Hu-Fu: Efficient and Secure Spatial Queries over Data Federation

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ABSTRACT

Data isolation has become an obstacle to scale up query processing over big data, since sharing raw data among data owners is often prohibitive due to security concerns. A promising solution is to perform secure queries over a federation of multiple data owners leveraging secure multi-party computation (SMC) techniques, as evidenced by recent federation work over relational data. However, existing solutions are highly inefficient on spatial queries due to excessive secure distance operations for query processing and their usage of general-purpose SMC libraries for secure operation implementation. In this paper, we propose Hu-Fu, the first system for efficient and secure spatial query processing on a data federation. The idea is to decompose the secure processing of a spatial query into as many plaintext operations and as few secure operations as possible, where no secure distance operation is involved and all secure operators are implemented dedicatedly. As a working system, Hu-Fu supports not only query input in native SQL, but also heterogeneous spatial databases (*e.g.* PostGIS, Simba, GeoMesa, and SpatialHadoop) at the backend. Extensive experiments show that Hu-Fu usually outperforms the state-of-the-arts in running time and communication cost while guarantees security.

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The source code, data, and technical report have been made available at https://github.com/BUAA-BDA/Hu-Fu.

1 INTRODUCTION

Efficient processing of spatial queries over large-scale data is essential for a wide spectrum of smart city applications including taxi-calling [50], logistics planning [27], map service [52], and contact-tracing [29] to name a few. Although the volume of spatial data continues to grow, it becomes increasingly difficult for these applications to take full advantage of the big spatial data due to the data isolation problem (*a.k.a.* isolated data) [7, 9, 48]. Spatial datasets at city or nation scale are often privately possessed and separately owned by multiple parties, where sharing raw data among parties is prohibitive due to legal regulations or commercial reasons.

A promising paradigm to tackle the data isolation problem is to perform *secure* queries over a *data federation* [2], which consists of multiple data owners *a.k.a.* data silos [25, 29], who agree on the same schema and manage their own data autonomously. Note that this paradigm differs from conventional federated databases [20, 37] in the extra security requirement. In general, secure query processing can be solved by well-known techniques such as secure multi-party computation (SMC) [5]. Yet it is only recently did pioneer studies such as SMCQL [2] and Conclave [40] take the first steps towards practice with efficient query execution plans upon SMC libraries for (relational) data federation.

Nevertheless, directly adapting the state-of-the-art secure query processing schemes designed for relational data [2, 40] to spatial data can be inefficient. From our empirical study (Sec. 2.2) of a kNN query on a real dataset, they are at least 143× slower, and have at least 1211× higher communication cost than plaintext query processing. There are two reasons for such inefficiency. *(i)* Existing solutions process spatial queries with excessive secure distance comparisons, which are time-consuming in practice. For example, SMCQL [2] and Conclave [40] would securely sort spatial objects by distance to the query point and pick the top-k objects, where each sorting involves excessive secure distance comparisons. *(ii)* Previous studies [2, 40] are built on general-purpose SMC libraries, which may sacrifice the efficiency of specific operations for other considerations. For example, our experiment shows that the secure summation in ObliVM [28], the SMC library adopted by SMCQL [2], can be accelerated by 16× via dedicated implementations [15].

In this paper, we aim at efficient and secure spatial queries over a data federation, which we call as *federated spatial queries.* We mainly study five queries (federated range query/counting, kNN query, distance join and kNN join) commonly seen in spatial database research [12, 34, 47] and follow the semi-honest adversary model adopted by previous work [2, 17, 40, 43]. Moreover, we develop a more complete solution than [2, 40] by eliminating the need for an honest broker and supporting more data silos (these work only supports no more than 3 data silos whereas we tested up to ten).

To this end, we propose Hu-Fu, a system for efficient and secure processing of federated spatial queries. The key idea is to decompose a federated spatial query into as many plaintext operations and as few secure operations as possible without compromising security, where *(i)* no secure distance-related operations are involved

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and *(ii)* the secure operations have implementations faster than those in general-purpose SMC libraries. To realize this idea, we identify a set of plaintext and secure operators to cover the queries of interest, and propose novel decomposition plans to minimize the usage of secure operators while ensuring security. We also provide efficient and unified execution of the decomposition plans by implementing secure operators with dedicated SMC protocols and plaintext operations as interfaces on top of the heterogeneous spatial databases adopted by different data silos. Hu-Fu also supports query input in SQL format for easy usage.

Our main contributions and results are summarized as follows.

- To the best of our knowledge, Hu-Fu is the first system on efficient and secure spatial queries over a data federation.
- We devise novel decomposition plans for federated spatial queries. After decomposition, an execution plan involves only a limited number of secure operators that can be effectively supported with fast and dedicated implementations.
- Hu-Fu is an efficient, easy-to-use system that supports query input in SQL and heterogeneous spatial databases, *e.g.* PostGIS [35], MySQL [44], SpatiaLite [38], Simba [47], GeoMesa [21], and SpatialHadoop [12].
- Extensive evaluations show that Hu-Fu usually outperforms the state-of-the-arts [2, 40] in efficiency. Comparing with two strong baselines, namely SMCQL-GIS and Conclave-GIS, which are extended from SMCQL [2] and Conclave [40] to spatial queries, Hu-Fu is up to 4 orders of magnitude faster and 5 orders of magnitude lower in communication than SMCQL-GIS and Conclave-GIS.

In the rest of this paper, we define our problem scope and identify the inefficiency of existing solutions in Sec. 2, we present an overview of Hu-Fu in Sec. 3 and elaborate on its functional components in Sec. 4, Sec. 5 and Sec. 6. Finally, we present the evaluations in Sec. 7, review the related work in Sec. 8, and conclude in Sec. 9.

2 PROBLEM STATEMENT

This section clarifies our problem scope (Sec. 2.1) and highlights the challenges (Sec. 2.2) that motivate the design of Hu-Fu.

2.1 Problem Scope

We consider a data federation F ("fedeartion" for short) consisting of n data silos ("silos" for short, denoted by F_i), where each silo holds multiple *spatial objects* o. Each spatial object o has a location l_o and other attributes a_o. The federation supports *federated spatial queries* over the spatial objects of all silos under the following settings.

- *Spatial queries:* The federation F should support mainstream spatial queries including range query, range counting, kNN query, distance join, and kNN join [39, 47].
- *Autonomous databases:* Each silo is an autonomous database that does not share its raw spatial objects with other silos. This is aligned with real-world data federations [2–4, 40].
- *Semi-honest adversaries:* Each silo honestly executes queries received and returns authentic results, but may attempt to infer data from other silos during query execution. This assumption is common in query processing over a data federation [2, 40].

We focus on query processing with the following requirements.

- **Efficiency requirements.** We care about the *running time* and *communication cost* to execute *exact* queries over multiple silos. Short running time is desirable since real applications may process massive queries and a long latency can have bad effects (*e.g.* it may cause an extended spread of diseases for contact tracing or degraded user experience for taxi-calling). Minimal communication cost is critical in distributed query processing [13, 34] and secure query processing [23]. Approximate query processing over data federation [4, 10] is out of our scope because applications such as contact tracing require accurate results. We consider multiple silos as aligned with real-world applications. Similar to existing federated query solutions [2, 40], the storage efficiency, which mainly depends on silos themselves, is not our primary concern.
- **Security requirements.** We target at the scenario where input queries are public to all silos yet neither the query user nor any silo could deduce extra information from the final results. For instance, in federated kNN query, the query user can only know the final result (*i.e.* k nearest neighbors), and cannot infer the ownership of these k nearest neighbors. Such requirements are common in secure query processing [5]. In addition, we do not assume an honest broker to assemble the final result as in previous studies [2, 40].

Formally, we define the federated spatial queries of interest below. They are common in existing spatial data systems [12, 34, 47]. Here, function $d(p, o)$ is the distance between spatial objects p and o.

Definition 1 (Federated Range Query/Counting)**.** Given a federation $F = \{F_1, \cdots, F_n\}$, and a query range $\mathcal{R}$, *federated range query* returns all objects $o \in F$ located in $\mathcal{R}$; *federated range counting* returns the number of these objects. These two queries should only return the final results without revealing any information of F_i (*e.g.* the ownership of objects, the number of objects) to F_j $(j \neq i)$.

Definition 2 (Federated kNN Query)**.** Given a federation $F = \{F_1, \cdots, F_n\}$, a query point p and an integer k, *federated kNN query* returns a set $\mathrm{kNN}(F, p, k)$ of k spatial objects such that

$$\forall o \in \mathrm{kNN}(F, p, k), \forall o' \in F - \mathrm{kNN}(F, p, k), d(p, o) \leq d(p, o')$$

without revealing information except the returned set to any F_i.

Definition 3 (Federated Distance Join)**.** Given an input dataset of spatial objects R, a federation $F = \{F_1, \cdots, F_n\}$ and a radius r, *federated distance join* returns each $o \in R$ with each $o' \in F$ that satisfies $d(o, o') \leq r$ as pairs, without revealing the ownership of $o' \in F_i$ to F_j $(j \neq i)$.

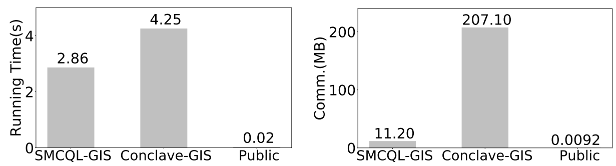
$$R \bowtie_r F = \{(o, o') | o \in R, o' \in F, d(o, o') \leq r\}$$

Definition 4 (Federated kNN Join)**.** Given an input dataset of spatial objects R, a federation $F = \{F_1, \cdots, F_n\}$ and k, *federated kNN join* returns each $o \in R$ with each $o' \in \mathrm{kNN}(F, o, k)$ as pairs, without revealing information except the returned set to F_i.

$$R \bowtie_{\mathrm{kNN}} F = \{(o, o') | o \in R, o' \in \mathrm{kNN}(F, o, k)\}$$

2.2 Challenges

Federated spatial queries can be realized by secure multi-party computation (SMC) [5], as in prior studies for relational data [2, 40]. Nevertheless, our empirical study shows that they are highly inefficient on spatial queries, as explained below.



(a) Running time **(b) Communication cost**

Figure 1: Inefficiency of Conclave-GIS and SMCQL-GIS on federated kNN query, where SMCQL-GIS and Conclave-GIS are our extensions on SMCQL [2] and Conclave [40] to spatial queries (see Sec. 7.1).

2.2.1 Inefficiency on Federated Spatial Queries. As an illustrative study, we perform federated kNN query by extending SMCQL [2] and Conclave [40], two representative solutions to secure query processing on (relational) data federations.

Overview of Existing Solutions. The general framework to apply SMC techniques for secure query processing over data federations is to decouple query execution into first *plaintext* queries within each silo and then *secure* computations of the final results across silos [2, 40]. This is because SMC protocols are slow and such a framework accelerates query processing without compromising security. Existing solutions differ in the underlying SMC techniques they apply for secure operations, where garbled circuit (GC) and secret sharing (SS) are two mainstream SMC techniques [5]. Specifically, SMCQL [2], the first solution for secure query processing on a data federation, uses ObliVM [28], a prevalent GC-based library. Since GC (thus ObliVM and SMCQL) only supports two parties, Conclave [40] adopts a SS based technique (Sharemind [8]), which enables query processing on three silos.

Setup. We extend SMCQL [2] and Conclave [40] to federated kNN queries as follows. Following the "plaintext + secure" processing pipeline, each silo first conducts a plaintext kNN query and returns the k nearest points to the query point. Then, the final k nearest neighbors are derived from these returned points, which are securely sorted by their distances to the query point and the k nearest ones are picked. We experiment with two silos with $k = 16$. Other implementation and experimental setup details are in Sec. 7.1.

Results. Fig. 1 plots the running time and communication cost to process a single federated kNN query leveraging existing solutions. The results are averaged over 50 queries. Compared with Public *i.e.* plaintext kNN query execution without the security requirement, the secure counterpart incurs 143× to 213× longer running time and $1,211\times$ to $22,455\times$ higher communication cost. Although SMCQL-GIS yields a shorter running time and a lower communication cost than Conclave-GIS, SMCQL-GIS is *only applicable to the scenario of two silos* for its usage of GC-based SMC techniques. Yet it still takes 2.86 seconds for a single federated kNN query, which can hurt user experiences in applications where time efficiency is critical.

2.2.2 Understanding the Efficiency Bottleneck. Prior studies are inefficient on spatial queries for the following reasons.

- **Excessive Secure Distance Operations.** When processing a federated kNN query, over 99% time is spent on SMC operations (see Table 1) and most of them are time-consuming secure distance comparisons. For example, SMCQL-GIS and Conclave-GIS adopt different sorting algorithms, both with $O(nk\log(nk))$ secure distance comparisons in the worst case.

Table 1: Percentage of time spent for *plaintext* or *SMC* operations for a federated kNN query via existing solutions.

System	Plaintext	SMC
SMCQL-GIS	0.14%	99.86%
Conclave-GIS	0.10%	99.90%

- **Reliance on General-Purpose Libraries.** Existing methods use general-purpose libraries to implement SMC operations (*e.g.* ObliVM [28] in SMCQL [2]). General-purpose libraries sometimes sacrifice efficiency for generalization or compatibility. For example, the secure summation we used can be 16× faster than that in ObliVM (see Sec. 7). As will be shown in Sec. 4, we can process federated spatial queries with only a few secure operations. This facilitates acceleration with libraries dedicated to such operations [8, 15, 22].

Takeaways. Our study shows that existing secure query processing solutions (*e.g.* [2, 40]) for data federation are inefficient for spatial queries. The inefficiency comes from *(i)* massive secure distance operations, and is exacerbated by *(ii)* adopting general-purpose libraries for these SMC operations. In response, we propose Hu-Fu, a solution with *(i)* a novel execution plan for federated spatial queries that involve notably fewer secure operations with no secure distance operations (see Sec. 4) and *(ii)* each secure operator can be implemented in high efficiency via dedicated algorithms (see Sec. 5). As next, we give an overview of Hu-Fu and elaborate on its functional modules in the following.

3 HU-FU OVERVIEW

Hu-Fu is a solution that enables efficient and secure spatial queries over a data federation. Hu-Fu addresses the inefficiency of federated spatial query processing (see Sec. 2.2.2) via two modules: *(i)* a novel **query rewriter** that decomposes federated spatial queries into *plaintext and secure operators*, with the former executed within each silo and the latter across silos, leaving secure distance operations out of query evaluation; *(ii)* **drivers** that implement these operators as *plaintext and secure primitives* leveraging dedicated algorithms and optimizations. Hu-Fu also contains a transparent **query interface** to support federated spatial queries written in native SQL. We briefly explain the architecture and workflow of Hu-Fu below.

3.1 Architecture

Fig. 2 illustrates the architecture of Hu-Fu, which consists of three modules: the query interface, the query rewriter and drivers. From a functional perspective, the query rewriter and drivers optimize the *efficiency* of federated spatial queries, and the query interface improves the *usability* of Hu-Fu.

- **Query Rewriter (Sec. 4).** It decomposes federated spatial queries into plaintext operators (executed within silos) and secure operators (executed across silos). We define two *plaintext* operators (plaintext range query and range counting) and three *secure* operators (secure summation, comparison and set union) as the basic operators, upon which we design novel execution plans that decompose mainstream federated spatial queries (federated range query, range counting, kNN query, distance join and kNN join) into these basic operators.

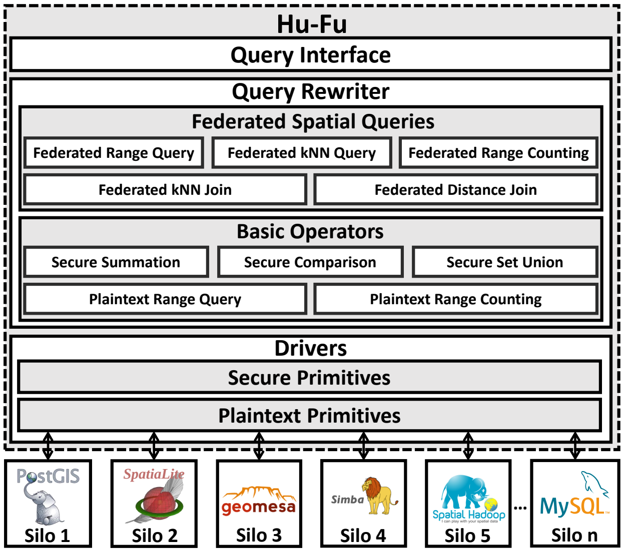


Figure 2: Illustration of Hu-Fu architecture.

- **Drivers (Sec. 5).** Hu-Fu's drivers implement the basic operators defined in the query rewriter as efficient *primitives* that can adapt to heterogeneous spatial databases at the backend. Each operator is implemented by a specific primitive. Specifically, secure operators are implemented as *secure primitives* with dedicated optimizations [8, 15, 22]. Plaintext operators are implemented as *plaintext primitives* on top of the underlying spatial databases, which support various systems, *e.g.* PostGIS [35], SpatiaLite [38], MySQL [44], GeoMesa [21], Simba [47] and SpatialHadoop [12].
- **Query Interface (Sec. 6).** This module *(i)* provides a transparent and unified federation view to users, and *(ii)* supports federated spatial queries written in SQL. We implement the query interface by extending the schema manager and parser of Calcite [6]. We also provide interfaces such as JDBC for easy integration of Hu-Fu to users' programs.

3.2 Workflow

Fig. 3 shows the workflow of Hu-Fu with a user querying a data federation of n silos. The query interface and query rewriter are deployed on the user machine to provide a portal for spatial services. Each silo runs an instance of Hu-Fu drivers to interact with its underlying spatial databases.

Suppose the user's spatial services issue a federated spatial query written in SQL. When a federated spatial query comes in, it is first parsed by the query interface. Then the query rewriter transforms and optimizes the query into a sequence of plaintext and secure operators. These operators are then sent to drivers for execution as plaintext and secure primitives. First, the plaintext primitives are executed on the underlying spatial databases at each silo to get the local results. Afterwards, the local results are collected to perform the secure primitives for the final query result, which is returned to the user by the query interface.

4 QUERY REWRITER

This section presents Hu-Fu's query rewriter, which decomposes federated spatial queries into multiple basic operators. We first define the basic operators in Sec. 4.1 before explaining the overall decomposition strategies in Sec. 4.2. Specifically, we categorize the five federated spatial queries into *radius-known* and *radius-unknown* queries, and elaborate on their decomposition in Sec. 4.3 and Sec. 4.4. We discuss other practical issues in Sec. 4.5.

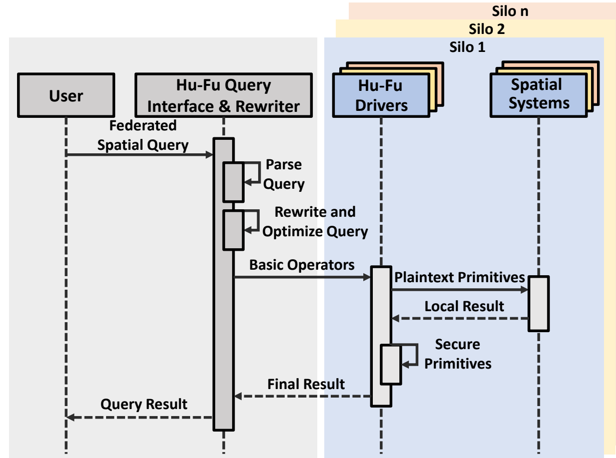


Figure 3: Illustration of Hu-Fu workflow.

4.1 Basic Operators

As mentioned in Sec. 2.2, existing solutions (*e.g.* [2, 40]) are inefficient for federated spatial queries due to excessive secure distance operations. Our acceleration strategy is to *decompose queries into basic operators such that distance-related operations are restricted within silos in plaintext, leaving only secure operations across silos.* The selection of basic operators is explained below.

4.1.1 Operator Selection Principles. We propose two categories of basic operators: *plaintext* and *secure* operators. The plaintext operators perform local queries within each individual silo, while the secure operators securely collect the local query results from different silos as the final output.

- **Plaintext Operators.** They can involve the distance-related operations compulsory in spatial queries, but should be common operations widely supported by diverse spatial databases.
- **Secure Operators.** They should avoid distance-related operations. Operators with high-efficiency secure implementation are preferable.

Following these principles, we choose two plaintext operators (*plaintext range query*, *plaintext range counting*) and three secure operators (*secure summation*, *secure comparison*, *secure set union*). We define each basic operator and justify our selections below.

4.1.2 Plaintext Operators. We define two plaintext operators: *plaintext range query* and *plaintext range counting*. These operators are performed within each silo F_i. Hence, they can be conducted in plaintext without compromising security.

Definition 5 (Plaintext Range Query/Counting)**.** For a silo F_i, given a query range $\mathcal{R}$, the *plaintext range query* $\text{PRQ}_{F_i}(\mathcal{R})$ returns in plaintext the spatial objects in F_i that are located in $\mathcal{R}$, and the *plaintext range counting* $\text{PRC}_{F_i}(\mathcal{R})$ further returns the number of such spatial objects.

The plaintext operators comply with the principles described in Sec. 4.1.1, because *(i)* the returned results can be securely collected without secure distance operations (see Sec. 4.1.3) and *(ii)* they are supported by almost all spatial databases [34]. These operators are implemented as *plaintext primitives* in Hu-Fu drivers, which we defer to Sec. 5.1. The query range can be a circle, a rectangle or other shapes. For ease of presentation, we focus on a circular range in Sec. 4.2-4.4 and discuss extensions to other shapes in Sec. 4.5.

4.1.3 Secure Operators. Based on the secure multi-party computation techniques [8, 15, 22], we define three secure operators: *secure summation*, *secure comparison*, and *secure set union*. These operators are performed across silos and responsible for secure result collection from local query results returned by plaintext operators.

Definition 6 (Secure Summation)**.** For a federation $F = \{F_1, \cdots, F_n\}$, where each silo F_i holds a number β_i, this operator calculates the sum $\sum_{i=1}^{n} \beta_i$, while avoiding leaking β_i to F_j $(j \neq i)$.

$$\mathsf{SSM}_F(\beta_1, \cdots, \beta_n) = \sum_{i=1}^{n} \beta_i$$

Definition 7 (Secure Comparison)**.** For a federation $F = \{F_1, \cdots, F_n\}$, where each silo F_i holds a number β_i, and a value k, this operator compares the sum $\sum_{i=1}^{n} \beta_i$ with k without leaking $\sum_{1}^{n} \beta_i$ to any F_i.

$$\mathsf{SCP}_F(\beta_1, \cdots, \beta_n, k) = sign\Big(\sum_{i=1}^{n} \beta_i - k\Big)$$

Definition 8 (Secure Set Union)**.** For a federation $F = \{F_1, \cdots, F_n\}$, where each silo F_i holds a set of spatial objects $S_i = \{o_1^i, \cdots, o_{m_i}^i\}$, this operator computes the union of spatial objects from all silos, without leaking the ownership of each $o \in S_i$ to F_j $(j \neq i)$.

$$\mathsf{SSU}_F(S_1, \cdots, S_n) = \bigcup_{i=1}^{n} S_i$$

The secure operators comply with the principles in Sec. 4.1.1 since *(i)* they do not involve distance operations and *(ii)* there are dedicated techniques for efficient implementations (see Sec. 5.2).

4.2 Overall Decomposition Strategies

The principle of our query rewriter is to decompose federated spatial queries into as many plaintext operators and as few secure operators as possible such that a large portion of the query can be executed in plaintext without compromising security. At a high level, a federated spatial query is first executed as plaintext operators in each silo, where the results are then securely assembled as the final result. At the minimum, one secure operator is compulsory, and additional secure operators may be necessary if there are extra interactions across silos. Given the basic operators defined in Sec. 4.1, we classify federated spatial queries into two categories and explain their decomposition strategies as follows. Here we mainly consider federated range query/counting with a circular range. Queries with other range shapes are discussed in Sec. 4.5.

- **Radius-Known Queries.** For federated spatial queries where a radius is explicitly given, the query needs only one secure operator for result collection in the ideal case. This is because our plaintext operators already support plaintext range query and counting. For result collection, a secure set union or summation operator is required. We introduce the decomposition plans for radius-known queries in Sec. 4.3.
- **Radius-Unknown Queries.** For federated spatial queries with no given radii, *e.g.* federated kNN query, we convert the query into multiple rounds of radius-known queries. There can be cross-silo communication between rounds, and extra secure operators are necessary, which is secure comparison in our case. We adopt binary search to minimize the numbers of rounds and secure operators involved. We explain the decomposition plans for radius-unknown queries in Sec. 4.4.

4.3 Decomposing Radius-Known Queries

Among the five federated spatial queries, range query, range counting, and distance join belong to radius-known queries.

Decomposition Plan. The decomposition plans of radius-known queries are trivial. *Federated range query* can be decomposed into n plaintext range queries with radius r, where each plaintext range query retrieves the local result from each one of n silos. Similarly, *federated range counting* can be decomposed into n plaintext range counting. Observing that a distance join can be viewed as $|R|$ times of range queries with different query points but the same radius, *federated distance join* is decomposed into $|R| \times n$ plaintext range queries with radius r. For result collection across silos, *federated range counting* needs a secure summation to aggregate the counts without revealing the count of any silo to others. For *federated range query*, it needs a secure set union to assemble the result without revealing the objects' ownership. For *federated distance join*, it also first assembles the results of the plaintext range query in each silo and then executes only one secure set union across silos.

Complexity Analysis. For ease of presentation, we denote the time complexity of plaintext range query/counting as T^q and T^c, respectively. For federated range query/counting, each silo executes a plaintext range query/counting and a secure set union/summation. Thus, their time complexities are $O(T^q + n + |S|)$ and $O(T^c + n^3)$, where $|S|$ is the size of returned set. The communication costs are $O(n + |S|)$ and $O(n^2)$, respectively. For federated distance join, each silo executes $|R|$ plaintext range queries, resulting in a time cost of $O(|R|T^q + n + |S|)$ with $O(n + |S|)$ communication cost. The complexity analysis of secure operators is deferred to Sec. 5.2.

4.4 Decomposing Radius-Unknown Queries

Federated kNN query and kNN join are radius-unknown queries, because there is no specific range in these queries. Thus, their decomposition plan is to first get an appropriate range and then filter the points in the range, as explained in detail below.

Decomposition Plan. Similar to the relation between federated range query and federated distance join in Sec. 4.3, federated kNN join can be viewed as $|R|$ independent federated kNN queries. Hence, we mainly explain how to decompose a federated kNN query.

- **Basic Idea.** Recall from Sec. 4.2, the strategy to decompose radius-unknown queries is to convert them into multiple rounds of radius-known queries. We first derive a radius (denoted by *thres*) via a binary search and then retrieve the spatial objects within this radius. Note that obtaining the exact counting result during the binary search via secure summation may leak extra information of silos. For example, the query user can get the number of objects within a range, which reveals the data distribution of the federation. Hence, we only judge whether the total counting result is larger than k and adopt a secure comparison instead. As long as *thres* is between the k^{th} and the $(k+1)^{th}$ nearest distance, the retrieved spatial objects should be the k nearest neighbors.

- **Algorithm Details.** Alg. 1 illustrates decomposing a federated kNN query. Lines 1-11 derive the radius. We initialize a lower bound ($l = 0$) and upper bound ($u = v_0$) of the radius, where v_0 can be set as the diameter of the area or defined by the user. We then perform a binary search in lines 2-11, where ϵ_0 is the precision lower bound of distance. In each iteration, *thres* is set as $(l+u)/2$ in line 3. For the current radius *thres*, we perform a *plaintext range counting* for each silo in line 4 and a *secure comparison* between the sum of each silo's count (β_i) and the integer k in line 5. Lines 6-11 adjust the boundary of the searching radius. If the total count is smaller than k, the current radius is too short, and we update l to *thres* as the new lower bound (lines 6-7). If the total count is larger than k, it means there are sufficient points within *thres* and we update the upper bound u as *thres* in lines 8-9. The binary search guarantees that *thres* is sufficiently close to the k^{th} nearest distance. In the last round (lines 12-13), a *plaintext range query* $\text{PRQ}_{F_i}(circle(p, thres))$ is performed on each silo and we use a *secure set union* to get the final result.

Complexity Analysis. In Alg. 1, the upper bound of binary search is a predefined value v_0. Thus, it takes at most $O(\log \frac{v_0}{\epsilon_0})$ rounds to get the threshold (lines 2-11). In each round, the plaintext range counting (line 4) takes $O(T^c)$ time, and the secure comparison (line 5) takes $O(n)$ time. The adjustment of the binary search boundary (lines 6-11) takes $O(1)$ time. After obtaining the final threshold, the algorithm calls a plaintext range query in $O(T^q)$ time to get local results (line 12) and a secure set union in $O(n+k)$ time to assemble the results. Thus, the total time complexity is $O(T^q + k + (n + T^c)\log \frac{v_0}{\epsilon_0})$. In secure comparison (line 5), each silo communicates with the other $n-1$ silos. Thus, the communication cost for a single round is $O(n^2)$ and there are $O(n^2 \log \frac{v_0}{\epsilon_0})$ rounds in total. The communication of secure set union (line 13) is $O(n+k)$. The time complexity of federated kNN join is similar to federated kNN query, multiplied by a factor $|R|$, *i.e.* $O(|R|T^q + |R|k + |R|(n+T^c)\log \frac{v_0}{\epsilon_0})$.

Example 1. We illustrate the execution of a federated kNN query over 3 silos. In Fig. 4, the objects marked with the same color belong to the same silo. Consider a federated kNN query with query point $(4,4)$ and $k = 4$. The query rewriter decomposes this query into multiple rounds of plaintext range counting and secure comparison. In the 1st round, a plaintext range counting in a circular range centered at $(4,4)$ with radius 4 is sent to each silo and a secure comparison with k is performed across silos. In Fig. 4, the number of objects within radius 4, which is 9, is greater than k. Hence in the 2nd round, the radius decreases to 2 and resent to silos for plaintext range counting and secure comparison. There are 2 objects within radius 2, which is smaller than k. Thus in the 3rd round, the radius increases to 3 and the procedure continues, where the range counting result equals to k and the search terminates. Finally, a plaintext range query in a circular range centered at (4,4) with radius 3 and a secure set union are performed to return the 4 objects.

Algorithm 1: Rewriter of the federated kNN query $\text{kNN}(F, p, k)$ over a data federation $F = \{F_1, \cdots, F_n\}$

```
1  [l, u] ← [0, v_0], where v_0 is a predefined upper bound;
2  while u − l ≥ ε_0 do
3      thres ← (l + u)/2;
4      β_i ← plaintext range counting PRC_{F_i}(circle(p, thres));
5      sgn ← secure comparison SCP_F(β_1, ··· , β_n, k);
6      if sgn = −1 then
7          l ← thres;
8      else if sgn = 1 then
9          u ← thres;
10     else
11         break;
12 S_i ← plaintext range query PRQ_{F_i}(circle(p, thres));
13 query answer res ← secure set union SSU_F(S_1, ··· , S_n);
```

Table 2 summarizes the amount of plaintext and secure operators for each federated spatial query.

4.5 Discussions

We highlight the following discussions on the query rewriter.

Security of Rewriter. We prove the security of our query rewriter based on the composition lemma in [18] (Section 7.3.1). The idea is to show the decomposition plans for radius-known queries and radius-unknown queries will not reveal any extra information other than the final result due to the usage of secure operators. Please refer to Appendix A of our technical report [11] for the detailed proof due to limited space.

Differential Privacy to Accelerate Radius-Unknown Queries. We exploit differential privacy [26] to further accelerate federated kNN query and federated kNN join from two aspects.

- **Tighten Predefined Upper Bound.** We ask each F_i to conduct a local kNN query in plaintext and return the k^{th} object's distance to the query point d_i^k. Since directly returning such value may expose the real distances of silos, we apply the truncated Laplace mechanism [3] on it. That is, let each silo add a positive noise and get the perturbed value $d_i'^k$. We can tighten the upper bound as the smallest distance in all silos, *i.e.* $v_0 = min_i d_i'^k$, since there are at least k points in this range.
- **Reduce Communication Cost in Secure Comparison.** The secure comparison in Alg. 1 compares $\sum_1^n \beta_i$ with k, which incurs at least $O(n^2)$ communication cost. It can be reduced to $O(n)$ when $\sum_1^n \beta_i$ notably differs from k. In this case, each silo can add a Laplacian noise [26] on its local counting result to hide the real counts of each silo, and then aggregate the perturbed results. If the perturbed result is much smaller/larger than k, we directly adjust the threshold. Secure comparison is only needed when the perturbed result is close to k.

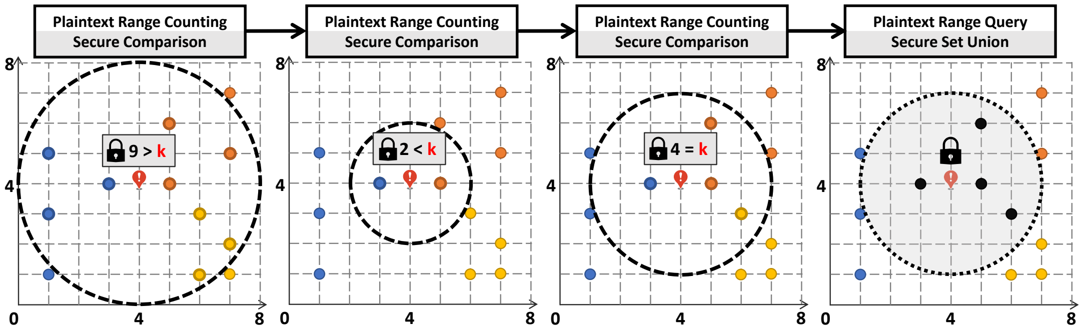


Figure 4: Running example of a federated kNN query ($k = 4$).

Table 2: The number of basic operators in the decomposition plans of federated spatial queries. Radius-known queries only involve one secure operator (secure set union/summation) for secure result collection. Radius-unknown queries are executed in multiple rounds which require extra secure operator (secure comparison) to ensure security. Here, n is the number of silos.

Category	Federated Spatial Query	Number of Plaintext Operator		Number of Secure Operator	
		Range Query	Range Counting	Comparison	Set Union/Summation
Radius-Known	Federated Range Query	n	0	0	1/0
	Federated Range Counting	0	n	0	0/1
	Federated Distance Join	$n\lvert R\rvert$ †	0	0	1/0
Radius-Unknown	Federated kNN Query	n	$O(n \log \frac{v_0}{\epsilon_0})$ ‡	$O(\log \frac{v_0}{\epsilon_0})$	1/0
	Federated kNN Join	$n\lvert R\rvert$	$O(n\lvert R\rvert \log \frac{v_0}{\epsilon_0})$	$O(\lvert R\rvert \log \frac{v_0}{\epsilon_0})$	1/0

† $|R|$ is the size of the input dataset R in the federated distance join and federated kNN join.
‡ v_0 and ϵ_0 are user-defined parameters for processing the federated kNN query and federated kNN join.

Beyond Mainstream Spatial Queries. The decomposition plan for radius-known queries applies to federated range query/counting with other query range types (*e.g.* rectangle). This is because the plaintext range query/counting with arbitrary shapes of query ranges is supported in each silo's underlying spatial data systems (*e.g.* PostGIS). The query rewriter also supports aggregation queries, *e.g.* the aggregate attribute on the result of kNN query or range query. Specifically, the aggregation of kNN query can be decomposed the same as the federated kNN query, by only replacing the last secure set union with a secure summation. The range aggregate query can be decomposed similar to a federated range counting.

5 DRIVERS

This section presents Hu-Fu's drivers, which offer interfaces and implementations on top of silos' spatial databases for unified and efficient execution of decomposition plans generated by the query rewriter. A driver, which consists of *plaintext primitives* and *secure primitives*, is deployed on each silo. Upon receiving a decomposition plan, plaintext operators are first executed at each silo with plaintext primitives and then secure operators are performed via the secure primitives for result assembling. As next, we elaborate on plaintext primitives (Sec. 5.1) and secure primitives (Sec. 5.2) to efficiently implement the basic operators defined in the query rewriter.

5.1 Plaintext Primitives

The plaintext primitives implement plaintext range query and plaintext range counting. They are implemented as an *interface* on top of the underlying spatial databases for portability and to harness existing range query and range counting implementations.

Primitive Implementation. The implementation of plaintext primitives is dependent on the underlying spatial databases.

- For databases where range query and range counting are available, *e.g.* Simba [47] and PostGIS [35], we directly call the corresponding functions for plaintext range query or counting. For example, in PostGIS, a plaintext range counting on silo F_i with the center p and radius r of a circular range can be implemented by calling the SQL below.

```
SELECT COUNT(*) FROM F_i
WHERE ST_DWithin(p, F_i.location, r);
```

- For databases without such queries, drivers provide a default implementation of range query and range counting. For example, GeoMesa [21] only provides an interface of range query. Thus, we implement range counting by first running a range query, and then counting the cardinality of the returned set.

Time Complexity. The time complexity of plaintext primitives depends on the native implementation in spatial databases. For example, plaintext range counting takes $O(\log m)$ time with spatial indices [36], where m is the data size. Yet plaintext range query may need $O(\log m + |S|)$ time, where S is the query result.

Discussions. We make two notes on the plaintext primitives.

- To support the differential privacy based acceleration for federated kNN query (see Sec. 4.5), Hu-Fu drivers provide an optional plaintext kNN query interface. The plaintext kNN is implemented by a function call on spatial databases with native kNN query (*e.g.* PostGIS [35] and Simba [47]).
- Since the time complexity of plaintext primitives varies, the efficiency of federated spatial queries can be limited by the slowest plaintext primitive if silos are using heterogeneous spatial databases. Our evaluation in Sec. 7.4 shows that the plaintext range query/counting provided in existing spatial databases such as PostGIS is sufficiently fast. Thus, more efficient plaintext range query/counting is out of our scope.

5.2 Secure Primitives

The Secure primitives implement secure summation, comparison, and set union, which are independent of the underlying spatial databases. Recall that secure primitives take the local results from plaintext primitives as inputs. To avoid idle waiting for slow silos and to reuse local results across silos, each silo buffers its local results of plaintext primitives executed on itself. We implement secure primitives on top of such a buffer, as explained next.

Primitive Implementation. Each secure primitive is implemented with a dedicated secure protocol for higher efficiency than the corresponding operation in general-purpose SMC libraries. We present the details of each secure primitive below.

- **Secure Summation.** This primitive is directly implemented as a Shamir's secret sharing based protocol [15]. Specifically, each silo generates an $n-1$ degree polynomial with a constant as its local counting result. It stores the values of this polynomial at n specific positions $u_1, \cdots, u_n$ in the buffer. Each silo gets the corresponding values of other silos and computes their summation. The result of secure summation is obtained by solving linear equations with LU factorization, which is notably faster than the secure summation by ObliVM [28].
- **Secure Comparison.** This primitive aims to compare the summation of each silo's β_i to a global value α. We equally divide the global value α into n pieces. Let x_i be $\beta_i - \frac{\alpha}{n}$. Thus, we only need to know the sign of $\sum_{i=1}^{n} x_i$. It can be securely obtained by asking each silo to generate a random positive value y_i. Then the sign of $\sum_{i=1}^{n} x_i$ is converted into the sign of $(\sum_{i=1}^{n} x_i)(\sum_{j=1}^{n} y_j)$, which is a classic secure multiplication problem solved by secret sharing based protocols [8].
- **Secure Set Union.** We implement this primitive as a random shares based two-phase union method [22]. Specifically, each silo adds its results and some fake records to a global set in the first phase and removes them from the set in the second phase. We use differential privacy to reduce the number of fake records and thus the communication cost. Observing that adding and removing fake records can be done independently, we split the global set into batches to allow parallel execution. Then each silo can add and remove noise data from each batch independently, resulting in a shorter latency.

Complexity Analysis. For secure summation, the time complexity to solve the linear equations is $O(n^3)$, with $O(n^2)$ communication cost [15]. For secure comparison, the time complexity of the secure multiplication is $O(n)$. It also has a communication cost of $O(n^2)$ [8]. The time complexity and communication cost of secure set union are both $O(n + |S|)$, where S is the final global set [22].

6 QUERY INTERFACE

This section presents the query interface of Hu-Fu. For easy usability, the interface offers a unified federation view to users (Sec. 6.1) and supports federated spatial queries in SQL (Sec. 6.2).

6.1 Unified Federation View

Hu-Fu's query interface provides a federation view to the query user, while the detailed information of silos is hidden. This allows the user to send queries without worrying about the silo organization and also protects the data security of individual silos.

We implement the unified federation view by extending the schema manager of Calcite [6], a popular query processing framework. In Calcite's schema manager, each table is independent and indivisible. We add silo as an abstraction layer below the table of schema manager. Thus each table contains multiple silo objects, and each object records the identity information of the corresponding silo. The silo identity information is used when executing secure primitives. Specifically, the query rewriter will attach the identifying information of all silo-level tables in the table of schema manager when distributing secure operators. Each silo only executes the corresponding secure primitives if the attached identity information matches the one locally stored.

6.2 Federated Spatial Queries in SQL

Based on the unified federation view, Hu-Fu query interface supports federated spatial queries in SQL by extending the SQL parser of Calcite. The semantics are almost the same as regular SQL queries. Specifically, we add two keywords: `DWithin` and `kNN`.

For example, a federated range counting on a circular range centered at the point p with radius r can be written in SQL as

```
SELECT COUNT(*) FROM F WHERE DWithin(p, F.location, r);
```

where `DWithin`$(p, F.location, r)$ returns whether the distance between p and an object $o \in F$ is shorter than r. A federated kNN join on a dataset R and federation F with k can be written in SQL as

```
SELECT R.id, F.id FROM R JOIN F
ON kNN(R.location, F.location, k);
```

where `kNN`$(R.location, F.location, k)$ indicates whether a spatial object $o' \in F$ is in the kNN set of query point $o \in R$. Other queries can be written as SQL similarly with these two keywords.

7 EVALUATION

This section presents the evaluations of Hu-Fu. We first introduce the experimental setup (Sec. 7.1), and then present the overall performance (Sec. 7.2), scalability (Sec. 7.3) and results with heterogeneous spatial databases across silos (Sec. 7.4).

7.1 Experimental Setup

We first introduce the experimental setup.

Datasets. We conduct experiments on the following two datasets, where each spatial object has a location and a unique ID.

- **Multi-company Spatial Data in Beijing (BJ).** This dataset was collected by 10 companies in Beijing, in June 2019, which has $1,029,081$ spatial objects in total. The locations of these objects fall into an area from 39.5°N ∼ 42.0°N and 115.5°E ∼ 117.2°E. We use the dataset to simulate a real-world federation, where each company can be naturally regarded as a silo. We do not alter the distributions of spatial objects across silos, and only vary the silo number n or query-specific parameters (*e.g.* k for federated kNN query) during the evaluation.
- **OpenStreetMap (OSM).** This is a popular open dataset to evaluate large-scale spatial analytics [12, 34, 47]. We mainly use this dataset in the scalability test, where we uniformly sample 10^4-10^9 spatial objects from the Asia dataset in the

OpenStreetMap [31]. Note that there is no natural data partition across silos in the OSM dataset. Hence, we simply adopt even partition of spatial objects across silos, as with evaluations of existing federated query processing solutions [2–4].

Baselines. We compare Hu-Fu with the following baselines.

- **Public.** It directly collects local results from each silo without any secure operation. It serves as the upper bound of query processing efficiency.
- **SMCQL-GIS.** It adopts the principles of SMCQL [2], a garbled circuit (GC) based solution for relational data, to support spatial queries. We implement SMCQL-GIS with ObliVM [28], which is also used in SMCQL and only supports two silos. So we only provide the results of SMCQL-GIS over two silos.
- **Conclave-GIS.** It adopts the principles of Conclave [40], the state-of-the-art secret sharing (SS) based federation solution for relational data, to support spatial queries. Note that we implement Conclave-GIS with a different SS based library, MP-SPDZ [23], rather than Sharemind [8] in the original Conclave. This is because Sharemind is devised for only three silos [5] and it is a commercial library. In contrast, MP-SPDZ is an open-source SS based library that supports more than three silos, which is gaining increasing popularity [5].
- **SMCQL-GISext.** It is a variant of SMCQL-GIS without assuming an honest broker. SMCQL and the SMCQL-GIS baseline need an honest broker to assemble local results from each silo without leaking ownership. SMCQL-GISext replaces the honest broker by the secure set union for assembling results. SMCQL-GISext also supports two silos only as SMCQL-GIS.
- **Conclave-GISext.** It is a variant of Conclave-GIS without assuming an honest broker. Similar to SMCQL-GISext, it also applies secure set union to assemble results.

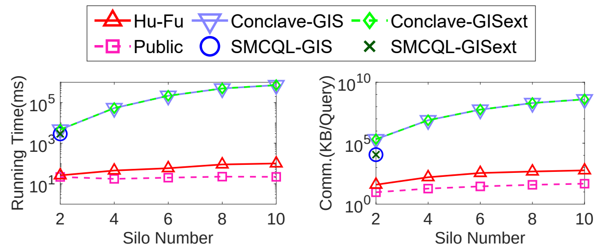
SMCQL-GIS, SMCQL-GISext, Conclave-GIS and Conclave-GISext implement federated spatial queries by exploiting similar queries for relational data of the original SMCQL and Conclave. Specifically, for federated *range query* and *range counting*, the only difference lies in the plaintext primitives (*i.e.* plaintext range query/counting), which are extended by replacing the underlying relational databases with spatial databases (*e.g.* from (relational) PostgreSQL to PostGIS). For federated *kNN query*, we regard it as a top-k query with a user-defined function (UDF) in a (relational) data federation. Thus, we first run a plaintext kNN query in each silo and then securely find the k nearest neighbors, which follows the secure retrievals of the top-k objects in SMCQL and Conclave. For federated *distance/kNN join*, we refer to the query plans of SMCQL and Conclave for join queries and regard a federated distance/kNN join as multiple federated range/kNN queries.

Metrics. We assess the query processing efficiency by two metrics.

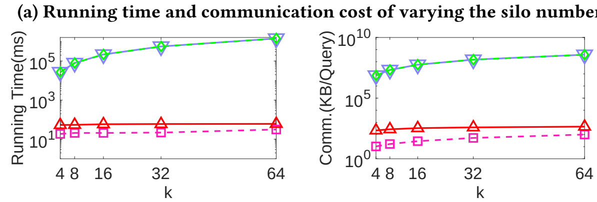
- **Running time.** It is the time cost from receiving the query from a user to returning the query result to the user.
- **Communication cost.** It is the total network communication among the user and all silos for this query.

All the experimental results are the average of 50 repetitions.

Environment. We run all experiments on a cluster of 11 machines. Each machine has 32 Intel(R) Xeon(R) Gold 5118 2.30GHz processors and 64GB memory with Ubuntu 18.04 LTS. The network bandwidth



(a) Running time and communication cost of varying the silo number



(b) Running time and communication cost of varying the value of k

Figure 5: Performance of federated kNN query.

between machines is up to 10 GB/s. Among the 11 machines, one is as the user and the honest broker for SMCQL-GIS and Conclave-GIS, and the other 10 are data silos. We use PostgreSQL 10.15 with PostGIS extension as the default spatial databases for all silos. To show the support of heterogeneous spatial database systems by Hu-Fu, we also use MySQL 5.7 [44], Sqlite3 with SpatiaLite extension [38], GeoMesa 3.0.0 [21], Simba 1.0 [47] and SpatialHadoop 2.4.3 [12] as different silos, as will be explained in Sec. 7.4. All the methods have built spatial indices (*e.g.* GiST in PostgreSQL and R-tree in Simba) to efficiently support plaintext primitives.

7.2 Results on Real Dataset

This series of experiments compare the efficiency of different methods for all five federated spatial queries on the real dataset BJ. All the query points are randomly sampled from the dataset. We vary the number of silos from 2 to 10, and also test the impact of query-specific parameters. We set k to 16 for federated kNN query and kNN join, and the default query area of federated range query, range counting and distance join as 0.001%, and vary them from 4 to 64 and 0.00001% to 0.1% respectively. The range of these query-specific parameters is aligned with previous studies [47]. When evaluating the query-specific parameters, we use 6 silos by default.

7.2.1 Performance of Federated kNN Query. Fig. 5a shows the running time and communication cost of federated kNN query. Hu-Fu is 109.6× to 7,198.8× faster than SMCQL-GIS and Conclave-GIS, and has 2 to 5 orders of magnitude lower communication cost. When the number of silos increases from 2 to 10, the running time and communication cost of Hu-Fu only increase by up to 2.9× and 13.9×, while those of Conclave-GIS drastically increase by up to 153.3× and 1,884.3×. Both metrics of Hu-Fu increase because the secure comparison and secure set union used in this query grow linearly with the silo number. Compare with Conclave-GIS and SMCQL-GIS, the running time and communication cost of Conclave-GISext and SMCQL-GISext increase marginally (less than 20ms and 200KB, respectively), which shows that our secure set union can efficiently assemble query results without an honest broker.

We also vary k from 4 to 64 and plot the running time and communication cost in Fig. 5b. As k increases from 4 to 64, the running time and communication cost of Hu-Fu only increase by 0.1× and

Table 3: Ablation of DP optimization for federated kNN query.

Silo Number		2	4	6	8	10
Running Time (ms)	Hu-Fu	26.1	45.1	58.6	89.6	100.5
	Hu-Fu without DP	26.9	50.3	72.9	107.0	116.9
Comm. (KB)	Hu-Fu	39.4	160.8	357.7	475.1	588.3
	Hu-Fu without DP	58.5	234.8	493.0	784.0	1125.2

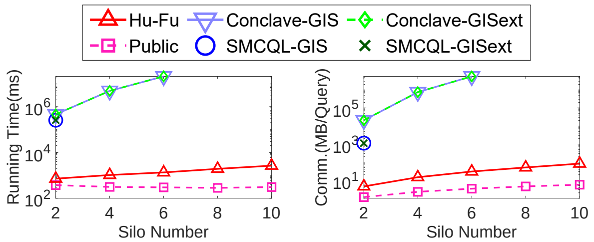


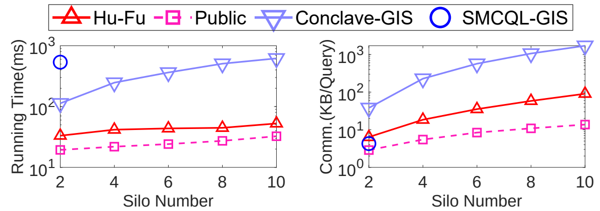
Figure 6: Performance of federated kNN join.

1.1×, while those of Conclave-GIS increase by 51.3× and 50.7×. The impact of k is less obvious than the silo number on Hu-Fu, because only the secure set union is linearly dependent on k. Again, the efficiency of Conclave-GISext is similar to that of Conclave-GIS. The drastic increase in running time and communication cost of Conclave-GIS and Conclave-GISext is expected because it involves time-consuming secure primitives (secure distance comparisons).

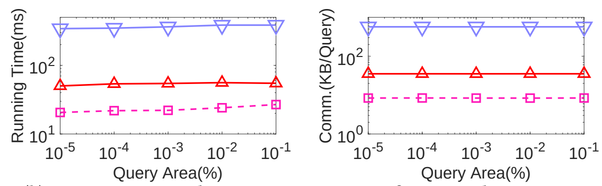
Recall that we apply differential privacy (DP) to accelerate kNN queries (see Sec. 4.5). To show the gain of such optimization, we list the running time and communication cost with and without DP in Table 3. With DP, the running time is reduced by up to 19.6%, and the communication cost by up to 47.7%. Note that Hu-Fu without DP still outperforms SMCQL-GIS and Conclave-GIS in the test.

7.2.2 Performance of Federated kNN Join. Fig. 6 shows the performance of federated kNN join. The results of Conclave-GIS and Conclave-GISext with over 8 silos are omitted since they incur over 6 hours for a single query. Hu-Fu is still the most efficient, which is up to 360.2×/15, 814.2× faster than SMCQL-GIS/Conclave-GIS with 247.8×/185, 151.0× lower communication cost. The running time and communication cost of SMCQL-GISext and Conclave-GISext slightly increase over SMCQL-GIS and Conclave-GIS. The impact of k is similar to federated kNN query. Please see Appendix B of our technical report [11] for the omitted results due to limited space.

7.2.3 Performance of Federated Range Counting. Fig. 7 shows the results of federated range counting. This query only returns the counting result and thus does not need a secure set union to protect data ownership. Hence, we exclude SMCQL-GISext and Conclave-GISext since they only differ from SMCQL-GIS and Conclave-GIS with an extra secure set union, which is unnecessary in this query. Hu-Fu is up to 15.2× faster than SMCQL-GIS with a slightly higher communication cost (within 7KB). Considering the increasing network bandwidth, the gap in communication cost is acceptable. Compared with Conclave-GIS, Hu-Fu is up to 10.8× faster with 17.9× lower communication cost. The running time and communication cost of Hu-Fu increase by 0.6× and 13.2× respectively when silo number increases to 10, mainly due to the secure summation.

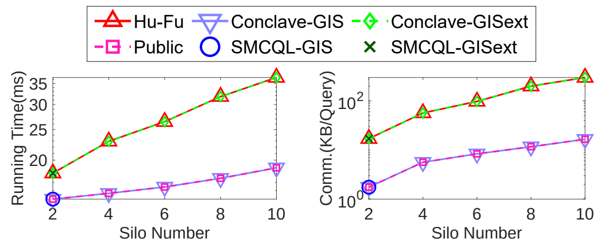


(a) Running time and communication cost of varying the silo number

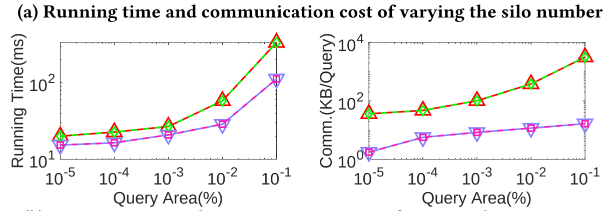


(b) Running time and communication cost of varying the query area

Figure 7: Performance of federated range counting.



(a) Running time and communication cost of varying the silo number



(b) Running time and communication cost of varying the query area

Figure 8: Performance of federated range query.

We also demonstrate the impact of the query area on query efficiency in Fig. 7b. As is shown, the running time of all methods is relatively stable. It is expected because secure operations are the bottleneck of running time whereas the larger query area only increases the running time of plaintext operations.

7.2.4 Performance of Federated Range Query. Fig. 8 illustrates the results of federated range query. The running time and communication cost of SMCQL-GIS and Conclave-GIS are the same as Public. It is because SMCQL-GIS and Conclave-GIS can perform range query by assembling local results at the honest broker without any secure operations. The three methods that do not assume an honest broker, Hu-Fu, SMCQL-GISext and Conclave-GISext, have the same efficiency because they all use our secure set union for results assembling. The use of secure set union only leads to a marginal increase in running time (within 250ms) and communication cost (lower than 3.1MB) over Public. Note that the order of increase in running time and communication cost matches the complexity analysis for the secure set union in Sec. 5.2, which grows linearly with the silo number and the amount of data returned.

As shown in Fig. 8b, when the query area expands, all methods have a higher running time and communication cost, due to the increase of the number of spatial objects in the final result.

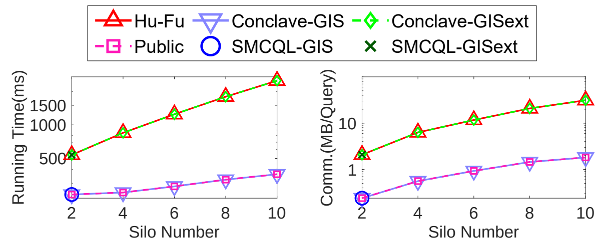


Figure 9: Performance of federated distance join.

7.2.5 Performance of Federated Distance Join. Fig. 9 presents the performance of federated distance join. Note that all the methods treat federated distance join as multiple independent federated range queries, where the total number of these range queries is $|R| = 100$ in this test. Thus, it is reasonable that the ranking of all the methods is similar to that in range query (see Fig. 8). Our Hu-Fu is comparably fast, because it saves up to 70.4% running time compared with a straightforward solution that sequentially runs 100 federated range queries. The gain comes from our secure set union, which splits the results of range queries into multiple batches, and allows parallel execution of these batches. Due to limited space, we omit the result of varying the query area, which has a similar pattern with that in federated range query. Please see Appendix B of our technical report [11] for the omitted result.

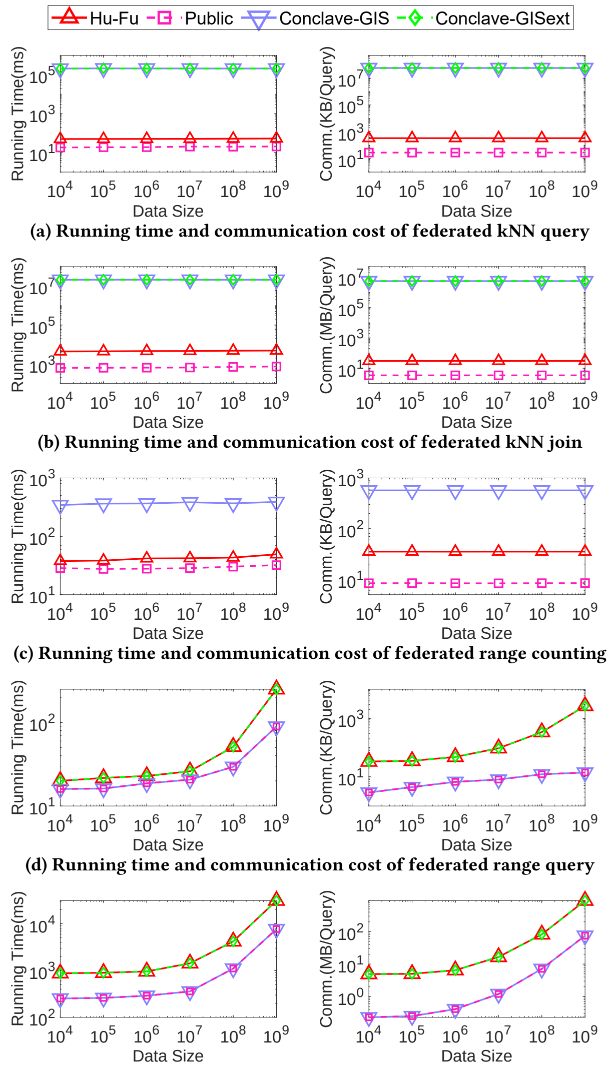
Takeaways. Overall, Hu-Fu is up to 15,814.2× faster than SMCQL-GIS and Conclave-GIS, with up to 5 orders of magnitude lower communication cost. The efficiency gain of Hu-Fu over the baselines is more notable in federated kNN query, kNN join, and range counting, which is at least 2.4× faster in running time and 4.9× lower in communication cost than Conclave-GIS. SMCQL-GIS and Conclave-GIS are more efficient than Hu-Fu in federated range query and distance join because under the assumption of an honest broker, these two queries can be fully conducted in plaintext without leaking data ownership. Note that for federated range query and distance join, Hu-Fu achieves the same efficiency as SMCQL-GISext and Conclave-GISext, the variants of SMCQL-GIS and Conclave-GIS without an honest broker.

7.3 Results on Scalability Test

In this experiment, we scale the total number of spatial objects from 10^4 to 10^9 in the OSM dataset to assess the scalability of Hu-Fu. Other parameters are set to the default values as in Sec. 7.2. For example, the number of silos is 6, $k = 16$ for federated kNN query and kNN join, and the query area for federated range query, range counting and distance join is 0.001%. Recall that SMCQL-GIS and SMCQL-GISext only support two silos and are thus excluded since 6 silos are used in this test. The running time and communication cost on the five spatial queries are shown in Fig. 10.

For a fixed data size, we observe that Hu-Fu is notably more efficient than Conclave-GIS and Conclave-GISext on federated kNN query, kNN join and range counting (see Fig. 10a-10c). For federated range query and distance join, Conclave-GIS behaves the same as Public due to the honest broker, while Hu-Fu achieves the same efficiency as Conclave-GISext, which requires no honest broker.

We are more interested in the efficiency with the increase of data size. We observe that the efficiency of federated kNN query,



(a) Running time and communication cost of federated kNN query

(b) Running time and communication cost of federated kNN join

(c) Running time and communication cost of federated range counting

(d) Running time and communication cost of federated range query

(e) Running time and communication cost of federated distance join

Figure 10: Scalability test of federated spatial queries.

kNN join and range counting is insensitive to the increase of the data size. This is because the increase of data size mainly affects the time cost of plaintext primitives, which only accounts for a small portion (due to efficient indices in each silo) in the running time. In contrast, the running time and communication cost of federated range query and distance join notably increase with the increase of the data size because more spatial objects are retrieved in each silo, which leads to a higher running time for both plaintext primitives (plaintext range query) and secure primitives (secure set union).

Takeaways. Hu-Fu trivially scales with data size for federated kNN query, kNN join and range counting because these queries are relatively insensitive to data size. The running time and communication cost of Hu-Fu increase with the data size for federated range query and distance join, yet Hu-Fu is still reasonably efficient for these two queries on large-scale data. For example, in Hu-Fu, a federated range query takes 250ms running time and 2.6MB communication cost on the data size of 10^9.

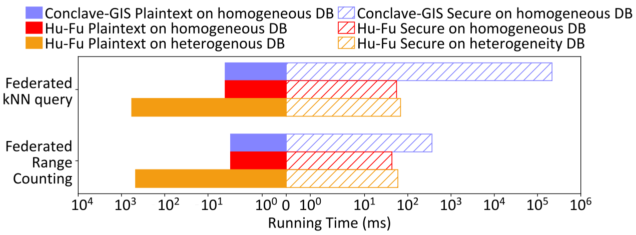


Figure 11: Running time breakdown.

7.4 Results on Heterogeneous Silos

This experiment aims to demonstrate the feasibility of Hu-Fu on heterogeneous spatial databases. Specifically, we use 6 different databases for each silo on the BJ dataset: PostGIS [35], MySQL [44], SpatiaLite [38], Simba [47], GeoMesa [21], and SpatialHadoop [12]. Other parameters are set as the default values as in Sec. 7.2.

Fig. 11 plots the running time breakdown *i.e.* plaintext vs. secure primitives for radius-unknown (kNN query) and radius-known (range counting) queries. We make the following observations.

- Given homogeneous underlying spatial databases (PostGIS), our Hu-Fu significantly reduces the running time of secure primitives *e.g.* $3,935.4\times$ compared with Conclave-GIS for federated kNN query. Such acceleration in secure primitives is the primary contributor to Hu-Fu's gain in running time.
- Heterogeneous underlying spatial databases affect the running time. Specifically, the running time of plaintext primitives is limited by the slowest spatial database, which may increase the overall query processing time. In this experiment, the running time of plaintext primitives notably increases from 4ms to 579ms when replacing PostGIS with heterogeneous databases (where SpatiaLite and MySQL are the slowest), which takes even longer than the secure primitives in Hu-Fu. The running time of secure primitives also marginally increases due to idle waiting for the local results from the slowest silo.

Takeaways. Hu-Fu functions with silos running heterogeneous databases. Although Hu-Fu dramatically speeds up the secure primitives in a federated spatial query, the efficiency of plaintext primitives in each silo's databases may affect the overall running time. Particularly, the time cost of plaintext primitives can be limited by the slowest database in the federation. To unleash the full potential of Hu-Fu, fast spatial databases in each silo are recommended.

8 RELATED WORK

Distributed spatial database systems are popular solutions to query processing on big spatial data. These systems improve query processing via data partition and indexing techniques (*e.g.* R-tree [36]) in Hadoop (*e.g.* SpatialHadoop [12] and Hadoop-GIS [1]) or Spark (*e.g.* Simba [47], GeoSpark [51], and LocationSpark [39]). However, the data partition techniques are inapplicable in a data federation since the entire data is held by the autonomous data silos. Moreover, security is not the major concern in these systems.

Past studies of secure spatial query processing mainly focus on encrypted databases [19], where data is encrypted and stored in a third-party platform (*e.g.* a cloud platform) to process queries securely. For example, [14, 24, 45, 49] study the secure kNN query on encrypted databases and [42, 46] focus on securely processing range queries. In these studies, a data owner outsources its data and hence the sensitive data is encrypted before being uploaded to a third party. Intuitively, homomorphic encryption techniques (*e.g.* Paillier [33] and SEAL [30]) are used to guarantee security. Different from this setting, in a data federation, data silos autonomously manage their own data and hence do not need to encrypt their own data and upload it to a third party.

Rather than the general distributed databases or outsourced databases, our work is more aligned with the problem settings of federated databases and data federation, where the entire dataset is held in multiple autonomous databases. The research on federated database dates back to 1979 (see surveys [20, 37]). Early efforts focused on finding solutions to access data in autonomous databases [32], while recent studies on federated databases support diverse data types, *e.g.* on federated graph databases [41].

Data federation is an emerging concept developed from federated databases. It shares a similar architecture with federated database. Yet, the *major difference* is that a data federation imposes certain secure requirements during query processing, while a federated database does not. For example, SMCQL [2] is the first secure query processing solution over a data federation and Conclave [40] is the state-of-the-art solution. Wang *et al.* [43] explored join-aggregate queries over a data federation of two silos and Ge *et al.* [17] studied secure functional dependency discovery in a data federation. All these studies adopt SMC techniques to achieve secure query processing for *relational* data with *exact* results.

Other studies investigate *approximate* query processing over a *relational* data federation. For example, Shrinkwrap [3], SAQE [4] and Cryptϵ [10] use differential privacy to trade off between accuracy and efficiency in query processing. In contrast, we focus on *exact* query processing, since accurate results can be crucial for spatial applications like contact tracing [16].

In short, our work is inspired by the emerging trend of secure query processing over a data federation, yet focuses on spatial queries with exact results. Our Hu-Fu significantly improves the efficiency of federated spatial queries over the extensions of SMCQL [2] and Conclave [40], the state-of-the-arts for relational data.

9 CONCLUSION

In this paper, we propose the first system Hu-Fu for efficient and secure spatial queries over a data federation. Existing solutions are inefficient to process such queries due to excessive secure distance operations and the usage of general-purpose secure multi-party computation (SMC) libraries for implementing secure operators. To overcome the inefficiency, we design a novel query rewriter to decompose the spatial queries into as many plaintext operators and as few secure operators as possible. In particular, our secure operators involve no distance operation and have dedicated implementations faster than general-purpose SMC libraries. Moreover, Hu-Fu supports heterogeneous spatial databases (*e.g.* PostGIS, Simba, GeoMesa, and SpatialHadoop), as well as query input in native SQL. Finally, extensive experiments show that Hu-Fu is up to 4 orders of magnitudes faster and takes 5 orders of magnitudes lower communication cost than the state-of-the-arts. In the future study, we plan to support more spatial queries and analytics in Hu-Fu, *e.g.* spatial keyword search.

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A SECURITY ANALYSIS

The security analysis of our query rewriter is based on the composition lemma in [18] (Section 7.3.1). The lemma states that given a secure protocol $\pi^{g|f}$ that can securely compute g based on a plaintext query f and a secure protocol π^f for operation f, the operation g can be securely computed by executing protocol $\pi^{g|f}$ but substitutes every plaintext query f with an execution of π^f. We prove the security of query rewriter for radius-known and radius-unknown queries separately.

- **Security of Radius-Known Queries.** Federated range query, range counting and distance join belong to *radius-known queries*. For *federated range query* and *distance join*, the secure protocol $\pi^{g|f}$ is the secure set union (Def. 8) based on the query results of one or multiple plaintext range queries over the federation. The protocol π^f corresponds to the plaintext range query (Def. 5). The protocol π^f is secure, since the plaintext range query only occurs in each silo, which will not leak any information to other silos. From the composition lemma, federated range query and distance join are secure against semi-honest adversaries. Federated range counting is also secure based on a similar proof (*i.e.* replacing $\pi^{g|f}$ with the secure summation in Def. 6 and π^f with the plaintext range counting in Def. 5).
- **Security of Radius-Unknown Queries.** The federated kNN query and kNN join belong to *radius-unknown queries*. For federated kNN query (Alg. 1), let protocol π^f be the secure comparison between k and the local counts. The security of π^f can be proved in the same way as before. Denote protocol $\pi^{g|f}$ as Alg. 1 based on the plaintext comparison query. We then show protocol $\pi^{g|f}$ is also secure. Assuming semi-honest adversaries, each silo can simulate its view of the execution of the protocol. Specifically, knowing the range $[l, u]$ used at the beginning of a round, each silo can compute *thres* used in that round. If *thres* is the same as the final radius, it concludes that the protocol must have ended in this round. Otherwise, it simply updates the range to that side of *thres* which contains the final radius. Along with the knowledge of the initial range, this shows that each silo can simulate the execution of the protocol, which means the protocol $\pi^{g|f}$ is secure. Thus, our Alg. 1 is secure against semi-honest adversaries based on the composition lemma. The security of federated kNN join can be proved similarly.

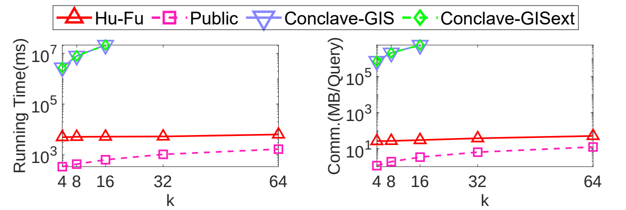

Figure 12: Performance of federated kNN join when varying k.

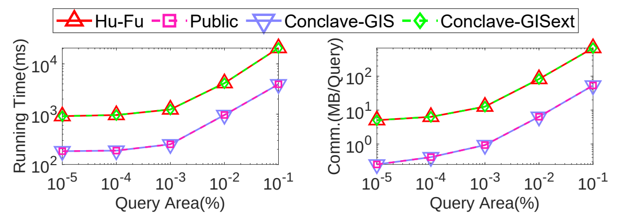

Figure 13: Performance of federated distance join when varying query area.

B ADDITIONAL EXPERIMENTAL RESULTS

Fig. 12 illustrates the results of federated kNN join on the BJ dataset when varying the value of k . As is shown, Hu-Fu is at least 553× faster and takes 27, 404× lower communication cost than Conclave-GIS. As the parameter k of federated kNN join increases from 4 to 64, the running time and communication cost of Hu-Fu only increase by 28% and 48% respectively, because the parameter k has relatively marginal impact on the federated kNN query and a federated kNN join is decomposed into multiple federated kNN queries for all the compared solutions.

Fig. 13 presents the performance of federated distance join on the BJ dataset when varying the query area. Note that partial results of Conclave-GIS and Conclave-GISext (when $k > 16$) are not provided, since they take longer than 6 hours to process this query. The result of federated distance join when varying the query area shows a similar pattern with that of federated range query. This is because a federated distance join is decomposed into multiple federated range queries for all the compared solutions. The increase of both running time and communication cost is caused by the increase of the number of retrieved spatial objects.