Private and Secure Fuzzy Name Matching

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ABSTRACT

Modern financial institutions rely on data for many operations, including a need to drive efficiency, enhance services and prevent financial crime. Data sharing across an organisation or between institutions can facilitate rapid, evidence-based decision making, including identifying money laundering and fraud. However, data privacy regulations impose restrictions on data sharing. Privacy-enhancing technologies are being increasingly employed to allow organisations to derive shared intelligence while ensuring regulatory compliance.

This paper examines the case in which regulatory restrictions mean a party cannot share data on accounts of interest with another (internal or external) party to identify people that hold an account in each dataset. We observe that the names of account holders may be recorded differently in each data set. We introduce a novel privacy-preserving approach for fuzzy name matching across institutions, employing fully homomorphic encryption with locality-sensitive hashing. The efficiency of the approach is enhanced using a clustering mechanism. The practicality and effectiveness of the proposed approach are evaluated using different datasets. Experimental results demonstrate it takes around 100 and 1000 seconds to search 1000 names from 10k and 100k names, respectively. Moreover, the proposed approach exhibits significant improvement in reducing communication overhead by 30–300 times, using clustering.

PVLDB Reference Format:

Harsh Kasyap, Ugur Ilker Atmaca, Carsten Maple, Graham Cormode, and Jiancong He. Private and Secure Fuzzy Name Matching. PVLDB, 14(1): XXX-XXX, 2020.

doi:XX.XX/XXX.XX

PVLDB Artifact Availability:

The source code, data, and/or other artifacts have been made available at https://github.com/harshkasyap/fuzzy-psi.

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Proceedings of the VLDB Endowment, Vol. 14, No. 1 ISSN 2150-8097. doi:XX.XX/XXX.XX

1 INTRODUCTION

Name matching presents distinct challenges compared to conventional string matching since name orthography cannot be standardized and continuously evolves with the creation of new variations in names. There is often not a single "correct" way to spell a name, presenting challenges that could be mistaken for typographical errors or misspellings; however, this is not necessarily the case. While conventional string matching can overcome misspellings by analyzing word frequency and rarity [35], each character in a name has substantial significance, thereby amplifying the complexity of the name search process. For example, although "Mary Janes" and "Marie Jones" are visually similar names, they are more likely to represent different individuals than result from a typographic error or a deliberate modification to avoid detection. Entity resolution, also referred to as record linkage or object matching, is designed for identifying records referring to the same real-world entity [31].

Entity resolution is a critical task in data management [49], with numerous applications in various sectors, including finance [11] and healthcare [23]. It is employed for data cleaning and integration. It is also used to improve the accuracy, efficiency, and security of transactions in finance. Particularly in scenarios lacking distinct identifiers, these systems are vital for mitigating the risks associated with misidentification, fraud, and potential security breaches. In financial services, it is common to encounter variations of customer names in different forms, including misspellings, abbreviations, inconsistent formatting of first, middle, and last names, nicknames, variations in case usage, acronyms, leading and trailing spaces, and other similar variations [3]. This can create multiple identities with different names for the same customer, which may result in extra time and research spent identifying customer accounts and corresponding risks. Furthermore, a customer could maliciously use name variations to avoid detection by fraud prevention or antimoney laundering systems [20].

International organisations operating within sectors such as finance are increasingly governed by expanding regulations for the sharing of customer data, including cross-border data sharing between the branches of the same organisation in different countries. However, efficient service execution, especially in areas such as fraud detection and anti-money laundering, requires data mobility while following regulatory compliance. Private set intersection (PSI) and fuzzy (i.e., approximate) PSI methods have been developed to privately compute exact and similar matches, respectively [12, 17, 30, 44, 47]. These methods typically comprise two

principal stages: (1) *blocking* to bring together potentially similar items, and (2) *matching* to report a set of matches [29].

Locality-Sensitive Hashing (LSH) is employed in fuzzy PSI methods. Unlike conventional hashing techniques, LSH allows similar inputs to be placed in the same hash bucket, thus creating effective signatures for given strings [1]. These signatures can be compared using a variety of metrics, including Jaccard similarity, Cosine similarity, Hamming distance and Euclidean distance. This versatility allows for the customisation of similarity measurement to meet the specific needs of the use case. Despite their lossy encoding nature, LSH signatures do not entail privacy protection [42]. Thus, we must adopt formal security measures to ensure privacy.

Fuzzy matching involves private computation of the distance between two items. This distance is then compared to a predetermined similarity threshold to determine a match. Privacy Enhancing Technologies (PETs), such as Secure Multi-Party Computation (SMPC) or Homomorphic Encryption (HE), are commonly employed for private similarity computation [17, 47]. SMPC-based approaches have been proposed for fuzzy name matching in recent studies [30, 47]. However, these solutions allow both parties to learn the matching items, and also incur huge communication costs. This does not meet the requirements of the scenario we consider, where one branch seeks to query another branch securely from a different jurisdiction. We require that the responding branch remains unaware of the query's content and any potential matches. Furthermore, while existing solutions tend to prioritize recall, precision can be of greater significance in the financial context. An increased occurrence of false positives may not only lead to privacy breaches but also jeopardise compliance with regulatory standards; hence, it can indirectly result in significant reputational harm.

Homomorphic Encryption-based approaches that process encrypted data can ensure that sensitive information remains private throughout the entire operation. This makes HE particularly attractive for cross-border financial data-sharing use cases subject to diverse data privacy regulations, since it reduces the risk of data breaches. HE simplifies compliance with these regulations by eliminating the need to decrypt data, even during processing [5, 10, 12, 44, 46]. However, a vital aspect to consider is the increasing computation cost, which introduces challenges in deploying HE-based approaches, particularly in real-time applications. The HE-based solutions presented thus far [17] have primarily utilised additive homomorphic encryption such as Paillier HE, based on the Decisional Composite Residuosity problem [36]. However, recent advancements in HE has shifted focus to lattice-based cryptography, such as CKKS (Cheon-Kim-Song) HE, which offers enhanced quantum resistance and is more adept at handling complex operations involving real or complex numbers [15]. In the context of fuzzy name matching in finance, where precision and security are paramount, the CKKS scheme's ability to handle real or complex numbers and its robustness against quantum computing threats make it an appropriate choice for secure computations.

This paper introduces a novel privacy-preserving fuzzy name matching scheme that offers a practical solution with a formal security guarantee for this real-world problem in the financial sector. Our scheme relies on the cosine similarity of the signatures produced by MinHash, employing an effective LSH technique for textual data within the context of CKKS HE. Cosine similarity is

preferred over other similarity metrics because of its independence over the length of records. Further, we utilise clustering to address the computational and communication overheads associated with using HE. Clustering is implemented using cosine similarity based K-Means, on the responder side. We present out implementation of the proposed scheme to validate its practicality for processing up to 1 million records. It has also been scaled for *m-to-n* unbalanced searching ($m \ll n$), using batching in HE. It results in only a partial increase (not linear) in computational and communication overheads. Clustering significantly reduces the search time, as the encrypted search operation is performed column-wise. A column has one element from each cluster, which is reduced to a single name from the closest cluster before performing a similarity check. All the operations are performed in the encrypted domain, thus leaking no information to the responder. It also reduces memory consumption due to the column-wise operations in the encrypted domain. Clustering reduces communication overhead by a huge margin. For example, it incurs 314GB of communication overhead if 100 names are searched serially in a million names because all the similarity results are returned in the encrypted domain. It reduces by orders of magnitude to 1-2GB using clustering. While clustering brings a drop in recall by a small amount, it preserves perfect precision. The key contributions of this paper are outlined as follows:

- We propose a novel secure and private fuzzy name matching scheme by computing encrypted cosine similarities using CKKS encryption over MinHash signatures of names. The proposed scheme facilitates approximate search without publishing record linkage to both parties.
- We enhance the practicality of the scheme by integrating clustering based on cosine similarity. Clustering reduces the search space and facilitates quicker matching by computing column-wise searches. It incurs a minor cost in recall while maintaining precision. It significantly reduces the computation and communication overheads.
- Evaluation of the scheme is presented in terms of security, accuracy, and performance through a proof-of-concept implementation over different datasets and settings. The empirical results, alongside our theoretical analysis, demonstrate the suitability of our solution.

2 PRELIMINARIES

This section provides an in-depth exploration of the foundational elements underpinning the privacy protocols required for the proposed framework.

2.1 Locality Sensitive Hashing (LSH)

Given a dataset \mathcal{A} comprising n records each with D dimensions, a query string q seeks to retrieve the closest k records based on a defined distance function. Locality Sensitive Hashing (LSH) is a widely adopted method for effective approximate nearest neighbor searches in high-dimensional space [26]. Consider a set of functions $\mathcal{H} = \{h: \mathcal{D} \to \mathcal{U}\}$, where each function h maps elements from a domain \mathcal{D} to a set \mathcal{U} . A function set \mathcal{H} is deemed *locality-sensitive* if it satisfies the following conditions:

- (i) for any $u, v \in \mathcal{D}$, if the distance $d(u, v) \leq r$, then the probability $\Pr_{\mathcal{H}}(h(u) = h(v)) \geq p_1$;
- (ii) if $d(u, v) \ge (r + \epsilon)$ where $\epsilon \ge 0$, then the probability $\Pr_{\mathcal{H}}(h(u) = h(v)) \le p_2$,

where $\Pr_{\mathcal{H}}$ denotes the probability with respect to a randomly chosen function h from the set \mathcal{H} [32]. The primary benefits of LSH lie in its ability to perform queries in sub-linear time in relation to the size of the data, with theoretical guarantees regarding accuracy, and in its usefulness for scenarios where data is dynamic or undergoes frequent modifications, as hash functions are data-agnostic and do not require any adjustments while in use.

MinHash is a prominent technique in LSH, particularly effective for estimating similarities between sets in high-dimensional spaces. It uses a random permutation function π , which maps a universal set Ω onto itself. Given a specific set u, which is a subset of Ω , MinHash applies this permutation function π to each element within u. The core idea of MinHash is to identify the smallest value resulting from these permutations. Formally, this is expressed as $h_{\min}^{\pi}(u) = \min\{\pi(x) \mid x \in u\}$, where $h_{\min}^{\pi}(u)$ denotes the MinHash value for the set u [9]. This minimum value effectively captures a signature of the set for similarity comparisons, making MinHash a powerful tool for approximate nearest neighbor searches in large and complex datasets [48].

2.2 Homomorphic Encryption (HE)

Conventional encryption is vital for protecting data confidentiality, stored and in transit, but typically requires decryption to allow computations. In 1978, Rivest introduced the concept of homomorphism for encryption, enabling computations on encrypted data without decryption, leading to numerous research efforts in homomorphic encryption (HE) schemes [39].

Existing schemes, namely BGV [7] and BFV [8], perform arithmetic on integers, while the CKKS scheme [15] enables approximate arithmetic on real or complex numbers. All these schemes are rooted in the ring-learning-with-errors (RLWE) assumption, ensuring their security. Despite variations in their encryption techniques, they share a common data structure (such as polynomials) for representing ciphertexts. They all feature analogous fundamental homomorphic operations and employ comparable methods for maintaining ciphertext integrity, such as key switching. For this study, we employ CKKS due to its ability to perform approximate homomorphic computations across both the real and complex number domains.

The security of the CKKS scheme relies on the Ring Learning With Errors (RLWE) problem. It incorporates Gaussian noise primarily in encryption and key switching. It addresses managing precision and approximation errors, particularly in operations like rescaling and encoding, which are vital to deal with to maintain the error within acceptable limits for the application.

Formally, let the quotient ring be defined as $R_Q = \mathbb{Z}_Q[X^N + 1]$, where Q represents a substantially large modulus integer and N signifies a degree which is a power of two. This is the polynomial degree over which the CKKS scheme operates. In this context, Q undergoes decomposition into the product of smaller, pairwise co-prime moduli, represented as $Q = \prod_{i=0}^L q_i$, where each q_i is one of these smaller moduli. Consequently, this allows for

a polynomial a to be represented in the Residue Number System as $a = ([a]_{q_0}, \ldots, [a]_{q_i}) \in \prod_{i=0}^L R_{q_i}$, where each component is defined as: $[a]_{q_i} = a_0 + a_1X + \ldots + a_{N-1}X^{N-1} \in R_{q_i}$.

Key Generation: The secret key sk is constructed by selecting a key s sampled from a distribution χ_{key} over R. The public key is then formed as a pair $pk = (b, a) \in R_Q^2 P$, where b is calculated using the equation $b = -a \cdot s + e$, and e represents the error polynomial from a Gaussian distribution.

Encryption and Decryption: To encode a vector of up to N/2 real numbers, a plaintext polynomial m with N coefficients modulo Q is used. The plaintext message is then encrypted to produce a ciphertext $ct = (ct_0, ct_1) \in R_Q^2 P$. The decryption process retrieves the original message as $m' = ct_0 + ct_1 \cdot s \mod Q$, which approximates of the original message, represented as $m' \approx m$. The error introduced during encryption is small and controlled, ensuring that the decrypted message remains a close approximation to the original plaintext.

Addition (CKKSAdd): Given two ciphertexts $ct = (c_0, c_1)$ and $ct' = (c'_0, c'_1)$, the homomorphic addition is $ct_{\rm add} = ct + ct' = (c_0 + c'_0, c_1 + c'_1)$. This operation produces a new ciphertext that encrypts the sum of the underlying plaintexts, maintaining the property $c_0 + c_1 \cdot s \approx m + m' \mod Q$, where m and m' are the encoded plaintexts corresponding to ct ct' respectively.

Multiplication (CKKSMult): The homomorphic multiplication of given ciphertexts $ct=(c_0,c_1)$ and $ct'=(c_0',c_1')$ for messages m and m' involves a component-wise product of the ciphertexts, followed by a relinearization step to reduce the degree of the resulting ciphertext as $(c_{\times,0},c_{\times,1},c_{\times,2})=(c_0\cdot c_0',c_0\cdot c_1'+c_1\cdot c_0',c_1\cdot c_1')$. This is a tensoring operation, where the ciphertext degree is increased from 2 to 3 [2]. The relinearization process, using key-switching, transforms the 3-degree ciphertext back to a 2-degree ciphertext and the final ciphertext ct_{mult} satisfies $c_{\times,0}+c_{\times,1}\cdot s+c_{\times,2}\cdot s^2\approx m\cdot m'$ mod Q, however, it is associated with the squared scaling factor which is later reduced back by the rescaling procedure.

Multiplication by constant (CKKSMult_{const}): When a ciphertext $ct = (c_0, c_1)$ is multiplied by a constant (plaintext), it becomes $(c_0, m, c_1, m) \mod Q$, where plaintext is first encoded to m.

On top of this, HE supports batching, which packs multiple messages in one ciphertext, thus enabling one operation to act over all the messages. It improves performance both in terms of computation and communication.

3 RELATED WORK

Privacy-preserving record linkage (PRL) represents a significant and common challenge in various application fields, such as finance and healthcare [19, 45]. The earlier techniques primarily focused on identifying records with the same identifiers across different datasets, known as private set intersection (PSI) [18]. A range of protocols have been developed for PSI, including circuit-based protocols [13, 37], oblivious polynomial evaluation enabled by homomorphic encryption for enhanced security and privacy [10, 14, 24], key agreement [28], and Bloom filters [16]. However, traditional PSI protocols typically lack the functionality to identify similar but not identical records. Such similarities often arise from data capture errors, particularly in genomics, surveillance, and finance. These challenges highlight the importance and relevance of the topic.

Fuzzy PSI protocols are formed by employing a 'closeness function' to assess the degree of similarity between records. Cryptographic techniques like SMPC [27] or HE [5] are integrated to ensure privacy. A predetermined distance threshold is commonly incorporated into the analysis to assess the degree of similarity between the records [12]. Uzun et al. [44] developed a protocol for computing private intersections of fuzzy biometric data with sublinear communication scalability as dataset sizes increase, mainly for real-time surveillance scenarios.

In the finance sector, however, regulatory compliance dictates specific requirements; notably, the responding party must remain unaware of matching items. HE-based protocols offer significant privacy benefits in PRL applications. Neither party should gain any knowledge about the recorded details of any items held by the other party. This ensures a stringent level of privacy for sensitive financial data. Thus, the focus is shifting from standard PRL to secure, private searches. A major limitation of SMPC-based PRLs [30, 47] is that they make the intersection of data accessible to both parties. This can unintentionally expose the querier's search criteria and underlying intentions by analysing the query's structure, such as the query range [34]. However, HE-based protocols can keep the responder unaware of any matching results, thereby preserving the complete privacy of the querier's inquiry, which is suitable for compliance requirements. Applying HE to string data requires a multi-step process, primarily due to HE's inherent design for numerical operations. The first step is converting the string into a numerical format [22], such as binary encoding, or assigning a number to each character based on encoding schemes like ASCII or Unicode. These privacy benefits provide reassurance and confidence in the effectiveness of HE-based protocols.

Fuzzy PSI protocols typically involve two primary phases: blocking and matching [29, 47], where the HE-based evaluation is employed for the matching phase. For blocking, LSH approaches are most often used for their ability to incorporate a numeric representation of a record [21]. Unlike traditional hash functions, LSH aims to hash similar inputs into the same hash value, encouraging collisions such as grouping all similar names into one single digest value or into lists of digests that share common elements [1, 30]. However, there is a potential risk if LSH hashes expose private information about the input data, as highlighted in Turati et al. [42]. Thus, LSH hashes are commonly processed using a privacy-preserving mechanism in the matching phase of PSI protocols [47]. Our approach not only ensures compliance with stringent privacy regulations in finance but also addresses the limitations of existing PRL methods for regularity compliance in finance, balancing the need for high precision and recall, thereby reducing false positives and enhancing data utility.

4 PROBLEM DEFINITION

4.1 Problem Statement

Consider two distinct private datasets managed by separate organisations *A* and *B*. Each record in both datasets represents an individual (or object) identified by their name and additional information such as date of birth. While these datasets may contain information about the same individuals, they might contain errors

due to misrecording or intentional manipulation, resulting in inaccuracies. The objective of this study is to securely search for a record (r_i^A) from A through all the records of B, retrieving all those that correspond to the same real-world identity. The search should ensure that no additional information is disclosed to either organisation, apart from the matching score.

The matching function relies on a distance function due to the presence of inaccuracies within the datasets. Let a similarity function be $S(\cdot,\cdot):\to [0,1]$ and a threshold value t>0. Given records r_i^A and r_i^B , the matching function $M(\cdot,\cdot):\to 0$, 1; $M(r_i^A,r_i^B)=1$, if $S(r_i^A,r_i^B)\geq t$, then the pair of (r_i^A,r_i^B) is declared to correspond to matching records.

4.2 Threat Model

This study assumes that the system's security is adequately safeguarded against external threats. The proposed approach primarily addresses internal privacy concerns between A and B. Thus, we consider a semi-honest (i.e., honest-but-curious) threat model where participating entities comply with the steps of the scheme and do not corrupt their inputs, yet they may attempt to gather/infer as much information as possible without deviating from or altering any aspect of the scheme [33, 38]. In a cross-border data sharing scenario, the proposed scheme is implemented between two branches of the same entity, operating under a mutual trust. Both branches execute the protocol using identical pre-processing steps and parameters for their respective local data repositories. These entities cannot share the data due to regulatory mandates. The scheme enables only the querying party to gain insights from the similarity evaluation while ensuring that the responding party does not acquire any information regarding the queries or the respective evaluation results. Moreover, the querying party should not be able to infer anything more than the matching.

4.3 Definitions

DEFINITION 1 (SEMANTIC SECURITY UNDER CHOSEN PLAINTEXT ATTACK). An encryption scheme E is semantically secure under a chosen plaintext attack if, for any efficient (polynomial-time) adversary $\mathcal A$ that is allowed to choose plaintexts and observe their corresponding ciphertexts, $\mathcal A$ cannot distinguish between the encryption of two equal-length messages. Formally, for all pairs of plaintexts N_A and N_B .

$$\Pr\left[\mathcal{A}\left(\operatorname{Enc}\left(N_{A}\right)\right)=1\right]\approx\Pr\left[\mathcal{A}\left(\operatorname{Enc}\left(N_{B}\right)\right)=1\right].$$

Even with the ability to choose plaintexts and after receiving the corresponding ciphertexts, \mathcal{A} should not be able to gain any information about the original plaintext or distinguish between them. This is fundamental to ensure the confidentiality of encrypted messages.

Definition 2 (Secure Matching). The scheme securely evaluates the similarity function (S) in the semi-honest threat model if there exist probabilistic polynomial-time algorithms P_A^* and P_B^* , such that

$$\left[P_{A}^{*}\left(N_{A},S(N)\right),S(N)\right]\stackrel{c}{\equiv}\left[\operatorname{View}_{\operatorname{Org}_{A}}(N),\operatorname{Out}_{\operatorname{Org}_{B}}(N)\right]$$
 and

 $[P_R^*(N_B, S(N)), S(N)] \stackrel{c}{=} [View_{Org_R}(N), Out_{Org_A}(N)].$

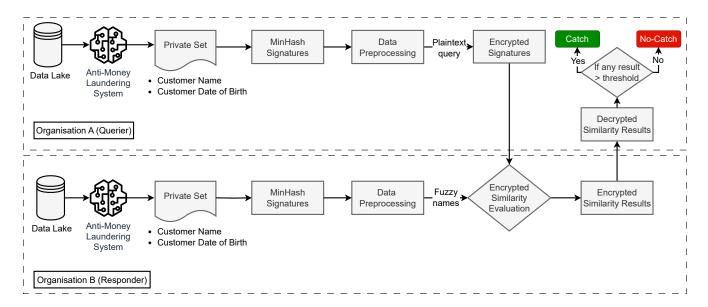


Figure 1: Workflow diagram of the proposed secure and private fuzzy name matching scheme in anti-money laundering systems; the homomorphically encrypted MinHash signatures from the querier are shared with the responder to conduct encrypted similarity comparisons. The querier decrypts the encrypted results to find 'Catch' or 'No-Catch', based on a threshold.

5 PROPOSED SCHEME

This section details the proposed scheme for privacy-preserving fuzzy name matching. We begin by describing the system architecture and providing a clear understanding of its foundation. Then, we break down the pivotal steps, encompassing local data preprocessing, the derivation of MinHash signatures, private similarity measurement, and adjustments for the system's viable real-world implementation.

Overview: Figure 1 demonstrates our proposed system architecture with two organizations, A and B. Both of them have their own private data lake and anti-money laundering (AML) systems. In this way, they develop their own private list of possible fraudsters, which includes their name and additional information like date of birth. Since LSH preserves the pattern of names, A and B encode names using MinHash and generate signatures. A is now looking for a possible fraudster in organisation B. A normalises the generated MinHash signatures (to query) and then employs fully homomorphic (CKKS) encryption to securely share it with B. B computes the dot product with the received encrypted query from A with all the normalised MinHash signatures held by B, serially. It should be noted that the dot product (sum of component-wise products) is a supported operation in fully homomorphic encryption. Here, the dot product between two normalised vectors represents the cosine similarity between them. Finally, A receives back the encrypted similarity result and decrypts it to determine whether the name is present in *B*'s data lake. Now, we discuss each component in detail.

5.1 Dataset Encoding

Algorithm 1 outlines the MinHash signature generation methodology. First, the sets of shingles (i.e., n-grams $\{g_1, g_2, ..., g_n\}$) are generated for the records in A and B which are two distinct entities. These sets contain all possible sequences of consecutive n

```
Algorithm 1: MinHash signature generation
 Data: Input Name N,
          Shingle Size S,
          Number of Permutations P
 Result: MinHash signature \vec{N} of length P
 begin
     Function GenerateShingles (N);
     begin
          shingles \leftarrow \emptyset;
                                      > sets of characters;
          for i \leftarrow 0 to length(N) - S do
              shingle \leftarrow SubString (N, i, i + S);
              shingles.add(shingle);
          return shingles;
      shingles \leftarrow GenerateShingles(N);
     hashes \leftarrow \emptyset;
     forall shingle \in shingles do
          hash \leftarrow HashFunction (shingle);
          hashes.add(hash);
     for i \leftarrow 1 to P do
          \vec{N}[i] \leftarrow \infty;
          forall hash \in hashes do
              PermutedHash \leftarrow i random permutation
                functions of hash;
               \vec{N}[i] \leftarrow \min(\vec{N}[i], \text{ PermutedHash});
     return \vec{N};
```

characters, including spaces. The hash value $h_i = H(g_i)$ for each g_i is calculated using a hash function H. Then, MinHash technique

is applied to find the minimum hash value among these n-grams, which represents the MinHash signatures as $\min(H(q_i))$.

The size of the *n*-gram is critical in determining the granularity of similarity detection. Here, the generated 3-grams are subjected to hashing using an approximate function, such as SHA-256, to produce a unique hash value. Subsequently, a set of random permutation functions is created. Increasing the number of permutation functions enhances the precision of the resultant MinHash signatures. Simultaneously, this increases the size of the signatures, thereby enhancing the accuracy, but also increasing computational cost and storage requirements. Following this, a list of buckets is constructed, which serves to constrain the dimensions of the hash values. This constraint plays a pivotal role in determining the probability of hash collisions. Adjusting the maximum hash value parameter expands the range of possible hash values, lowering the probability of collisions occurring. It can be fine-tuned to balance between accuracy and computational efficiency in the hashing process.

However, performing the search in an encrypted domain serially incurs high costs, particularly huge communication overhead. Typically, B may have a huge list of names, say, $|N_B| \approx 10^6$. Computing and returning encrypted similarity scores for 10^6 names is a computation and communication-intensive task. Moreover, it will reveal the similarity scores associated with each name owned by B.

5.2 Clustering-based Matching

We integrate a clustering-based approach to enhance the performance of the scheme, in terms of computation, communication, memory, and time. The responding organisation (B) clusters its private dataset to reduce the search space for the query.

The proposed clustering-based approach entails sending approximately $\sqrt{|N_B|}$ similarity scores. It reduces both the number of comparisons and communication overhead. Algorithm 2 outlines this scheme. Assume that A has an encoded name, $\vec{N_A}$, with which it intends to perform fuzzy name matching with B's list of encoded names ($\vec{N_B}$). The following steps are executed.

- **1.** Organisation B forms approximately $\sqrt{|N_B|}$ (say k) clusters of MinHash signatures, ensuring that similar encoded values are grouped together. B uses the K-means clustering algorithm, based on the cosine similarity measure. Clustering can be performed offline at B before the search operation, as described in Algorithm 3. As a preprocessing step, B performs normalization and standardization of the MinHash signatures before clustering. Conceptually, we can imagine that B creates a $k \times k$ matrix, where each row represents a distinct cluster. However, it is impractical to cluster such that B gets a perfectly square matrix. For realistic datasets and distributions, it is common that some clusters will collect a much higher number of names. Thus, B needs to pad all the clusters up to the maximum number of names in any cluster. This is all handled by the Clustering function called by Algorithm 2, executed by B.
- **2.** Organisation A normalises the encoded query vector $(\vec{N_A})$ to get \hat{N}_A . It also performs standardization to get \hat{N}_{As} . Then, A encrypts $\vec{N_A}$ and $\vec{N_{As}}$ using its public key. First, A sends $E(\hat{N}_{As})$ to B, to match with centroids. This is performed by executing CompareToCentroids function of Algorithm 2.

Algorithm 2: Private Fuzzy Name Matching

Data: Query Signature $\vec{N_A}$,

Cosine Similarity Threshold τ

Result: catch (1 if match else 0)

Function CompareToCentroids $(\vec{C_k}, E(\hat{N_{As}}))$;

begin

 $E(\text{sim_scores}) \leftarrow \text{DotProduct}(\vec{C_k}, E(\hat{N_{As}});$

Serialise and send the encrypted similarity scores $E(\text{sim_scores})$ of the encrypted query (normalised and scaled MinHash signature) with the centroids;

Function ColumnWiseMatching $(C, E(\hat{N}_A), E(\vec{S}))$;

for each column in C do

 $E(\hat{N}_{B_{ij}}) \leftarrow \text{DotProduct}(E(\vec{S}), \hat{N}_{B_{column}}); \rightarrow \text{This results in}$ the encrypted name from the possible matching cluster (i) in this column (j);

 $E(\cos_score) \leftarrow \text{DotProduct}(E(\hat{N}_{B_{ij}}), E(\hat{N}_{A})); \rightarrow \text{This is}$ an in-place dot product resulting in the cosine similarity between the encrypted name and the encrypted query;

 $E(\text{score}) \leftarrow r * (E(\text{cos_score}) - \tau);$ > Subtract the threshold τ and multiply with a random number $r \in \mathbb{Z}_p^*$; Serialise and send E(score) of the encrypted name from the matching cluster in this column and the encrypted query;

begin

B completes execution of Algorithm 3 (Clustering) in offline to get clustered matrix (*C*) and centroids ($\vec{C_k}$);

A executes the below steps online;

$$\hat{N_A} \leftarrow \frac{\vec{N_A}}{|\vec{N_A}|};$$
 > Vector Normalisation;

 $\hat{N_{As}} \leftarrow \text{StandardScaler}(\hat{N_A}); \rightarrow \text{Standardize by removing the mean and scaling to unit variance;}$

 $E(\hat{N_A}) \leftarrow \text{Encrypt } \hat{N_A} \text{ with the public key of } A;$

 $E(\hat{N_{As}}) \leftarrow \text{Encrypt } \hat{N_{As}} \text{ with the public key of } A;$

 $E(\text{sim_scores}) \leftarrow \text{Sends } E(\hat{N_{As}}) \text{ to } B \text{ to invoke the function } \text{CompareToCentroids and receive encrypted similarities scores } \text{with the centroids;}$

 $sim_scores \leftarrow Decrypts E(sim_scores);$

 $\vec{S} \leftarrow$ Prepares an indicator/sign (one-hot) vector with 1 for the most matching cluster and 0's for the remaining;

 $E(\vec{S}) \leftarrow \text{Encrypts } \vec{S} \text{ with the public key of } A;$

 $E(\cos_score) \leftarrow Sends \ E(\hat{N}_A)$ and $E(\vec{S})$ to B to invoke the function ColumnWiseMatching and keeps receiving encrypted cosine similarities for each column;

 $score \leftarrow Decrypts E(score);$

 $catch \leftarrow 1 \text{ if any score} > 0$

3. Organisation B calculates the dot (inner) product of $E(\hat{N}_{As})$ with all the centroids (\vec{C}_k) . This is an inner product between ciphertext and plaintext, as defined in Algorithm 4. Thus, B calculates a vector of k similarity scores, encrypted with A's public key, as $E(\text{sim_scores})$, and sends to A.

```
Algorithm 3: Offline Data Preparation - Clustering
```

```
Data: MinHash signatures \vec{N_B}

Result: Clustered matrix (C) and Centroids (\vec{C_k})

Function Clustering (\hat{N_B}, k, iterations);

begin

Initialize random centroids \vec{C_k} = \{\vec{c_1}, \vec{c_2}, \dots, \vec{c_k}\};
```

```
\hat{N_B} \leftarrow \frac{\vec{N_B}}{|\vec{N_B}|};

\hat{N_{Bs}} \leftarrow \text{StandardScaler}(\hat{N_B});
```

repeat

Assign each \hat{N}_{Bs} to the nearest centroid based on the cosine similarity measure;

Update clusters (C) and centroids $(\vec{C_k})$ using KMeans;

until iterations;

max_size ← maximum number of elements in any cluster ofC;
Need to pad remaining clusters to this size;

for each cluster in C do

Pad *max_size* – len(cluster) dummy elements.

return clustered matrix (*C*) and list of centroids ($\vec{C_k}$);

begin

B chooses the number of clusters k close to $\sqrt{(|\vec{N}_B|)}$; Set the maximum number of repeats *iterations*; $C, \vec{C}_k \leftarrow \text{Clustering}(\vec{N}_B, k, iterations)$;

Algorithm 4: CKKS Dot (Inner) Product

for $i \leftarrow 0$ to size - 1 do

return *dotp*;

```
Data: ciphertext message 1 ct_{m1},
        ciphertext message 2 ct_{m2}/plaintext message pt_{m2}
Result: Encrypted Dot Product dotp
Function DotProduct (ct_{m1}, pt_{m2});
begin
    size ← length of the ciphertext vector;
    vector(Ciphertext) dotp;
    # parallelised for loop;
    for i \leftarrow 0 to size - 1 do
        m \leftarrow \text{CKKSEncode}(pt_{m2}[i]);
        ct_{mult} \leftarrow \mathsf{CKKSMult}_{\mathsf{const}}(ct_{m1}[i], m);
        dotp \leftarrow \text{CKKSAdd}(dotp, ct_{mult})
   return dotp;
Function DotProduct (ct_{m1}, ct_{m2});
begin
    size ← length of the ciphertext vector;
    vector(Ciphertext) dotp;
    # parallelised for loop;
```

4. Upon receiving the encrypted similarity scores with centroids, *A* decrypts to get sim_scores. Then *A* prepares an indicator (sign) vector, which assigns a score of 1 to the highest matching centroid,

 $ct_{mult} \leftarrow \texttt{CKKSMult}(ct_{m1}[i], ct_{m2}[i]);$

 $dotp \leftarrow \text{CKKSAdd}(dotp, ct_{mult})$

while all other scores are set to 0. This results in a one-hot vector (\vec{S}) of 0's and 1 of size $1 \times k$.

- **5.** Organisation A encrypts \vec{S} with its public key and sends the encrypted indicator vector $E(\vec{S})$ along with the encrypted normalised query $E(\hat{N}_A)$ to B.
- **6.** Organisation B performs column-wise operations over the matrix prepared in step 1. Each column contains one element from each cluster. B performs multiplication and addition operations to find dot/inner product between $E(\vec{S})$ and a column. This is an inner product between ciphertext and plaintext, as defined in Algorithm 4. After this operation, in the encrypted domain, B gets the normalised LSH encoded signature from the matching cluster (represented by 1 in the encrypted indicator vector). Since the result is encrypted by the public key of A, B does not learn about the position (cluster/row) of the name. For instance,

$$E([0,0,1,0,0]) \times \begin{bmatrix} \hat{N}_{B_{11}} \\ \hat{N}_{B_{12}} \\ \hat{N}_{B_{13}} \\ \hat{N}_{B_{14}} \\ \hat{N}_{B_{15}} \end{bmatrix} = E([\hat{N}_{B_{13}}])$$

where $\hat{N}_{B_{13}}$ represents the third name from the first column.

- 7. Now B finds the dot product of the output from the previous step to $E(\hat{N}_A)$. This is an inner product between ciphertext and ciphertext, as defined in Algorithm 4. This represents the encrypted cosine similarity $E(\cos_s core)$ between the querying name and the name from the matching cluster in this column.
- **8.** B subtracts the threshold (τ) from the $E(\cos_score)$ and multiplies it with a random number $(r \in \mathbb{Z}_p^*)$ to get E(score). Then, B sends E(score) to A for each column. Thus, the cosine similarities above the threshold remain positive, and others remain negative, after subtracting τ . Also, since every score is multiplied by a different random number, no relation is preserved among the distribution of scores. Steps 6-8 can be referred to in the ColumnWiseMatching function of Algorithm 2.
- **9.** Organisation A receives E(score) and decrypts it with its secret key. If the score is positive, then it can be considered as a potential approximate match present with B.

In this way, A and B execute the above steps for secure and private fuzzy name matching. After executing this protocol, A only learns whether there exists a potential match or not. These similarity results do not reveal any closeness to the query. Meanwhile, B does not learn anything throughout the whole process, neither about the query nor the response.

A novel feature of our scheme is that A does not need to wait until it receives all scores from B. There is a high probability that it may get a match (if it exists) from the results received only for a few columns. Hence, it can be understood that padding does not impact the performance of other (smaller) clusters. As we see empirically, it is common that 80-90% of names are covered in only half of the columns. The remaining half only includes 5-10% of names from one or two clusters with larger sizes.

In summary, the proposed scheme provides secure, private, efficient, fuzzy name matching based on fully homomorphic encryption. In the subsequent section, we formalize the security properties and accuracy guarantees.

6 THEORETICAL ANALYSIS

This section presents the security, privacy, and correctness analysis of the proposed scheme.

6.1 Security and Privacy Analysis

As discussed in the threat model, we consider a semi-honest (*honest-but-curious*) threat model. It means both organizations, querying (*A*) and responding (*B*), execute the secure matching (Definition 2), but are curious to learn/infer facts from the other's messages.

Theorem 1 (Querying Organisation A's Privacy). Let A's input to the scheme be (a, pk, sk) and B's input be (b), and their combined input be x. View $_{\rm Org_B}$ represents the view of B during the execution and ${\rm Out}_{\rm Org_A}$ is the output of A. Then there exists a probabilistic polynomial-time algorithm $P_{\rm R}^*$, such that,

$$[P_B^*(b, \perp), F(x)] \stackrel{c}{\equiv} [\text{View}_{\text{Org}_B}(x), \text{Out}_{\text{Org}_A}(x)],$$

where \perp denotes no output and F denotes the functions defined in Algorithm 2.

Proof. Organisation *A*'s privacy can be proved simply because *B* receives only a fixed number of ciphertexts from *A*. Ciphertexts are computationally indistinguishable [4], because of the semantic security of the encryption scheme (Definition 1). To simulate *B*'s view, P_B^* samples a random MinHash signature of the agreed encoding size, and encrypts it using *A*'s public key (Step 2 in Section 5.2). Then, it generates an array of size equal to the number of centroids, with 0's and 1 (at any random position), followed by encryption using *A*'s public key (Step 5 in Section 5.2). The remaining steps can be simulated at *B* over its inputs. □

Theorem 2 (Responding Organisation B's Privacy). Let $View_{Orga}$ represent the view of A during the execution and all other inputs as defined above. Then, there exists a probabilistic polynomial-time algorithm P_A^* , such that,

$$\left[P_A^*\left(a,F(x)\right),\bot\right]\stackrel{c}{\equiv}\left[\mathrm{View}_{\mathrm{Org}_A}(x),\bot\right].$$

Proof. Organisation *B*'s privacy relies on the randomness of the result. To simulate *B*'s view, *A* needs to generate random samples to match the outputs generated by Step 8 in Algorithm 2. The original outputs returned by *B* are the scores, *i.e.*, $r*(E(\cos_s - \tau), \text{ where cos_score})$ is the cosine similarity between the encoding of *A*'s input and encodings of *B*, τ is the threshold defined for cosine similarity match, and *r* is a random number $(r \in \mathbb{Z}_p^*)$. Cosine similarity ranges between 0 and 1. Subtracting τ rescales it between $-\tau$ and $1-\tau$. Multiplying *r* with $\cos_s - \tau$ results in either a positive or negative number, which depends on the sign value of $\cos_s - \tau$. Since the returned score is random, due to *r*, it does not leak anything about actual cosine similarity, other than revealing whether there is a potential match or not.

6.2 Correctness

The correctness of our proposed scheme depends on the cosine similarity of encoded names (MinHash signatures). To calculate cosine similarity, we implement a CKKS dot (inner) product between normalised ciphertext-plaintext and ciphertext-ciphertext encoded names. Thus, we prove the correctness of the dot product under

both scenarios. First, we describe our assumptions based on the arithmetic of approximate numbers in CKKS [15, 25].

Assumption 1. A ciphertext $\left(ct \in \mathcal{R}^2_{q_\ell}, \ell, v, B\right)$ is a valid encryption of $m \in \mathcal{S}$ if $\|m\|_{\infty}^{\operatorname{can}} \leq v$ and $\langle ct, sk \rangle = m + e \pmod{q_\ell}$ for some polynomial $e \in \mathcal{S}$ with $\|e\|_{\infty}^{\operatorname{can}} \leq B$.

Assumption 2. The noise due to encoding and encryption is bounded by $B_{\text{clean}} = 8\sqrt{2}\sigma N + 6\sigma\sqrt{N} + 16\sigma\sqrt{hN}$.

Assumption 3. The noise due to rescaling is bounded by $B_{\text{scale}} = \sqrt{N/3} \cdot (3 + 8\sqrt{h})$.

Assumption 4. For addition and multiplication by plaintext (constant) a, $(ct_{\mathrm{add}}, \ell, \nu + \|a\|_{\infty}^{\mathrm{can}}, B)$ and $(ct_{\mathrm{mult}}, \ell, \|a\|_{\infty}^{\mathrm{can}} \cdot \nu, \|a\|_{\infty}^{\mathrm{can}} \cdot B)$ are valid encryptions of m+a and am, respectively.

Assumption 5. For addition and multiplication between any two ciphertexts, ct_1 and ct_2 , $(ct_{add}, \ell, v_1 + v_2, B_1 + B_2)$ is valid encryption of $m_1 + m_2$ and $(ct_{mult}, \ell, v_1v_2, v_1B_2 + v_2B_1 + B_1B_2 + B_{mult}(\ell))$ for $m_1 \cdot m_2$, where $B_{ks} = 8\sigma N/\sqrt{3}$ and $B_{mult}(\ell) = P^{-1} \cdot q_\ell \cdot B_{ks} + B_{scale}$.

Theorem 3. Let $m_1 = P_N(v_1), m_2 = P_N(v_2)$ be the polynomial representations of $\frac{N}{2}$ -dimensional vectors v_1, v_2 , respectively. The ciphertext $ct_1 \in R_{q_l,N}$ is the encryption of m_1 , while m_2 is the encoding of a plaintext (constant) vector $v_2 = [a_1, a_2, \ldots, a_{\frac{N}{2}}]$. Algorithm 4 takes the input of ciphertext and plaintext, then returns the ciphertext of a polynomial $P_N(\langle v_1, v_2 \rangle, \langle v_1, v_2 \rangle, \ldots, \langle v_1, v_2 \rangle)$ with a noise bounded by $B_{\text{dotp}} \leq \frac{N}{2} \cdot \|a\|_{\infty}^{\text{can}} \cdot B$.

Proof. Consider two vectors of size $\frac{N}{2}$, with an encrypted vector $\vec{ct_1} = (ct_{11}, ct_{12}, \dots, ct_{1\frac{N}{2}})$ and a plaintext vector $(a_1, a_2, \dots, a_{\frac{N}{2}})$,

the dot product of these two vectors is computed as $\sum_{i=1}^{\frac{N}{2}} (ct_{1i} \cdot a_i)$. Based on Assumptions 1, 2, and 4, and a polynomial $e \in \mathcal{R}$ such that $\langle ct, sk \rangle = m + e \pmod{q_\ell}$ and $\|e\|_{\infty}^{\operatorname{can}} \leq B$. It is obvious that $\langle ct_{\mathrm{m}}, sk \rangle = a \cdot (m + e) = am + ae \pmod{q_\ell}$ and $\|a \cdot e\|_{\infty}^{\operatorname{can}} \leq \|a\|_{\infty}^{\operatorname{can}} \cdot B$. Based on Assumption 5, the addition of ciphertexts is bounded by

Based on Assumption 5, the addition of ciphertexts is bounded by the sum of the upper bounds of their respective noises. Therefore, the noise is bounded by B_{dotp} , i.e., $\frac{N}{2} \cdot ||a \cdot e||_{\infty}^{\text{can}} \leq \frac{N}{2} \cdot ||a||_{\infty}^{\text{can}} \cdot B$. \square

Theorem 4. Let $m_1 = P_N(v_1), m_2 = P_N(v_2)$ be the polynomial representations of $\frac{N}{2}$ -dimensional vectors v_1, v_2 , respectively. The ciphertexts $ct_1, ct_2 \in R_{ql,N}$ are the encryptions of m_1, m_2 , respectively. Algorithm 4 takes the input of two ciphertexts, then returns the ciphertext of a polynomial $P_N(\langle v_1, v_2 \rangle, \langle v_1, v_2 \rangle, \ldots, \langle v_1, v_2 \rangle)$ with a noise bounded by $B_{\text{dotp}} \leq \frac{N}{2} B_{\text{mu}} + \frac{N}{2} B_{\text{mult}}(l)$, where $B_{\text{mu}} = (v_1B_2 + v_2B_1 + B_1B_2)$.

Proof. This involves the summation of ciphertexts produced by the multiplication of ciphertexts. Given ciphertexts ct_1 and ct_2 as $(m_1+e_{10},e_{11}) \bmod q_l$ and $(m_2+e_{20},e_{21}) \bmod q_l$, where $e_{10}+e_{11}s=e_1 \bmod q_l$ and $e_{20}+e_{21}s=e_2 \bmod q_l$. With the evaluation key as $\left(Ps^2+e_0',e_1'\right)$, where $e_0'+e_1's=e' \bmod Pq_l$. Then, the noise for the ciphertext is $m_1e_2+m_2e_1+e_1e_2+\frac{e_{11}e_{21}e'}{P}+e_{\mathrm{scale},10} \bmod q_l$ bounded by B_{mu} .

Based on Assumptions 1, 2, and 5, the noise for the multiplication of two ciphertexts is bounded by $v_1B_2 + v_2B_1 + B_1B_2 + B_{\text{mult}}(\ell)$, where $B_{\text{mult}}(\ell) = P^{-1} \cdot q_{\ell} \cdot B_{\text{ks}} + B_{\text{scale}}$ is the noise induced due to relinearization. v_1 and v_2 are numbers greater than $\|m_1\|_{\infty}^{\text{can}}, \|m_2\|_{\infty}^{\text{can}}$,

respectively. B_1 and B_2 are upper bounds of the noise of ct_1 and ct_2 , respectively. σ is the standard variation of the original noise.

Based on Assumption 5, the addition of ciphertexts is bounded by the sum of the upper bounds of their respective noises. Therefore, the noise is bounded by B_{dotp} , *i.e.*, $\frac{N}{2}B_{\text{mul}} + \frac{N}{2}B_{\text{mult}}(l)$.

7 EXPERIMENTAL STUDY

This section evaluates the proposed secure and private fuzzy name matching scheme over different datasets with multiple name encoding and clustering settings. The scheme has been empirically evaluated both for accuracy and performance measures.

7.1 Experimental Settings

The implementation of the proposed scheme uses a Python library TenSEAL¹, supporting homomorphic operations over tensors, including addition, and multiplication. These are also supported as in-place operations, saving memory and time. Further, it also supports batching, which enables packing multiple plaintexts in one ciphertext, enabling parallelization and significantly improving the performance. TenSEAL also has an implementation for serialization and deserialization, which helps evaluate the real-time communication cost. The experiments have been benchmarked on Apple MacBook M2 Pro with 32 GB RAM.

Parameter Settings: The experimental setup configuration includes setting the parameters for data encoding, clustering and CKKS homomorphic encryption in TenSEAL.

For data encoding, we configure (1) shingle_size: the granularity of similarity depends on this; (2) num_permutations: length of encoding, and a large number produces a more accurate encoding; however, it also increases the computational and communication overheads associated; (3) max_hash: the size of the hash values is bound by this, which also affects the likelihood of hash collisions. For evaluation, (1) shingle_size is set to 3, based on the existing studies; (2) num_permutations as 50, 100 and 200; (3) max_hash is set to 20-bit hash values, which is a large space to avoid collisions.

For clustering, we set the number of clusters close to the square root of the number of samples held by the responder. However, we investigate the impact with varying numbers of clusters. The number of iterations is set to 20.

For the CKKS homomorphic encryption scheme in TenSEAL, we configure (1) scaling factor, which defines the precision of encoding for the binary representation; (2) polynomial modulus degree: a larger degree has higher security but increased computation and communication; (3) coefficient modulus sizes: a list of primes indicating the level of multiplication supported. For evaluation, (1) scaling factor is set as 2⁴⁰; (2) polynomial modulus degree as 8192; (3) coefficient modulus sizes as [60, 40, 40, 60].

Datasets: The experiment is conducted using three datasets, the first of which is derived from the North Carolina Voter Registration (NCVR) Statistics [41], which North Carolina has been maintaining since 2005 to track both active and inactive voters and provide temporal snapshots of voter data within the system. The snapshots dated January 1, 2014, and January 1, 2017, are selected for the study. The North Carolina identification number (NCID) field is used as the identifier for establishing the ground truth of a matching record.

The concatenation of the first name, middle name, last name, and name suffix was used to generate the full name as registered. These records are chosen based on the lowest NCID values to ensure no duplication. Out of 1,000,000, 912,989 records share the same NCIDs.

The second dataset integrates two library catalogue datasets: (1) shadow library book downloads sourced from one of LibGen's mirror sites [6], and (2) a collection of books from bookdepository.com [40]. This dataset encompasses the metadata of books, including ISBN, title, and author. We employed the ISBN to establish the ground truth and title for fuzzy matching. We applied a filter to select records where the titles have at least a 90% similarity based on the Levenshtein distance between the matching pairs, similar to related work [30], and we selected 18,636 matching records across the two datasets. Despite not being directly related to our use case, we use this dataset because it contains longer names.

Utilising data sourced from the US Census [43], the third dataset is constructed, featuring the most frequently occurring given and family names. We generated random pairs of given and family names, each assigned a unique ID number. For every pair, we then applied random modifications for Levenshtein distances that varied from 1 to 5 to introduce five fuzzy variants to each name pair in the dataset. We study this dataset to show the effectiveness of the scheme to varying distances.

Compared Approaches: We consider state-of-the-art approaches for fuzzy private record linkage, HE-based [17], and SMPC-based [30, 47] for comparison. However, our requirement is not a private fuzzy linkage but an unbalanced private fuzzy search. Thus, we compare in approximately similar settings.

Evaluation metrics: We measure the computation and communication costs to evaluate the practicality of the scheme. In terms of search efficiency, accuracy measures the overall correctness of the classifier by calculating the ratio of correct predictions against the total number of predictions made. Complementing accuracy, recall focuses on the classifier's capability to accurately identify positive instances out of all actual positive cases. Precision emphasises the accuracy of positive predictions made by the classifier. The F1 Score synthesises these metrics using a harmonised mean that effectively balances precision and recall. The sensitivity analysis is also conducted to observe the efficiency in handling increasing fuzziness in the records measured by Levenshtein distances.

7.2 Results and Discussion

Accuracy Evaluation: We study the search efficiency of the proposed scheme and report the accuracy, precision, recall and F1-score under different settings. First, we perform an experiment to select a threshold for a cosine similarity score. Figure 2 demonstrates the performance with varying cosine similarity from 0.5 to 0.95 on the NCVR dataset. It can be observed that recall is approximately 1 for threshold 0.65, but precision is near to 0. Recall and precision are nearly the same, from 0.8 to 0.9, while accuracy is also nearly the same at 0.9. However, recall drops when the threshold is 0.95. Thus, we chose 0.9 as the threshold for the remaining experiments.

Figure 3 demonstrates the accuracy evaluation on the NCVR dataset under different settings. Figure 3 (a), (b) and (c) show the performance for the 10k dataset with encoding lengths 50, 100 and

 $^{^{1}}https://github.com/OpenMined/TenSEAL \\$

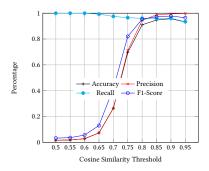


Figure 2: Varying cosine similarity threshold.

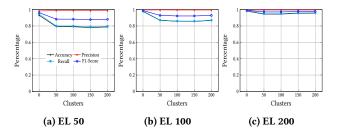


Figure 3: Accuracy evaluation on NCVR dataset (10k-10k). EL: Encoding Length (MinHash Signature Size).

200 and a varying number of clusters. It can be observed that the performance degrades significantly with length 50 after clustering. This is because a small length of encoding does not capture sufficient information, and results in poor clustering. With increased encoding length, we observe improvement in accuracy for both precision and recall. Thus, we suggest encoding length 200 for better performance with clustering.

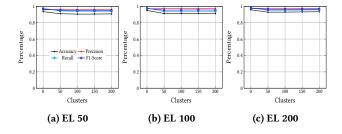


Figure 4: Accuracy evaluation on library catalogue datasets.

Figure 4 demonstrates the accuracy evaluation on the library catalogue dataset. It can be observed that the performance does not vary much with different encoding lengths. Encoding length 200 shows the best performance, with almost no difference in precision and recall. This gain in performance is observed because of longer names in the book dataset, resulting in better representation even with smaller encoding lengths.

Figure 5 studies the sensitivity of the proposed scheme based on varying Levenshtein Distance (LD) over the US Census dataset. It can be observed that fuzzy names with LD 0 and 1 are getting

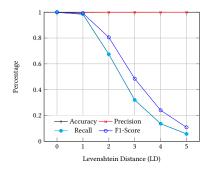


Figure 5: Sensitivity analysis on US Census dataset.

searched with almost 100% precision and recall. Recall drops to 70% with LD2 and up to 10% with LD5 while maintaining the precision. **Performance Evaluation:** We evaluate the computation and communication cost of executing our protocol in fully homomorphic (CKKS) settings. The results, as detailed in Table 1, are based on various dataset settings, encoding length, and the number of clusters. It presents the time, memory, computation and communication costs. The number of queries is set to 100. These results are reported over the North Carolina dataset. However, most of these results are standard and not specific to a particular dataset; they depend on encoding length and the number of clusters.

Based on accuracy evaluation, it can be observed that an encoding length of 200 is more suitable for clustering. Therefore, we use a signature of length 200 for clustering, followed by matching with centroids. Further, matching with individual signatures of the most matching clusters is done over encoding length 50. This is because accuracy is similar with different encoding lengths without clustering, and operations over smaller encoding lengths reduce computation and communication costs, a crucial consideration in real-world applications.

If we cluster a dataset of size 10k into 50 clusters, the maximum size of a cluster is 308. To execute the scheme, the responder (B) finds the cosine similarities of the received encrypted query with all the centroids. It takes 1.53 seconds to find cosine similarities with 50 centroids (of length 200). The size of the encrypted query in this round is 89.1MB. This is the same throughout the experiment, irrespective of datasets, since it is based on the encoding length 200. Similarly, the size of the encrypted query for further matching is 22.3MB with or without clustering, as it is based on the encoding length 50. The size of encrypted cosine similarities with centroids from the first round is 15.7MB, which is sent back to the querier (A). Then, A sends the encrypted sign values to B, which is 22.3MB. Both these sizes depend on the number of clusters. The time taken to perform the operation on each column is 0.26 seconds. This time involves operations of multiplying sign values to one column of names, adding them, and then finding cosine similarity. Then, B returns the encrypted cosine similarity score to A for each column. The size of the encrypted score is always 175 KB for each column. If no clustering had been used, the total communication involved in only sending back the result would have been 3.14GB. Even in the worst scenario with 308 columns, it will reduce to $175\text{KB} \times 308$,

Table 1: Computation and	Communication Cost A	Analysis with 100 queries.
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data size	clusters	total cols	first round	time/col	memory	enc_msg	enc_msg	sim_cent	sign_vec	comm/col	
			secs	secs	GB	first round	MB	MB	MB		
	0			97	0.4					3.14 GB	
	50	308	1.53	0.26	6.63	89.1 MB	15.7	22.3			
10K	100	213	7.66	0.51	12.75			31.4	44.6	175 KB	
	150	154	15.6	0.75	18.88	09.1 MD		47.1	66.9	1/3 KD	
	200	125	21.5	1	25			62.8	89.1		
	0			986	1.2					31.4 GB	
	50	4206	1.53	0.26	6.63	89.1 MB			15.7	22.3	
100K	100	2544	7.66	0.51	12.75		22.3	31.4	44.6	175 KB	
	200	1769	21.5	1	25 89.1 MID			62.8	89.1	173 KD	
	400	1173	229.22	2.21	50				126	178	
	0			9945	6					314 GB	
1000K	50	45,619	1.53	0.26	6.63	— — 89 1 MB		15.7	22.3		
	100	37,310	7.66	0.51	12.75			31.4	44.6	175 KB	
	500	14,348	304.99	2.6	77.75			157	223	1/3 KD	
	1000	4,206	-	-	-			314	446		

first round: time for matching with centroids; enc_msg: encrypted message; sim_cent: encrypted vector of similarity with centroids; sign_vec: encrypted sign vector mentioning most matching cluster; col (column): length of largest cluster, reported for NCVR dataset.

i.e., 53.9 MB. The complete operation consumes 6.63 GB of memory. Increasing the number of clusters reduces the communication costs because of fewer columns. However, it has a higher memory requirement.

Similarly, if we cluster a dataset of 100k with 100 clusters, the maximum size of a cluster is 2544. The time taken to find the cosine similarity between the encrypted query and the centroids is 7.66 seconds. The time taken to compute each column is 0.51 seconds. The size of the encrypted score is 175 KB for each column. If no clustering had been used, the total communication involved in only sending back the result would have been 31.4 GB. Even in the worst scenario, with 2544 columns, it will reduce to 175 KB \times 2544, i.e., 445.2 MB. When simulated on a single machine, the complete operation consumes 12.75 GB of memory.

For a dataset of 1000k with 500 clusters, the maximum size of a cluster is 14348. If no clustering had been used, the total communication involved in only sending back the result would have been 314 GB. However, even in the worst scenario, with 14348 columns, it will reduce to 175 KB \times 14348, i.e., 2.51 GB. The complete operation consumes 77.75 GB of memory when simulated on a single machine. This demonstrates the reduction in communication cost that clustering offers. Due to higher memory requirements, we could not run experiments with 1000 clusters. In summary, it is evident that clustering not only reduces the communication cost significantly but also offers substantial computational gains. Next, we discuss the performance of clustering in terms of gain in computation.

Due to the maximum number of elements in a cluster, the time to search could grow very long. However, this is the worst-case scenario due to higher numbers of names in a particular cluster. Figure 6 demonstrates clustering done on the North Carolina dataset for varying numbers of clusters over different data sizes. As shown in Table 1, for a dataset of 100k, the time taken for linear search with 100 queries is 986 seconds. With clustering, it can be observed in Figure 6 (b) that though the maximum number of columns with

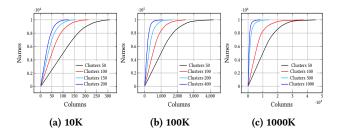


Figure 6: Clustering coverage on NCVR dataset.

50 clusters is 4206, more than 50% of names are covered in 1000 columns, 80% in 2000 columns and 90% in 2500 columns. As the time taken to compute on each column in the given settings is 0.26 seconds, it would take a maximum of 260 seconds to search from 50k names, 520 seconds from 80k names, and 650 seconds from 90k names. Thus, it improves the search time for most cases.

Similarly, for a dataset of 1000k, it takes 9945 seconds to search 100 queries linearly. With clustering, the maximum number of columns with 100 clusters is 37,310, but around 80% of names are covered only in 10000 columns and 90% in 15000 columns, as shown in Figure 6 (c). As the time taken to perform the operation on each column in the given settings is 0.51 seconds, it would take a maximum of 5100 and 7650 seconds to search from 800k and 900k names, respectively. It also shows a significant gain in search time for most cases compared to linear search for most cases.

Increasing the number of clusters increases the time for the first round and operation per column; however, a large number of clusters results in better coverage. Consequently, the maximum number of searches is covered in fewer columns. Hence, choosing the number of clusters influences the performance.

Table 2 logs the evaluation results with varying numbers of queries. The result is reported over the NCVR dataset with 10k,

Table 2: Performance Scaling Evaluation.

No of	first round	time/col	memory	comm/col
queries	secs	secs	GB	KB
1	0.72	0.26	6.63	
10	1.4	0.26	6.63	175
100	1.53	0.26	6.63	1/3
1000	1.98	0.26	6.63	

and the number of clusters is set as 50 (308 columns). The number of queries is varied from 1 to 1000. Batching with more than 1000 queries failed due to higher memory requirements in the current simulation environment. It can be observed that, increasing the number of queries causes a marginal increase in first-round computation time. Other computation and communication costs are constant. Thus, it does not impact overall search time.

Comparison: We compare our scheme in terms of security, accuracy and performance to similar works in [17, 30, 47].

Security: The secure approximate string matching proposed in [17] is based on additive (partial) homomorphic encryption (AHE/PHE) schemes. The security of such schemes is typically based on wellstudied mathematical assumptions specific to the homomorphic property they support. Because they simplify certain aspects of HE, they also bring a trade-off with security. For example, the security of the Paillier cryptosystem is based on the Decisional Composite Residuosity Assumption. FHE schemes often rely on more advanced mathematical structures, such as lattice-based cryptography, which provides a higher level of security. SMPC-based schemes [30, 47] performed private record linkage. These schemes make both parties learn about the fuzzy private set intersection, which does not fulfill the requirements for financial regulations. Moreover, they reveal the number of comparisons, which also reveal sensitive information to both parties. Thus, these approaches are not suitable from the regulatory and security perspectives.

Table 3: Accuracy comparison on NCVR dataset.

SFour [30]	SFour (Best)	SPRL [47]	Ours	Ours (Best)
97.9	98.6	99.97	96.1	98.6

Accuracy comparison: The HE-based solution in [17] discusses the effectiveness of the scheme in terms of reducing false positives. It achieves a negligible false positive rate with a match threshold of 0.8, based on their scheme. Similarly, our approach achieved a high precision of 99.5% with a matching threshold of 0.8, as shown in Figure 2. SMPC-based schemes [30, 47] consider the effectiveness of the scheme in terms of high recall. The precision is supposed to be achieved based on the effectiveness of the blocking scheme. Table 3 logs recall as the accuracy measure for comparison. SFour [30] achieved 97.9% with $\log(n)$ window size, and 98.6% (best) and secure PRL [47] achieved 99.97% over the North Carolina dataset. Under comparable settings over 10k records, our clustering-based search has 96.1% recall, while linear search achieved 98.6% recall. The drop in accuracy is due to clustering and homomorphic error.

Performance comparison: Our scheme's performance cannot be directly compared to existing solutions [17, 30, 47] due to its focus on

Table 4: Performance comparison (in one hour).

Schemes	SFour [30]	SPRL [47]	Ours (L)	Ours (C)
Records	4000	40000	33000	45000

unbalanced secure and private fuzzy search in contrast to private record linkage. Our solution aligns with regulations that prohibit the sharing of matching records with both parties. The search capability of our scheme allows for finding a match within a few seconds (or minutes), with longer search times limited to data distributions with large clusters. Our scheme requires only 175 KB of ciphertext to send a matching response per column. Table 4 compares our work in similar settings for the number of comparisons possible in an hour. It is possible to perform a private fuzzy search between two datasets with 33,000 records, using our algorithm employing linear search. With clustering, it can be scaled to 45,000.

Table 5: Computation and Communication costs.

	Ciphertext	Time (H)	Configuration
AHE [17]	76 GB	1.8	Intel Xeon CPU E5-2697A
Ours (L)	63 GB	0.6	Macbook M2 Pro, 32 GB
Ours (C)	1 GB	0.45	Wiacook Wiz FTO, 32 GD

Compared with additive homomorphic encryption-based solution [17], our algorithm achieved improved results both in terms of computation and communication. Table 5 reports the result in terms of generated ciphertext and time taken for matching 20,000 fuzzy records between two parties. AHE-based solutions incur higher communication costs and take at least thrice the time to search compared to our algorithm. In summary, the proposed algorithm is more secure and scalable for secure and private fuzzy name matching.

8 CONCLUSION

This paper explored the intersection of privacy regulations and the increasing requirement for swift data access to strengthen financial security measures. The proposed secure and private fuzzy name matching scheme can be used for approximate string searching in encrypted settings. It preserves the privacy of the query, including the private dataset of the responding organisation. The proposed scheme uses LSH with CKKS encryption, which has been proven semantically secure in semi-honest settings. Longer encoding provided better accuracy, but increased communication and computational overheads. Clustering is integrated to reduce the search space and enhance performance. It also reduces the search time, as the results are returned column-wise. While clustering maintains precision, it does bring a drop in recall. This gives an opportunity for future work to minimize this recall drop.

ACKNOWLEDGMENTS

This work was supported by the UKRI Prosperity Partnership Scheme (FAIR) under the EPSRC Grant EP/V056883/1, HSBC and the Alan Turing Institute.

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