that is not present in the source view. \square

This property guarantees that the query’s processing will

remain k -anonymous with regard to its instruction traces and intermediate cardinalities as tuples propagate up the query tree. We illustrate these properties with the query in Figure 1. Recall that here $C = \{sex, id^+, diag\}$. The join has two equivalence classes for the IDs, 0^* and 1^* , and it evaluates each of them separately and obliviously. By the subset property, the filter ignores the diagnosis column and remains k -anonymous in its query processing. Using the generalized IDs in the view, the output cardinality of the join remains k -anonymous despite the true tuples not having this property. Owing to the transitivity property, the aggregate’s inputs will produce k -anonymous traces because of the size of the dummy-padded equivalence classes. With these two properties, we guarantee that the information revealed to a curious observer during a KloakDB query execution will remain k -anonymous.

4.4 K-anonymous Database Operators

Once the query’s input data is redistributed for processing, we continue to uphold the security guarantees in Section 4.2 as tuples pass through the query tree. We process the data one equivalence class at a time with algorithms that build on full-oblivious operators in [19, 67]. We extend these algorithms to make their instruction traces k -anonymous by modifying how they handle input and output.

For input we feed batches of tuples into the operators one equivalence class at a time. The equivalence class may be over all of the control flow attributes or a subset thereof. Processing data at this fine granularity minimizes the end-to-end overhead we accrue owing to our k -anonymity guarantees since it reduces the number of dummy tuples we create and process. In the running example in Figure 1, the join processes two pairs of equivalence classes, 0^* and 1^* . This substantially reduces the number of tuple comparisons and subsequently how many records the aggregate will process.

One way that KloakDB reduces the complexity of its query evaluation from its worst-case full-oblivious overhead by curtailing the explosion of intermediate result sizes. At the end of each k -anonymous operator, the evaluator checks if the output size is greater than zero. If so, it outputs the fully-padded results. Otherwise, it produces an empty set. Filters, projections, joins, and set operations all use this logic. Limit and sort naturally oblivious in their output size. This approach is k -anonymous because the observer only learns that either all of the tuples passed through the operator or none did.

For group-by aggregates, when the operator begins to process an equivalence class it checks its metadata to see if it has one or many values for its group-by clause. If it has a single value, then the operator makes one pass over the data, updating the partial aggregate as it goes along. It checks at the end to see if the output is not a dummy and if so it outputs the record. For equivalence classes with multiple group-by values, it uses an oblivious aggregate algorithm from the literature and it outputs a fully-padded output equal in length to the input.

4.5 Privacy-Performance Trade Off

K -anonymous query processing enables federation members to achieve a profitable trade off between performance and privacy. We visualize this decision space in Figure 3. Consider a medical researcher querying their electronic health records that are stored using encryption in the cloud. She

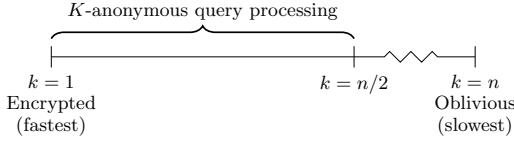


Figure 3: The privacy-performance decision space offered by k -anonymous query processing.

wishes to set her k to a higher value when she is querying highly sensitive data. For example, many states require records pertaining to the treatment of HIV and other sexually transmitted infections have greater k -values than more common diagnoses [26]. When accessing these records, she would use oblivious querying. For more common ailments, she is willing to forgo stronger privacy guarantees in exchange for faster query runtimes.

This decision space, a range of k values for anonymization, arises in many settings. In clinical data research, guidelines for k -anonymization vary. A k from 5-11 is recommended for most health contexts [33, 43, 49], although some data providers suggest $k = 3$ [37] and other, more sensitive studies call for $k = 30$ [9]. For educational data, the US’s FERPA has various k -anonymization guidelines for a variety of data release scenarios in [12, 55]. Energy data is also has a range of k values for its release from $k = 5$ [13] to $k = 15$ [17].

By tapping into the expertise of the coordinator, we will realize substantial performance gains by adjusting k to the sensitivity of the query at hand. In practice, a private data federation may have heterogeneous security policies on client queries to address these domain-specific nuances.

5. KLOAKDB QUERY PLANNER

K -anonymous query processing substantially changes how we run queries in a federation. First we describe the query planner for k -anonymous query processing. The KloakDB query planner builds upon the SMCQL platform [5]. Hence, it generalizes this open-source federation’s query parser, security type system, and its query planner for k -anonymous query processing within secure enclaves.

The query planner translates the client’s SQL statement into a directed acyclic graph by extending an off-the-shelf query parser. It employs standard heuristics (such as pushing down filters), but with no information about the private records of any data owners. We leave the question of optimizing the order of commutative k -anonymous query operators to future work. The planner then uses a security type system to model the information flow of tuples through the query tree and we use this to identify the operators that must run in secure enclaves to uphold the federation’s security policy while computing on data from multiple mutually distrustful parties. The remaining operators run in their source databases in parallel.

When a relation is horizontally partitioned among multiple data owners, the planner inserts a union operator between source relations. It pushes up the union past any operators that compute exclusively on public data. This increases the fraction of a query that runs in plaintext.

Optimizations Like its predecessor, KloakDB generalizes techniques in distributed databases to 1) reduce the operators it runs in k -anonymous mode and in secure enclaves; and 2) minimize the data we process in secure enclaves. Hence, we use semi-joins on public attributes to only bring

public keys that appear on more than one host into the enclaves. We use this for equi-joins as well by identifying values that reside in both joining relations in greater than one host. If a query has an aggregate, if it is possible to process it k -anonymously on a data owner’s local data, we partially aggregate it before combining it with the data of others. In addition, if we are doing a top- k query on distributed data, rather than collocating its inputs on one host, we distribute the limit operator over all hosts and coalesce the top- k tuples in the coordinator’s enclave.

6. EXPERIMENTAL RESULTS

We now evaluate KloakDB with benchmark queries on both real-world data and synthetic data generated with a uniform distribution. We first analyze the performance of supporting operators that create a query’s k -anonymous processing view and redistribute trace-anonymized data for processing. Next, we verify the scalability of KloakDB queries with varying k parameters for anonymization. We use joins for this analysis because it is the operator that incurs overhead for semi-oblivious processing at the highest rate. We first examine KloakDB’s sensitivity to k for a single join and then reveal how it scales when we have a series of joins. After that, we evaluate the performance of k -anonymous operators in a complex query tree and focus on the system’s performance with data of increasing size. Here, we benchmark the system’s end-to-end query performance and assess its runtime compared to running with no instruction-trace protection in encrypted mode, in a hypothetical, insecure plaintext mode, and in a full-oblivious mode. All results are the average over five runs. Unless stated otherwise, our experiments are anonymized with a k of 5.

Experimental Setup We implemented KloakDB in approximately 4,000 lines of C++ code. In our experiments, the data is all in memory, and its distributed k -anonymous operators execute on the data owners’ servers using Intel SGX with a single-threaded execution. We run our benchmarks on 4 Ubuntu 16.04 servers running Intel Core i7 7700k processors, with 32 GB RAM, and a 1 TB 7200 RPM HDD. Our data is stored in a PostgreSQL 10.6 instance on each node.

We first evaluate KloakDB on synthetic data that is randomly generated with a uniform distribution using PostgreSQL’s built-in random() function. We do this to measure how this platform performs in the absence of significant data skew that may distort our results. After these initial tests, we reveal the federation’s performance with a real-world clinical data workload.

Real-world Workload We test KloakDB over electronic health records from the *HealthLNK* data repository [48]. This clinical data research contains records from seven health-care sites. The data repository contains about six million electronic health records from a diverse institutions—including research hospitals, clinics, and a county hospital—from 2006 to 2012. We map each site in the federation to a machine in our four-node testbed.

We experiment with queries that are based on real clinical data research protocols for c. diff infections and heart disease [28, 47]. We use public patient registries for common ailments to bound the duration of our experiments. A registry lists the patient identifiers associated with a condition with no additional information about the individual. We maintain a patient registry for heart disease sufferers

Name	Query
<i>aspirin profile</i>	SELECT gender, race, avg(pulse) FROM demographics de, diagnosis di, vitals v, medications m WHERE m.med = 'aspirin' ^ di.diag = 'hd' ^ dd.pid = di.pid ^ di.pid = v.pid ^ m.pid = di.pid;
<i>comorbidity</i>	SELECT diag, COUNT(*) cnt FROM diagnoses WHERE pid ∈ cdiff.cohort ^ diag <> 'cdiff' ORDER BY cnt DESC LIMIT 10;
<i>dosage study</i>	SELECT pid FROM diagnoses d, medications m WHERE d.pid = m.pid AND medication = 'aspirin' AND icd9 = 'internal bleeding' AND dosage = '325mg'

Table 1: HealthLNK query workload.

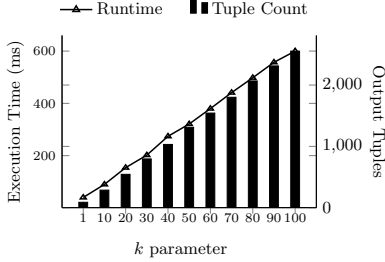


Figure 4: Join runtime with varying levels of anonymization.

(*hd_cohort*) and one for individuals affected by *c.diff* (*cdiff_cohort*), an infection that is frequently antibiotic-resistant. Our queries are shown in Table 1.

The *comorbidity* query counts the most common afflictions that arise in *c.diff* sufferers. It has a k -anonymous aggregate followed by an oblivious sort. This query demonstrates the cost of k -anonymous query processing in a simple, one-relation query tree. *Dosage study* identifies patients who were prescribed a significant aspirin dose and suffered from internal bleeding. Its filters and joins are k -anonymous. We use it to study the system’s performance when we have multiple relations in a query. *Aspirin profile* studies the average pulse of heart disease sufferers by aggregating over each demographic group. This is a complex query and we use it to test how the system performs with a substantial series of k -anonymous operators. Its k -anonymous operator tree has two filters, three joins, and an aggregate.

6.1 Sensitivity Analysis of K Parameter

Joins provide an excellent lens with which to probe the performance of semi-oblivious query processing because they incur up to n^2 tuple comparisons per operator and thus have an outsized impact on the performance of their runtimes. In comparison, the other principle database operators—filters, projections and aggregates—have lower worst-case overhead. Hence, we regard joins as a conservative demonstration of the impact of k -anonymous processing on query runtimes.

We use two queries to verify the performance of KloakDB’s join processing. In the first experiment we evaluate the performance of a single equi-join while scaling the k parameter with which we anonymize the query’s instruction traces. In the second, we increase k while measuring the performance of a left-deep query plan with four joins. Both of these experiments showcase the decision space illustrated in Figure 3. As k increases, we realize increased protection of the input data in exchange for a longer runtime. Naturally, with a lower k value we expect to see substantial performance gains from semi-oblivious query processing.

Equi-join For this experiment we demonstrate the overhead incurred by k -anonymous query processing on join performance. To focus on anonymized join processing, we evaluate on a single host running one equi-join. We evaluate this query with a k parameter starting at 1 for encrypted query processing and going up to $k = 100$ in increments of 10. We

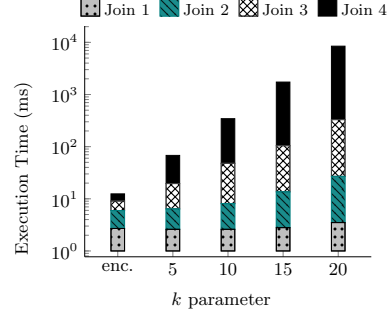


Figure 5: Multi-way join runtime with increasing k

run this experiment over 25,200 randomly generated tuples in the range $0 \dots 10,000$. The selectivity for the input join is approximately .1%. Recall that k -anonymous operators are suitable for execution in trusted hardware, secure multi-party computation, or local plaintext evaluation. To control for the impact of secure enclaves on k -anonymous joins, we run this experiment outside of the enclave.

Figure 4 shows the join’s performance as we tune the security parameter. We see that the join’s overhead grows linearly in proportion to k . This is a dramatic improvement over the n^2 tuple comparisons of oblivious query processing. We realize this very efficient result with the following intuition: given n input tuples in each relation, and an anonymization parameter of k , each matched equivalence class produces $O(k^2)$ tuples. The view generator produces approximately n/k equivalence classes per relation. Hence, the output size of a k -anonymous join is $O(nk)$. In addition to growing linearly with k , the join’s execution time is proportional to the size of its inputs. Therefore as n increases, we will see a commensurate increase in the size number of tuple comparisons and the join’s output size.

Multi-way join We now look at the performance impact of tuning k for a cascade of joins in a distributed setting. This demonstrates how KloakDB scales as we incrementally increase the complexity of its queries. Here, we compute over four hosts with five horizontally partitioned input relations. Each relation has 128 randomly-generated tuples in the range $[0, 512]$. We first run statistics collection, k -anonymous processing view generation, and redistribution once per relation. Lastly, we execute a left-deep four-way join. We measure the time of each join from the perspective of the query coordinator. We run the experiment in encrypted mode and with $k = 5, 10, 15, 20$.

Figure 5 shows how the query runtime increases in response to a growing k parameter. This slowdown disproportionately impacts joins that run later in the query’s execution. Additionally, the runtime per join goes up as we increase k . To understand this slowdown, we extend the analysis from earlier in this section. As we increase k , the output cardinality for a single join increases approximately linearly with k . As tuples move up the query tree, the output cardinality increases multiplicatively with the k pa-

parameter. For example, with $k = 20$, the runtime for join 4 is approximately 5X slower than with $k = 15$. We look to the ratio between two k parameters to develop an intuition for this slowdown. Consider a join where each equivalence class matches one other and emits a full cross-product between the two and our output size is $O(nk)$. When we add the second join and hold n constant, we have an output cardinality of $O(k^2)$ and the same number of tuple comparisons. With all four joins, we do $O(k^4)$ tuple comparisons. When we examine our performance under increasing k parameters, we may explain our slowdown in terms of the ratio of the k parameters. If we consider the ratio of our performance between $k = 20$ and $k = 15$, we have a ratio of $\frac{4^4}{3^4}$ or 3.2.

6.2 HealthLNK Workload Performance

We evaluate the performance of KloakDB with a real-world query workload on HealthLNK data. Hence, the federation’s query runtime and setup costs are subject to the skewness and wide range of values of data collected in the field independently at several locations. We experiment on the queries in Table 1. This enables us to measure the performance of this system during query setup and on a mix of operators to verify the performance benefits of k -anonymous query processing. Additionally, we show that this semi-oblivious processing offers an attractive middle ground between encrypted and full-oblivious mode. In k -anonymous mode, each query starts with its three setup steps of statistics collection, view generation, and redistribution. Since it is not trivial to parallelize oblivious query processing, queries running in this mode start by collocating all tuples being processed on a single host. In encrypted mode, tuples are partitioned by join keys and group-by columns at startup to parallelize their evaluation.

K -anonymous Operator Performance We now verify that k -anonymous query processing provides substantial speedups compared to full-oblivious query processing for complex analytical queries. The *aspirin profile* query is an example of this setting and we use this one to evaluate KloakDB in Figure 6. We measure this query’s runtime in encrypted, k -anonymous ($k = 5$), and full-oblivious mode. To bound the scope of our experiments, we randomly select 25 patients from the *HealthLNK* dataset from one year of data.

Figure 6 presents the operator runtime in each execution mode. Filters in k -anonymous mode and oblivious mode run locally in C code, while in encrypted mode they are computed in PostgreSQL. All other operators run inside of the secure enclave. The anonymization step for full-oblivious execution consists of assigning each tuple to the same equivalence class and collecting all of the input data together for evaluation. Accordingly, it takes an multiple orders of magnitude less time than anonymizing the input relations.

The sequence of three joins demonstrates the cumulative cost of full-oblivious and semi-oblivious query processing. In full-oblivious mode the intermediate results (and tuple comparisons) performed by each successive join grows exponentially. Hence, its first join emits n^2 tuples, the second produces n^3 , and so on. This is not practical in many settings. In contrast, the expected cardinality of a k -anonymous join’s output is $O(nk)$ tuples. A second join incurs a cost of $O(nk^2)$ and so on. Our complexity grows in proportion to k , the security parameter, instead of n , the tuple count. We see this in our results. The third join takes approximately 6 ms in encrypted mode, 650 ms in k -anonymous, and 93000 ms

for full-oblivious processing. This yields a 103x slowdown between k -anonymous and encrypted, and a 143x slowdown between full-oblivious and k -anonymous execution.

The aggregate in encrypted mode takes approximately 5ms, in k -anonymous 6700ms, full-oblivious 27900ms. The dramatic performance gap between k -anonymous mode and encrypted mode is due an unoptimized implementation. Our implementation does not optimize for the setup and tear down for running each equivalence class in k -anonymous mode. Even with this naive implementation, the k -anonymous aggregate is 5x faster than full-oblivious execution.

The overall runtime for encrypted execution, k -anonymous, and full-oblivious is 320 ms, 8,700 ms, 123,000 ms respectively. The slowdown incurred by k -anonymous execution compared to encrypted execution is 27X, and the speedup of k -anonymous execution in comparison to full-oblivious execution is 14X. Due to the prohibitively expensive overhead of full-oblivious execution, we sampled only 25 patients for *aspirin profile*. As the data size increases, we expect the gap between full-oblivious and k -anonymous execution to grow in response as the data becomes too large to fit into memory. This will often result in more equivalence classes per query and more I/Os to disk. This sampling abstracts away these complexities, giving us a conservative measurement of the performance benefits of k -anonymous query processing.

Data Scale Up In this section we verify that as the input tuple size increases, the gap between k -anonymous execution and full-oblivious execution widens. We use *dosage study* so that full-oblivious execution may complete. We vary the number of patients we sample to measure performance changes for data of increasing size in encrypted, 5-anonymous, and full-oblivious mode. Figure 7 shows the runtime of this query. K -anonymous execution is slightly slower than oblivious execution with 500 sampled patients owing to the overhead of its k -anonymous processing view setup. As the input size increases, k -anonymous query processing offers significant performance benefits over full-oblivious query processing. With 3,000 patients, the runtime for encrypted, k -anonymous, and full-oblivious query processing respectively are approximately 181ms, 1689ms, and 198369. This yields 9X slowdown for k -anonymous mode compared to encrypted, and 117X speedup for it in comparison to full-oblivious. The stark slowdown for full oblivious mode is due to the substantial memory pressure imposed by exploding cardinalities, leading the join output to spill to disk one equivalence class at a time. In k -anonymous mode, scaling the input size from 500 to 3000 patients yields a 1.07X slowdown. This stands in contrast with the 171X slowdown we observe in full-oblivious mode. This experiment highlights an important feature of this system: KloakDB enables substantial speedups for query processing as input data scales.

6.3 End-to-End System Performance

In this section we run the full query workload in Table 1. We do so on the HealthLNK dataset, and a heterogeneous workload. We demonstrate that k -anonymous query processing provides substantial performance improvements over full-oblivious query execution while providing moderate data protection in comparison to encrypted execution. We run the queries in four modes: *plain*, encrypted, k -anonymous, and full oblivious. *Plain* mode runs using PostgreSQL’s Foreign Data Wrapper (FDW) to simulate a conventional data federation. FDW enables clients to run

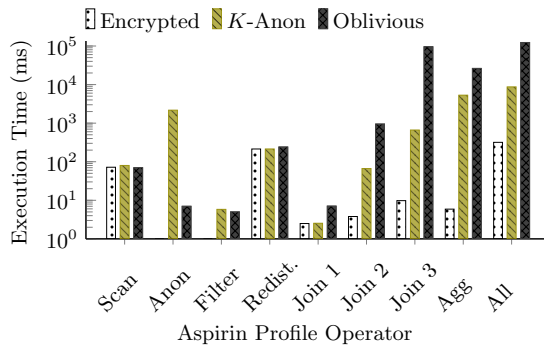


Figure 6: K -anonymous operator performance

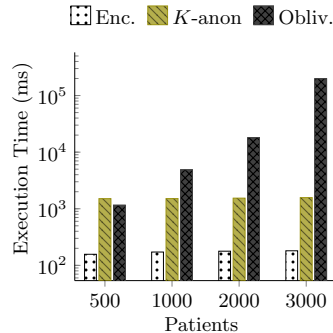


Figure 7: Scale up of *dosage study* inputs.

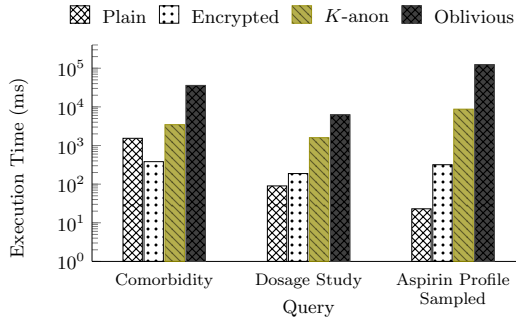


Figure 8: Distributed HealthLNK performance end-to-end.

distributed queries by manually unioning tables of multiple data owners. For the *comorbidity* and *dosage study* queries we run the queries on a full year of data in all four modes. However, the *aspirin profile* queries were unable to complete in full oblivious mode on a full year of data due to the explosion in tuple size from its joins. Therefore, we sample 25 unique *patients* per host, and run the query only on data *patients* that are distributed across all four hosts.

Figure 8 has the results of the full workload. The *comorbidity* query demonstrates that even with a simple query, k -anonymous query processing is an attractive alternative to full-oblivious query processing. When the query is run in k -anonymous execution mode, the k -anonymous processing view setup steps introduce significant overhead, yet still experiences over 10X speedup compared to full-oblivious query execution. Compared with encrypted execution, k -anonymous execution has a 9X slowdown. The k -anonymous processing view setup steps take approximately 35% of the overall runtime for this query in k -anonymous mode.

The *dosage study* query sees a 3X speedup in k -anonymous execution compared to full-oblivious execution, and a 10X slowdown in k -anonymous execution compared to encrypted. This verifies the performance benefits we witnessed during the scale up experiment in Figure 7. With the *aspirin profile* query, it is important to note that it is able to run a full year of data on our test bed in both encrypted mode and k -anonymous mode. Even with a small input data set size, full-oblivious execution is nearly 14X slower than k -anonymous query processing. We expect the performance gap between full-oblivious and k -anonymous mode to widen as the input tuple size increases. We detailed the per operator performance of this query in Figure 6.

7. RELATED WORK

KloakDB builds on principles in query processing, applied security, and automated access control policies. There is

substantial active research in all of these areas and we survey them in this section.

Speaking broadly, there are two common methods for methods for general-purpose computing over the data of two or more mutually distrustful parties: in software with secure multi-party computation [25, 66] and in hardware using secure enclaves [10, 30]. The former is possible on any system, but exacts a substantial overhead in making the computation oblivious and encrypting its contents. The latter requires specialized hardware, but is more efficient. We chose secure enclaves for this work, and the principles of k -anonymous query processing readily generalize to secure multi-party computation.

There has been substantial work on oblivious query processing using secure enclaves [3, 4, 19, 51, 67]. In this setting a curious observer of an enclave learns nothing about the data upon which they compute by observing its instruction traces. We build on this work by offering semi-oblivious query processing for querying data of moderate sensitivity.

KloakDB is a private data federation. This challenge was researched with the use of secure multi-party computation to combine the private data of multiple parties in [5, 8, 63, 65]. We extend this work, but examine how to do it semi-obliviously—rather than with full guarantees of cryptographic hardness—in exchange for faster query runtimes.

K -anonymous data releases were proposed in [53]. There has been substantial work on efficiently generating k -anonymous views of a given dataset [7, 16, 29, 35, 36, 58]. KloakDB extends the techniques in [14] to build k -anonymous processing views. We generalize the requirements of multi-relational k -anonymous data releases in [45] to KloakDB’s computational model. Automatically enforcing k -anonymous access control policies in a dataset was researched in [18].

Most of the prior work on oblivious query processing focuses on outsourced computation from a single data provider, either in software with secure multi-party computation [2] or in hardware with secure enclaves [3, 67]. Some of them [5, 8, 63, 65] offer interoperability for multiple data owners.

There has been limited work on semi-oblivious computation. The most common method for this is computational differential privacy [40]. Protocols of this kind leak noisy information about the data and they are analogous to computing on a differentially private version of the dataset.

There is also work about computing queries in the cloud over data stored with fully homomorphic encryption [50, 59]. Encrypted databases have reduced expressiveness since they cannot readily compose operators for nested blocks of select statements. Because KloakDB protects the query’s computation instead of the data, it supports nested queries.

8. CONCLUSIONS AND FUTURE WORK

In this work we introduce the first *in-situ* k -anonymous query processing engine that produces precise query results. We generalize k -anonymity from an access control policy and a data release technique to a method of semi-oblivious computation. We formalize the notion of k -anonymous semi-oblivious computation, and build an end-to-end system which upholds its guarantees. This is an important step towards more approaches that strike a balance between security and performance for querying private data, whether it is in out-sourced storage in the cloud or the union of sensitive records from multiple sources. This middle ground enables clients to run complex analytical queries at scale. We demonstrate that even with the overhead induced by the k -anonymous database operators, our system still outperforms the full-oblivious baseline. With our workload, we see speedups of at least 3X, and up to 117X over the full-oblivious baseline. We have identified a real-world use case for k -anonymous query processing in electronic health records and we are preparing to get more feedback on its performance from experiments in the field. Through extending the well understood privacy model of k -anonymity to a semi-oblivious computation setting, we provide intuitive security guarantees for practitioners. Combined with massive the speedups compared to full-oblivious computation, our proof of concept enables usable security for many domains that use k -anonymity for data releases.

9. ACKNOWLEDGMENTS

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