Multi-Party Privacy-Preserving Record Linkage using Bloom Filters

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Abstract—Privacy-preserving record linkage (PPRL), the problem of identifying records that correspond to the same real-world entity across several data sources held by different parties without revealing any sensitive information about these records, is increasingly being required in many real-world application areas. Examples range from public health surveillance to crime and fraud detection, and national security. Various techniques have been developed to tackle the problem of PPRL, with the majority of them considering linking data from only two sources. However, in many real-world applications data from more than two sources need to be linked. In this paper we propose a viable solution for multi-party PPRL using two efficient privacy techniques: Bloom filter encoding and distributed secure summation. Our proposed protocol efficiently identifies matching sets of records held by all data sources that have a similarity above a certain minimum threshold. While being efficient, our protocol is also secure under the semi-honest adversary model in that no party can learn any sensitive information about any other parties’ data, but all parties learn which of their records have a high similarity with records held by the other parties. We evaluate our protocol on a large real voter registration database showing the scalability, linkage quality, and privacy of our approach.

Index Terms—Record linkage, privacy, Bloom filters, secure summation, multi-party, approximate matching.

1 INTRODUCTION

Many organizations collect and process datasets that contain many millions of records to analyze and mine interesting patterns and knowledge in order to support efficient and quality decision making. Analyzing and mining such large datasets often require data from multiple sources to be aggregated. Linking records from different data sources with the aim to improve data quality or enrich data for further analysis is occurring in an increasing number of application areas, such as in healthcare, government services, crime and fraud detection, national security, and business applications. The analysis of data linked across organizations can, for example, facilitate the detection of an outbreak of an infectious disease early before it spreads widely around a country or even worldwide, or enable the accurate identification of fraud, crime, or terrorism suspects. The health outbreak system described above requires data from several organizations, such as human health data, travel data, consumed drug data, and even animal health data. The second above example of fraud and crime detection requires data from law enforcement agencies, Internet service providers, businesses, as well as financial institutions.

Today, record linkage not only faces computational challenges due to the increasing size of datasets, and quality challenges due to the presence of real-world data errors, but also the challenge of preserving privacy and confidentiality due to growing privacy concerns by the public. In the absence of unique entity identifiers in the databases that are linked, personal identifying attributes (such as names, addresses, gender, and dates of birth) are often used for the linkage. Known as quasi-identifiers (QIDs), values in such attributes are in general sufficiently well correlated with the corresponding real-world entities to allow accurate linkage. Using such personal information across different organizations, however, often leads to privacy and confidentiality concerns.

The privacy challenges posed in the record linkage process has led to the development of techniques that facilitate ‘privacy-preserving record linkage’ (PPRL). PPRL tackles the problem of how to identify records that refer to the same entity in different databases across organizations using the masked QIDs that are revealed. Generally, the original QID values are transformed (masked) such that a specific functional relationship exists between the original and the masked values, and linkage is conducted using those masked QIDs without privacy and confidentiality of the entities represented by the records being compromised.

A viable PPRL solution that can be used in real-world applications needs to address all three challenges (or properties) of PPRL: scalability (which is dependent on the computation and communication complexity of a protocol), linkage quality (dependent on data quality and the comparison functions and classifiers used), and privacy (dependent on the privacy techniques employed). While there have been many different approaches proposed for PPRL, most work in this research area thus far has concentrated on linking records from only two sources (or parties). As the example applications described above have shown, linking data from several sources is however commonly required.

The pipeline of PPRL for multiple databases is shown in Fig. 1. PPRL on multiple databases introduces additional challenges with respect to scalability (complexity),
linkage quality, and privacy. Complexity increases significantly with multiple parties in terms of both computational efforts and communication size. The number of all-to-all comparisons required between \( P \) different databases \( (D_1, D_2, \ldots, D_P) \) is equal to the product of the size of these databases (i.e., \( |D_1| \times |D_2| \times \cdots \times |D_P| \)). As shown in Fig. 1, the quadratic or exponential complexity (for linking two databases or multiple databases, respectively) has been addressed by using two-step algorithms where in the first step a private blocking approach is used in order to reduce the number of candidate record sets, that will then be compared and classified in the second step using private comparison and classification functions. However, in multi-party PPRL the total number of candidate record sets increases exponentially with the number of parties, and thus even using existing private blocking techniques would not sufficiently reduce the number of comparisons. Efficient and advanced blocking and filtering approaches for multi-party PPRL need to be used in order to reduce this potentially huge number of comparisons. Computations should also be distributed among the different parties to reduce the computational efforts at each individual party.

The risk of privacy breaches also increases with multiple parties due to possible collusion between a sub-set of parties with the aim to learn about another (sub-set of) party’s private data. All computations should be distributed among the parties in such a way that each party can learn only a limited amount of information of other parties’ data that cannot be used to infer the represented entities. Employing computationally expensive privacy techniques such as Secure Multi-party Computation (SMC) provides strong privacy guarantees at the cost of increased computational and communication complexities with the increasing size of datasets and the increasing number of parties, making SMC solutions not scalable and practical in real applications.

With regard to quality, private comparison and classification on multiple databases is another challenging aspect due to the need of calculating the similarity of multiple values. How to efficiently calculate the similarity of more than two values using approximate comparison functions in PPRL is an important research question that needs to be addressed. Existing PPRL solutions for multiple parties only support exact matching (which classifies sets of records as matches if their masked QIDs are exactly the same and as non-matches if they differ), or they are applicable to QIDs of categorical data type only (while in most PPRL applications QIDs of string data type, such as names and addresses, are commonly required).

Despite these challenges, PPRL on multiple databases is required in many real-world applications (as described above). A recent work by Ranbaduge et al. aimed to reduce the number of candidate record sets that need to be compared by using a multi-party private blocking approach. In this paper, we focus on the private comparison and classification step in the PPRL pipeline for multiple databases and propose a solution that performs efficient (distributed) and approximate matching of string values using computation and space efficient privacy techniques: Bloom filters and distributed secure summation. We also include a filtering approach into our protocol that can be used to considerably reduce the number of comparisons (in addition to a private blocking approach).

The main contributions of this paper are: (1) an efficient multi-party protocol for private comparison and classification in PPRL; (2) a filtering approach on candidate sets of records that are likely to correspond to non-matches; (3) an analysis of the protocol in terms of the three properties, scalability (complexity), linkage quality, and privacy; and (4) an empirical evaluation and comparison of our protocol with a baseline multi-party approach in terms of the three properties of PPRL using the large North Carolina Voter Registration (NCVR) datasets.

The remainder of the paper is structured as follows: In the following section we review related work in multi-party PPRL. In Section we describe the steps of our multi-party protocol for efficient and approximate private comparison and classification in PPRL. We analyze our solution in terms of complexity, linkage quality, and privacy in Section and in Section we conduct an empirical study on the large real NCVR datasets to validate these analyses. Finally, we summarize and discuss future research directions in Section.

2 RELATED WORK

Various techniques have been developed to address the PPRL research problem, but few among these have considered PPRL on multiple databases. An early approach to PPRL links multiple databases by comparing the hash-encoded (using one-way secure hash algorithms) QID...
values from all data sources by using a third party. However, this approach only performs exact matching (i.e. a single variation in a QID value results in a completely different hash-encoded value).

An SMC-based approach using an oblivious transfer protocol was presented by O’Keefe et al. [19] for PPRL on multiple databases. The approach improves on the security and information leakage characteristics of several previous protocols, including Agrawal et al.’s [20] two-party secure intersection and equi-join protocols that use commutative encryption schemes. While provably secure, the approach only performs exact matching of masked values (i.e. variations and errors in the QID values are not considered). The approach is also computationally expensive compared to perturbation-based privacy techniques [5].

A multi-party approach based on the k-anonymity and secure equi-join privacy techniques was introduced by Kantarcioglu et al. [15]. The database owners individually k-anonymize their databases and send the anonymized databases to a third party that constructs buckets corresponding to each combination of k-anonymous values. For each bucket, the third party performs a secure equi-join. This approach is only applicable to categorical data.

Recently, a multi-party PPRL approach for approximate matching of categorical values based on k-anonymity was proposed [16]. The database owners find the global winner candidate attribute with the best score that provides the least amount of information to the other parties according to some criteria. Then they perform a top-down specialization on that attribute for generalizing the databases. The well-known C4.5 classifier is used to recursively block (generalize) and classify the records in the databases. Similar to [15], this approach is only applicable to linking records using attributes that contain categorical data.

An efficient multi-party PPRL approach for exact matching using Bloom filters was introduced by Lai et al. [13]. Fig. 2 illustrates this approach for P = 3 example databases. The database values (QIDs) are first converted into one Bloom filter $b_i$, $1 \leq i \leq P$ per party. Each party then partitions its Bloom filter into segments according to the number of parties involved in the linkage, and sends these segments to the corresponding other parties. The segments received by a party are combined using a conjunction (logical AND) operation. The final combined Bloom filter segments are then exchanged among the parties. Each party compares its Bloom filter of each QID value with the final result, and if the membership test of a QID value is successful then it is considered to be a match. Though the cost of this approach is low since the computation is completely distributed among the parties and the creation and processing of Bloom filters are very fast (linear complexity in the size of the database), the approach can only perform exact matching.

Since existing private comparison and classification solutions for multi-party PPRL either (1) support exact matching only (which is not applicable in most real-world applications due to the common occurrences of data errors and variations [21]), (2) employ expensive privacy techniques such as SMC, or (3) they are only applicable to categorical data, we aim to overcome these three problems by proposing a multi-party approximate string matching protocol for PPRL using efficient privacy techniques. As we describe in the next section, we use Lai et al.’s [13] multi-party Bloom filter based exact matching approach (described above) as one building block for our approximate matching solution.

### 3 Multi-Party Linkage Protocol

We now describe our approach to efficiently and approximately link databases from three or more parties. We use the following notation: $P$ is the number of parties involved in our protocol, where each party $p_i$ holds a database $D_i$ containing sensitive or confidential identifying information. Database $D_i$ contains $N_i = |D_i|$ records. We assume a set of QID attributes $A$, which will be used for the linkage, is common to all these databases. Our protocol will calculate the similarity between sets of records using the values in $A$.

In the following sub-section we describe the building blocks of our protocol, then in Section 3.2 we explain the steps of our protocol in detail, and in Section 3.3 we propose a filtering approach to improve the efficiency of our protocol.

#### 3.1 Protocol Building Blocks

1. **Bloom filter encoding:** A Bloom filter $b_i$ is a bit array data structure of length $l$ bits where all bits are initially set to 0. $k$ independent hash functions, $h_1, h_2, \ldots, h_k$, each with range $1, \ldots, l$, are used to map each of the elements in a set $S$ into the Bloom filter by setting $k$ corresponding bit positions to 1. Bloom filters are one efficient perturbation-based privacy technique that has successfully been used in several PPRL solutions [22, 23, 24].

Schnell et al. [22] were the first to propose a method for approximate matching in PPRL of two databases using Bloom filters. In their work, as in our protocol, the character $q$-grams (sub-strings of length $q$) of QID values in $A$ of each record in the databases to be linked are hash-mapped into a Bloom filter using $k$ independent hash functions. These Bloom filters are then sent to a third party that calculates the Dice coefficient [3] similarity of pairs of Bloom filters.

Bloom filters can be susceptible to frequency attacks [25] depending on the values of the parameters $k, l$, and $q$. Hence, these Bloom filter parameters need to be set carefully.
as the values provide a trade-off between privacy and linkage quality (as will be discussed in Section 4). Several Bloom filter encoding methods [23, 26, 27] have been proposed to improve privacy by reducing the risk of such frequency attacks while not compromising the linkage quality.

Schnell et al. [26] proposed to hash-map several QID attribute values of a record into one Bloom filter, known as Cryptographic Long term Key (CLK) encoding. Durham et al. [23] investigated composite Bloom filters (record-level Bloom filters in detail by first hash-mapping different attributes into attribute-level Bloom filters of different lengths (depending on the weights [23] of QID attributes that calculate the discriminatory power in resolving identity using a statistical approach) and then combining these attribute-level Bloom filters into one record-level Bloom filter (known as RBF) by sampling bits from each attribute-level Bloom filter. Vatsalan et al. [27] recently introduced a hybrid method of CLK and RBF (known as CLKRBF) where the Bloom filter length is kept to be the same as in CLK while using different number of hash functions to map different attributes into the Bloom filter based on their weights as used in RBF.

2. Dice coefficient: Any set-based similarity function can be used to calculate the similarity of pairs or sets of Bloom filters. The Dice coefficient has previously been used for matching of Bloom filters in PPRL since it is insensitive to many matching zeros in long Bloom filters [22]. The Dice coefficient similarity of two Bloom filters \( (b_1, b_2) \) is calculated as [3]:

\[
\text{Dice}_{\text{sim}}(b_1, b_2) = \frac{2 \times c}{x_1 + x_2}
\]

where \( c \) is the number of common bit positions that are set to 1 in both Bloom filters \( b_1 \) and \( b_2 \) (common 1-bits), \( x_1 \) is the number of bit positions that are set to 1 in \( b_1 \), and \( x_2 \) is the number of bit positions that are set to 1 in \( b_2 \). For example, mapping the bigrams \( (q = 2) \) of two string values ‘peter’ and ‘pete’ into \( l = 14 \) bits long Bloom filters using \( k = 2 \) hash functions and calculating the Dice coefficient similarity of these two Bloom filters are illustrated in Fig. 3.

We define the Dice coefficient similarity of \( P \) \( (P \geq 2) \) Bloom filters \( (b_1, \cdots, b_P) \) as:

\[
\text{Dice}_{\text{sim}}(b_1, \cdots, b_P) = \frac{P \times c}{\sum_{i=1}^{P} x_i}
\]

where \( c \) is the number of common bit positions that are set to 1 in all \( P \) Bloom filters (common 1-bits), and \( x_i \) is the number of bit positions set to 1 in \( b_i \) (1-bits), \( 1 \leq i \leq P \).

3. Multi-party Bloom filter matching: In our protocol the calculation of the number of common 1-bits \( c \) is distributed among the parties, such that \( c = \sum_{i=1}^{P} c_i \).

\[
\text{Dice}_{\text{sim}}(b_1, \cdots, b_P) = \frac{P \times \sum_{i=1}^{P} c_i}{\sum_{i=1}^{P} x_i}
\]  

(3)

Following Lai et al.’s approach [13], Bloom filters are split into \( P \) segments and each party sends its segments to the corresponding other parties. Each party then individually calculates the number of common 1-bits \( c_i \) in its respective segment of the Bloom filters it receives from the other parties for all sets of records. As an example, the distributed Dice coefficient calculation of a set of three Bloom filters from three parties is shown in Fig. 4.

4. Secure summation: Once each of the \( P \) parties has calculated its \( c_i \) and \( x_i \) values for each set of Bloom filters, the summations of values \( c = \sum_{i=1}^{P} c_i \) and \( x = \sum_{i=1}^{P} x_i \) need to be calculated in a secure way in order to calculate the Dice coefficient similarity of the set of Bloom filters. A secure summation protocol [29], which has been used as an efficient tool for privacy-preserving data mining [6], can be efficiently employed for this purpose. This protocol uses a random number \( r \) (any integer number) to hide the actual sensitive values \( c_i \) and \( x_i \), and employs a ring-based communication pattern over all parties which allows each party to learn the final values \( c \) and \( x \), but no party will learn the individual values (i.e. \( c_i \) and \( x_i \)) of the other parties. A simple example illustrating the secure summation protocol is shown in Fig. 5.

3.2 Protocol Steps

In this section we describe in detail the steps of our protocol to approximately and privately link databases from \( P \geq 3 \) sources/parties. We illustrate the steps using three example datasets held by three parties, as shown in Fig. 6. In Fig. 7 to Fig. 9 we illustrate the steps of our protocol for the three example datasets.

- **Step 1:** The parties agree upon the following parameter values: the Bloom filter length \( l \) such that \( l \mod P = 0 \) to allow splitting of Bloom filters.
such that each party

Fig. 5. Secure summation of a set of three private values (a = 11, b = 7, and c = 15) using a random value r = 20 in a ring-based communication pattern between three different parties (p1, p2, and p3, respectively). Four communication phases are involved in the secure summation of three values.

into segments of same size; the k hashing functions h1, . . . , hₖ to be used; the length (in characters) of grams q; a minimum Dice similarity threshold value, sₜ, above which a set of records is classified as a match; a private blocking function block(·); the blocking keys [3] B used for blocking; and a set of QID attributes A used for the linkage.

The setting of Bloom filter parameters and the encoding method is crucial to determine the privacy of our protocol. We propose to perform a simulation attack [24] by the database owners on their own sets of Bloom filters in terms of the sensitivity of each bit in the Bloom filters before agreeing on the parameter setting, as will be discussed in detail in Section 4.

- **Step 2:** Each party pᵢ (1 ≤ i ≤ P) individually applies a private blocking function [5] block(·) (step 1 in Fig. 1) to reduce the number of candidate sets of records (from \( \bigcap_{i=1}^{P} N_i \)). It is important to use a blocking function as the total number of sets of records from P databases quickly becomes prohibitive even for moderate P or N. block(·) groups records according to the blocking key values (BKVs) [30] and only records with the same BKV (i.e. records in the same block) from different parties are then compared and classified (step 2 in Fig. 1) using our protocol.

In the running example we consider the five records with record identifiers (RIDs) RA1, RA2, RB1, RB2, and RC1 in the three databases which we assume are blocked into the same block (i.e. have the same BKV - ‘bk1’, while record RC2 having a different BKV - ‘bk2’), so that there exist the following four candidate sets of (three) records from the three parties (excluding sets of records from the same party): (RA1, RB1, RC1), (RA1, RB2, RC1), (RA2, RB1, RC1), and (RA2, RB2, RC1) for comparison and classification.

- **Step 3:** Each party pᵢ hash-maps the q-gram values of A of each of its Nᵢ records in their respective databases Dᵢ into Nᵢ Bloom filters of length l using the hash functions h₁, . . . , hₖ. It is crucial to set the Bloom filter related parameters in an optimal way that balances all three properties of PPRL (complexity, quality, and privacy). We further discuss the parameter setting for Bloom filters used in our protocol in Section 4. For all records and their Bloom filters, each party pᵢ calculates the total number of 1-bits in the Bloom filters (xᵢ) and stores these values along with RIDs and BKVs, as shown in Fig. 6.

- **Step 4:** Each party pᵢ segments its Bloom filters into P equal sized segments of length l/P bits and sends the jth segment of each of its Bloom filters along with the (encrypted) RIDs and BKVs to party pᵢ, with 1 ≤ j ≤ P and j ≠ i. This step is illustrated for the three example datasets in Fig. 7.

- **Step 5:** Each party pᵢ receives the ith segment of Bloom filters from all other parties pⱼ, with 1 ≤ i, j ≤ P and i ≠ j. For each set of Bloom filters (b₁, b₂, . . . , b_P) of the records from all parties that are in the same block, party pᵢ applies a logical conjunction (AND) on the Bloom filter segments
(b_1 \land b_2 \land \cdots \land b_P). This results in the common bit pattern for segment i from all parties which allows party p_i to calculate the number of common 1-bits (c_i) in the ith segment. Fig. 8 illustrates this distributed calculation of c_i values for the running example candidate sets (in block ‘bkv’).

The distributed common 1-bits calculation (c_i, 1 \leq i \leq P) is described in Algo. 1 for one party p_i (this algorithm is executed by each party individually). The party first generates the candidate sets of records candidate_sets in lines 1-8. For each candidate set cand in candidate_sets the ith segments from all parties are conjuncted (\land) in lines 11-13 to generate the bit pattern of that segment that contains only the common 1-bits. The number of common 1-bits in the ith segment (c_i) is calculated in line 14 for each candidate set by using a count_1bits() function and stored in C_i along with the number of 1-bits in the full Bloom filter of party p_i’s record in the set (x_i, which is calculated in line 10), and the list of all RIDs (cand) in the set.

- **Step 6:** Once the common 1-bits in each segment c_i are calculated by each respective party p_i, a ring-based communication pattern is used among the parties to securely calculate the summation of the c_i and x_i values, c = \sum_{i=1}^{P} c_i and x = \sum_{i=1}^{P} x_i, respectively, for each candidate set using the secure summation protocol, as illustrated in Fig. 9 for the running example.

Algo. 2 provides an overview of the secure summation of common and total 1-bits (\sum_{i=1}^{P} c_i and \sum_{i=1}^{P} x_i) for each candidate set. The party that initiated the communication (we assume the first party, p_1) adds two random values R_c[cand] and R_x[cand] stored in C_i along with the number of 1-bits in the full Bloom filter of party p_i’s record in the set (x_i, which is calculated in line 10), and the list of all RIDs (cand) in the set.

- **Output:**
  - C': Candidate record sets with summed values of c_i and x_i

- **Input:**
  - C_i: Candidate record sets of party p_i with c_i and x_i values, 1 \leq i \leq P
  - R_c and R_x: Lists of random values used by party p_1 for secure summation of c_i and x_i, respectively

Fig. 8. The calculation of values for c_i and x_i individually by each party p_i for all the candidate sets of records from all three parties. Different colors represent the Bloom filter segments received from different parties. This figure illustrates Step 5 of the protocol.
Fig. 9. The secure summation of the $c_i$ and $x_i$ values to calculate $c = \sum_{i=1}^{P} c_i$ and $x = \sum_{i=1}^{P} x_i$, respectively, for each candidate set of records, in order to calculate the Dice coefficient similarity of those record sets. The lists of random values used by party $p_1$ for the secure summation of the $c_i$ and $x_i$ values are $R_c = [7, 12, 9, 15]$ and $R_x = [20, 13, 10, 5]$, respectively. This figure illustrates Step 6 of the protocol.

Algo. 3: Similarity calculation of record sets (by $p_1$).

Input:
- $C'$: Candidate record sets with summed values of $c_i$ and $x_i$ from party $p_p$
- $R_c$ and $R_x$: Lists of random values used by party $p_1$ for secure summation of $c_i$ and $x_i$ values, respectively
- $s_t$: Minimum similarity threshold to classify record sets

Output:
- $M$: List of matching record sets

1. $M = []$
2. $C'.receive_from(p_p)$
3. for $cand \in C'$ do:
   4. $sum_{c_i} = C'.get_{c_i}(cand) - R_c[cand]$
   5. $sum_{x_i} = C'.get_{x_i}(cand) - R_x[cand]$
   6. Dice_sim(cand) = $\frac{sum_{c_i} \times sum_{x_i}}{sum_{c_i} + sum_{x_i} - sum_{c_i} \times sum_{x_i}}$
   7. if Dice_sim(cand) $\geq s_t$ then:
       8. $M.append((cand, Dice_sim(cand)))$
   9. for $2 \leq j \leq P$ do:
      10. $M.send_to(p_j)$

with its values for $c_i$ and $x_i$ ($i = 1$), respectively, for each candidate set $cand$, and sends the summed values $R_c[cand] + c_i$ and $R_x[cand] + x_i$ to parties $p_{i+1}$ (i.e. $p_2$) in lines 3-8. Party $p_i$, $1 < i \leq P$ receives the summed values from $p_{i-1}$, and adds its values for $c_i$ and $x_i$ for each candidate set and sends the summed values to the next party $p_{i+1}$. This process is repeated until the last party (i.e. $p_P$) sums its $c_P$ and $x_P$ values with the received summed values $R_c[cand] + \sum_{i=1}^{P-1} c_i$ and $R_x[cand] + \sum_{i=1}^{P-1} x_i$ from party $p_{P-1}$, respectively, and sends the final summed values to $p_1$ (as explained in lines 9-17 in Algo. 2).

- Step 7: Finally, the first party, $p_1$, that initiated the communication subtracts $R_c[cand]$ and $R_x[cand]$ from the received final summed values $R_c[cand] + \sum_{i=1}^{P} c_i$ and $R_x[cand] + \sum_{i=1}^{P} x_i$, respectively, for each candidate set $cand$ from the last party $p_P$. This is outlined in Algo. 3 (lines 2-5) and illustrated in Fig. 10 for the running example. As shown in lines 6-8, $p_1$ then calculates the Dice coefficient similarity of each set of Bloom filters using $\sum_{i=1}^{P} c_i$ and $\sum_{i=1}^{P} x_i$ following Equation 3 to classify the compared sets of records within a block into matches and non-matches based on the similarity threshold $s_t$. The final similarities of matching sets of records are sent to all the other parties $p_j$, with $2 \leq j \leq P$ in lines 9-10 in Algo. 3 (right side of Fig. 10).

3.3 Filtering Candidate Record Sets

The most challenging aspect of multi-party PPRL is that the number of candidate record sets can become prohibitively very large even with a blocking technique employed. This imposes the need for using advanced blocking and filtering approaches in order to make multi-party PPRL scalable and practical in real applications with large datasets. In this section, we describe a filtering approach that can be used in our private comparison and classification protocol to further reduce the number of candidate record sets resulting from the blocking step in the PPRL pipeline.

Filtering techniques are commonly employed in similarity calculations, such as length, position and prefix filtering in PPJoin [31]. Recent work in converting such techniques into a privacy-preserving framework [32] highlighted the difficulty of applying such traditional filtering techniques on Bloom filters. In order to achieve high linkage quality and preserve privacy, as will be discussed in Section 4, the Bloom filters used in PPRL protocols should ideally have
half of their bits set to 1 (i.e. be half filled), making length, position and prefix filtering ineffective.

In our protocol, we therefore investigate the following filtering approach which exploits the fact that parties only have access to a fraction of all Bloom filters. Our assumption is that the positions of 1-bits in the Bloom filters are uniformly distributed (due to the random behavior of hash functions) across the Bloom filters [22, 33]. This assumption of uniform distribution of 1-bits in the Bloom filters means that the segments of Bloom filters of a set of records \( (b_1, \cdots, b_j) \) need to have a segment similarity \( \text{seg}_j \sim (b_1, \cdots, b_j) \), with \( 1 \leq i, j \leq P \), of at least \( s_m \) in order to achieve the overall Bloom filter similarity \( \text{Dice}_j \sim (b_1, \cdots, b_j) \geq s_t \) to be classified as a matching set.

When each party \( p_i \) computes the number of common 1-bits, \( c_{ij} \) in the \( i \)th segments of each candidate set (Step 5 of the protocol as described in Section 3.2), the party can calculate its \( \text{seg}_j \sim (b_1, \cdots, b_j) \) as it knows the \( i \)th Bloom filter segments of all \( P \) records from the \( P \) parties in a set. If the \( \text{seg}_j \sim (b_1, \cdots, b_j) < s_m \) for any sub-set of \( j \) \((j < P) \) records in the set of \( P \) records, then the comparison and calculation of \( c_{ij} \) can be stopped without proceeding to compare any other sub-sets of records from the remaining \( P-j \) parties with the sub-set of records of \( (b_1, \cdots, b_j) \). This basically expands lines 9-15 of Alg. 1 as shown in Alg. 4 for party \( p_i \), \( 1 \leq i \leq P \).

Lines 15 to 19 show the extension of Alg. 1 for the filtering approach. Party \( p_i \) iterates over the \( i \)th segments of the other parties \( p_j \) \((1 \leq j \leq P, j \neq i) \) in line 13. The number of common 1-bits and the total number of 1-bits in the \( i \)th segments of \( j \) parties are calculated in lines 14-16, which are then used to calculate the segment similarity \( \text{seg}_j \sim (b_1, \cdots, b_j) \) in line 17. If \( \text{seg}_j \sim (b_1, \cdots, b_j) < s_m \) (line 18), then the comparison of remaining segments \((b_{j+1}, \cdots, b_P)\) with these segments and the calculation of \( c_i \) and \( x_i \) can be stopped without proceeding further, as they are with high likelihood non-matching sets.

Assuming uniform distribution of bits in the Bloom filters, \( s_m \) can be set to the same as \( s_t \) so that each segment contributes the same to the overall Bloom filter similarity \( s_t \). An alternative is to set \( s_m \) to a value smaller than \( s_t \) to incorporate the trade-off between the number of false negatives (due to random hash-mapping of \( q \)-grams) and the number of resulting candidate sets.

As an example of filtering, assume three databases \( D_1 \), \( D_2 \), and \( D_3 \) with records \( (RA_1, RA_2) \) from \( D_1 \), \( (RB_1, RB_2) \) from \( D_2 \), and \( (RC_1, RC_2, RC_3) \) from \( D_3 \) in the same block (resulting from a private blocking function) need to be compared in order to identify the matching sets of records from all three databases. This requires private comparison of 12 sets of Bloom filter segments from the three databases by each party. If the \( i \)th Bloom filter segments for records \( RA_1 \)

---

**Fig. 10.** The calculation of the Dice coefficient similarity of candidate record sets using Equation 3 and the classification of sets of records into matches and non-matches. The minimum similarity threshold is set to \( s_t = 0.8 \) in this example. We classified one matching set of records \( \text{cand}_2 = \text{(RA}_1, \text{RB}_2, \text{RC}_1) \) across the three datasets. This figure illustrates Step 7 of the protocol.
and RB2 do not have a similarity of at least $s_m$, as calculated by party $p_i$, then the comparisons of RA1 and RB2 with RC1, RC2 and RC3 are not required, which reduces the number of comparisons for a block by party $p_i$ from 12 to 9. This reduction is significant when the number of parties increases (as will be empirically shown in Section 5).

4 Analysis of the Protocol

In this section we analyze our multi-party PPRL protocol in terms of complexity, privacy, and linkage quality.

4.1 Complexity Analysis

We assume $P$ parties participate in the protocol, each having a database of $N$ records, and we assume a private blocking/indexing technique employed in the private blocking step forms $B \leq N$ blocks for each party. In Step 1 of our protocol, the agreement of parameters has a constant communication complexity, and blocking the databases in protocol Step 2 has $O(N)$ computation complexity at each party. Finding the intersection of blocks from all parties has a communication complexity of $O(PB)$ and a computation complexity of $O(B \log B)$ at each party. Assuming the average number of $q$-grams in the QID attributes $A$ of each record is $Q$, the masking of QID values of records into Bloom filters of length $l$ using $k$ hash functions for $N$ records in Step 3 is $O(NQk)$ at each party.

In Step 4, each party sends its Bloom filter segments (each of length $l/P$) to the other parties. If we assume direct communication between parties, then $P(P-1)$ messages are required in this step, each of these of size $N \times l/P$ (thus $O(NP)$ total communication). With the simplified assumption that all blocks are of equal size $(N/B)$, then in each block $(N/B)^p$ sets of Bloom filters (i.e., all candidate sets of records in a block) have to be generated and their logical conjunctions calculated in Step 5, leading to a total of $O(B(N/B)^p)$ calculations by each party.

Filtering reduces the number of comparisons from $(N/B)^p$ to $(N/B - F)^p$, where $F$ is the number of Bloom filter segments filtered from each party in each block. Filtering more non-matching record sets by increasing $F$ will improve the efficiency of our protocol.

Steps 6 and 7 consist of the secure summation of the calculated number of common 1-bits ($c_i$) and total 1-bits ($x_i$) in order to calculate the similarity of candidate sets. This requires for each candidate set of Bloom filters two integer numbers to be sent in a ring communication ($P$ messages) over all parties with a total communication of $O(PB(N/B - F)^p)$, followed by the distribution of the final results which is again $O(PB(N/B - F)^p)$.

4.2 Privacy Analysis

To assess the privacy of our protocol, we assume all parties follow the honest-but-curious adversary model [5], in that they are curious and try to find out as much as possible about the other parties’ data while following the protocol. In order to analyze the privacy of our solution, we discuss what the parties can learn from the data exchanged among them during the protocol. There are two communication steps in our protocol where the parties reveal some information regarding their data.

In Step 4 of our protocol, the parties split and exchange their Bloom filter segments (of $l/P$ length) to the corresponding other parties to calculate the common 1-bits in the segments. Since calculations are distributed among the parties, each party only learns $l/P$ bits of each of the other parties’ Bloom filters, which will make it difficult to exploit a cryptanalytic attack [25]. This is the highest amount of information a party can learn about data of other parties in our protocol. It is important to note that this amount of information ($1/P$ fraction of bits) that can be learned by a party about another party’s Bloom filters reduces (and thus privacy improves) with increasing $P$.

The values for the number of hash functions used ($k$) and the length of the Bloom filter ($l$) provide a trade-off between the linkage quality and privacy [22], as will be discussed in detail in the next sub-section. The higher the value for $k/l$, the higher the privacy and the lower the quality of linkage, because the number of $q$-grams mapped to a single bit (and therefore the number of resulting collisions) increases, which leads to lower linkage quality but makes it more difficult for an adversary to learn the possible $q$-gram combinations [25]. The CLK Bloom filter encoding method (as discussed in Section 3.1) of hash-mapping several QID values from each record into one compound Bloom filter [24, 26] makes it even more difficult for an adversary to learn individual QID values that correspond to a revealed bit pattern in a Bloom filter.

In addition, the parties can individually mount a simulation attack on their own masked databases in the data masking and preparation step (Step 1 of our protocol) to learn the sensitivity of each bit in their Bloom filters, as discussed in Section 3.2. Following Durham’s work [23], the sensitivity of bit position $\beta_x$, $1 \leq x \leq l$ in masked Bloom filters of $D$, is referred as $S(\beta_x)$ and calculated as:

$$
\text{dist}(\beta_x) = |u| : \forall u \in U \text{ and } h_y(u) = \beta_x, 1 \leq y \leq k,
\text{freq}(\beta_x) = |r| : \forall r \in D \text{ and } r.\beta_x = 1,
S(\beta_x) = \frac{1}{\min \{\text{dist}(\beta_x), \text{freq}(\beta_x)\}},
$$

where $U$ is a set of all unique $q$-grams in dataset $D$, $r.\beta_x$ is the value (0 or 1) in bit position $\beta_x$ of $r$’s Bloom filter, and $h_y$, $1 \leq y \leq k$, are the hash functions used to map $q$-grams into Bloom filters. The distribution of $q$-grams in the bits is represented by the $\text{dist}(\beta_x)$ function which calculates the number of unique $q$-grams that are mapped to a certain bit position $\beta_x$, and the frequency of bits is calculated by $\text{freq}(\beta_x)$ function that counts the number of records that set the bit position $\beta_x$ to 1. The minimum of these two functions is used to calculate the sensitivity of bit $S(\beta_x)$, since a bit that maps to a larger number of $q$-grams is not secure (not less sensitive) if all those $q$-grams correspond to the same record. The higher the value for $S(\beta_x)$ is, the higher the sensitivity of bit $\beta_x$. Based on such a sensitivity analysis, the parties can perturb their masked datasets, for example by adding random noise [23, 24], to improve the privacy of the masking at the cost of some loss in linkage quality.

The second communication step, where the secure summation protocol is used (Step 6), requires parties to send their sums of $c_i$ and $x_i$ values (with the respective summed
values received from the previous party) for each candidate set to the next party in a ring-based communication. During this communication, however, no party $p_j$ can learn any information regarding the individual values for $c_i$ and $x_i$ of any other party $p_i$ (with $1 \leq i \leq P$ and $i \neq j$), except the final results of $\sum_{i=1}^P c_i$ and $\sum_{i=1}^P x_i$.

Party $p_1$ initiates the secure summation protocol learns more information than the other parties in that it can subtract the random values and its own values from the final sums in order to learn $\sum_{i=2}^P c_i$ and $\sum_{i=2}^P x_i$. Since these two results are in the range of $0 \leq \sum_{i=2}^P c_i \leq (P-1)l$ and $(P-1)k \leq \sum_{i=2}^P x_i \leq (P-1)l$, respectively, it would be difficult to infer the individual values of each party due to the large number of combinations. The larger the number of parties ($P$) is, the larger the range and the number of combinations, and thus the inference would be harder with more parties. The only information that $p_1$ can learn is that if all the other segments have common 1-bits or not, i.e. if $\sum_{i=2}^P c_i > 0$ or not. However, with this information, it is difficult to infer which bit positions are in common in the other segments.

This process can also be distributed in such a way that each party calculates the final sums (by initiating the secure summation protocol) for a certain sub-set of all the candidate sets in order to improve the privacy of our protocol. Another alternative approach is to use an external party to perform the secure summation which can then send the final summed values (and the similarities) to all the $P$ parties.

4.3 Quality Analysis

Our protocol supports approximate matching of QID values, in that data errors and variations are taken into account depending on the minimum similarity threshold $s_t$ used.

The quality of Bloom filter encoding based masking is dependent on the Bloom filter parameterization [13], [22], [23], [24]. For a given Bloom filter length, $l$, and the number of elements $Q$ (e.g. $q$-grams) to be inserted into the Bloom filter, the optimal number of hash functions, $k$, that minimizes the false positive rate $f$ (of a collision of two different $q$-grams being mapped to the same bit position), is calculated as [34]:

$$k = \frac{l}{Q} \ln(2),$$  \hspace{1cm} (5)

leading to a false positive rate of

$$f = \left( \frac{1}{2^{l/\ln(2)}} \right)^{l/Q}. \hspace{1cm} (6)$$

For a given $l$, we can calculate $k$ based on the average number of $q$-grams, $Q$, that are generated from a record, as calculated from the datasets. While $k$ and $l$ determine the computational aspects of our approach, linkage quality and privacy will be determined by the false positive rate $f$. A higher value for $f$ will mean a larger number of false matches and thus lower linkage quality. At the same time, a higher false positive rate $f$ will also mean improved privacy, as false positives mean an adversary cannot be absolutely sure that a certain bit pattern (or a Bloom filter segment) corresponds to a certain record [22], [54].

It was proven [54] that a Bloom filter should ideally have half of its bits set to 1 (i.e. 50% filled) to achieve the lowest possible false positive probability for given values of $Q$, $l$ and $k$. Equations [5] and [6] in fact lead to a probability that a bit in a Bloom filter is set to 1 as $p = e^{-kQ/l} = 0.5$ [54].

For PPRL this is important, because the bit patterns and their frequencies in a set of Bloom filters can be exploited by a cryptanalysis attack [25]. Such an attack exploits the fact that Bloom filters that are almost empty can provide information about rare $q$-grams and thus rare QID values.

In our experimental evaluation we will set the Bloom filter parameters for our approach according to the discussion presented here and following earlier Bloom filter work in PPRL [22], [23], [24].

5 Experiments and Discussion

In this section, we empirically evaluate the performance of our multi-party approximate matching protocol (which we refer as ‘MPAM’) in terms of the three properties of PPRL, which are scalability (complexity), linkage quality, and privacy. We use Lai et al. [13]’s exact matching PPRL approach (referred as ‘Lai’) as a baseline to compare with our solution, as other existing multi-party PPRL solutions require data types of categorical only and / or they are based on computationally expensive SMC-based privacy techniques (as reviewed in Section 4).

We implemented both our proposed approach and the baseline approach in Python 2.7.3, and ran all experiments on a server with four 6-core 64-bit Intel Xeon 2.4 GHz CPUs, 128 GBytes of memory and running Ubuntu 14.04. The programs and test datasets are available from the authors. Following the discussion in Section 4.3 and other work in PPRL [1], [22], [23], [24], we set the parameters as $l = 500$, $k = 20$, $q = 2$, $s_t = 0.8$, and $P = [3, 5, 7]$. We apply a Soundex-based phonetic blocking [3] for the private blocking step in the PPRL pipeline (step 1 in Fig. 1), which results in a set of blocks on which we individually conduct private comparison and classification (step 2 in Fig. 1) using our approximate matching linkage protocol.

5.1 Datasets

To provide a realistic evaluation of our approach, we based all our experiments on a large real-world database, the North Carolina Voter Registration (NCVR) database as available from ftp://alt.ncsbe.gov/data/. This database has been used for the evaluation of various other PPRL approaches [17], [23], [27], [35]. We have downloaded this database every second month since October 2011 and built a combined temporal dataset that contains over 8 million records of voters’ names and addresses [18]. We are not aware of any available real-world dataset that contains records from more than two parties that would allow us to evaluate our multi-party approach. We therefore generated, based on the real NCVR database, a series of sub-sets for multiple parties, as will be described next.

To allow the evaluation of our approach with different number of parties, with different dataset sizes, and with data of different quality, we used and modified a recently proposed data corruptor [36] to generate various datasets with different characteristics based on randomly selected records (with given name, surname, suburb name, and postcode attributes as QIDs) from the NCVR database. During
the corruption process we kept the identifiers of the selected and modified records, which allows us to identify true and false matches and therefore evaluate linkage quality of our protocol.

Specifically, we extracted sub-sets of 5,000, 10,000, 50,000, 100,000, 500,000, and 1,000,000 records to generate datasets for 3, 5, and 7 parties, where the number of matching records is set to 50% (i.e. half of all selected records occur in the datasets of all parties). We then applied various corruption functions in different numbers (ranging from 1 to 3) on randomly selected attribute values which allows us to investigate how our approximate matching approach can deal with ‘dirty’ data. We applied various corruption functions, including character edit operations (insertions, deletions, substitutions, and transpositions), and optical character recognition and phonetic modifications based on look-up tables and corruption rules.

We created several series of datasets for each of the datasets generated above, where we included a varying number of corrupted records into the sets of overlapping records (0%, 20%, and 40%). This means that a certain percentage of records in the overlap were modified for randomly selected parties, while the original values were kept for the other parties. Therefore, some of these records are exact duplicates across some parties in a set, but are only approximately matching duplicates across the other parties in the set. This simulates, for example, the situation where three out of five hospitals have the correct and complete records for the same patient are different, while in the fourth and fifth hospitals some of the details of the patient are different.

5.2 Evaluation Measures

We evaluate the three properties of PPRL for our multi-party approach using the following evaluation measures:

The scalability of our protocol is measured by runtime and memory size required for the linkage. Similar to the reduction ratio (RR) measure that has been used for measuring the efficiency of blocking approaches [3], the efficiency of our filtering approach (referred as ‘MPAM-F’) can be measured (RRf) as follows:

\[
RR_f = 1.0 - \frac{|\text{candidate sets after filtering}|}{|\text{all record sets}|} \\
RR_f = 1.0 - \frac{|\text{candidate sets after filtering}|}{|\text{candidate sets before filtering}|} 
\]

The quality of the achieved linkage is measured using the standard F-measure (F1) that is widely used in information retrieval and data mining [3]. F-measure is the harmonic mean of precision and recall, calculated as [3, 27]:

\[
F_1 = 2 \times \frac{(\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})} 
\]

where precision is the fraction of record pairs classified as matches by a decision model that are true matches and recall is the fraction of true matches that are correctly classified as matches by a decision model.

In line with other work in PPRL [17, 27, 35], we evaluate privacy using disclosure risk (DR) measures based on the probability of suspicion (p_s), i.e. the likelihood a masked database record in D^M can be matched with one or several (masked) record(s) in a publicly available global database G. The probability of suspicion for a masked value/record r^M, p_s(r^M), is calculated as 1/ng where n_g is the number of possible matches in G^M to the masked value r^M. We conduct a frequency linkage attack [27] on our protocol using equivalent datasets as used in the linkage to be the global databases (i.e. G \equiv D in the worst case, because when G \equiv D there will be one-to-one exact matching of global value for each value in D) by mapping the revealed bit patterns (segments) in the Bloom filters in D^M to the Bloom filters in G^M in order to calculate the following disclosure risk measures, as proposed by Vatsalan et al. [27].

- **Mean disclosure risk (DRMean):** This takes into consideration the distribution of probability of suspicion of all values in D^M and is calculated as the average risk (\(\sum p_s / |D^M|\)) of any sensitive value being re-identified.
- **Marketer disclosure risk (DRMark):** This is calculated as the proportion of masked records (Bloom filter segments) in D^M that match to exactly one masked record in G^M (|\{r^M \in D^M : p_s(r^M) = 1.0\}|/|D^M|).

5.3 Experimental Results

Figs. 11(a) and 11(b) show the scalability of our approach, measured by runtime and memory size required for the linkage as averaged over all parties, and the number of candidate record sets to be compared and classified for the linkage. Runtime slightly increases with larger number of parties (P) and is almost linear in the size of the datasets. Interestingly, memory size decreases with P because the Bloom filter segments at each party become shorter (l/P) and the similarity calculations are distributed among the parties. However, memory size increases on the larger datasets with larger P, because the number of record sets becomes large with more parties even with the phonetic blocking [3] and our filtering approach (as described in Section 5.3) employed.

The reduction ratio of record set comparisons (RRf) by our filtering approach is shown in Fig. 11 (b). The RRf is not significant on smaller datasets. However, it achieves a moderate RRf in the number of comparisons on larger datasets and it increases with the number of parties, P. This opens up a research direction of developing advanced filtering and blocking/indexing approaches, and efficient communication patterns for multi-party PPRL techniques to be studied further.

Compared to the baseline approach by Lai et al. [13], our approach is more scalable and efficient in terms of linkage time and memory size, and is linear in the number of parties, as shown in Fig. 12 (a). The reason is that in the baseline approach by Lai et al., after the Bloom filter segments are distributively processed by the parties to compute the segments with common 1-bits (conjugated), each party has to perform a membership test of its own Bloom filters with the conjugated Bloom filters in order to classify them as matches or non-matches [13]. However, in our proposed approach only one party (or alternatively an external party) calculates
the similarities of record sets based on the sums of the number of 1-bits and common 1-bits of all parties, which are then distributed to all parties. An interesting aspect is that the time required by our approach slightly increases and memory size decreases with more parties (increasing $P$), while they increase significantly with the baseline approach.

The quality of linkage, as measured using the F-measure ($F_1$), achieved with our approach (both MPAM and MPAM-F) and the baseline approach (Lai) is compared in Fig. 12 (b) on the NCVR-10,000 datasets. As can be seen from the figure, $F_1$ is high on the non-modified datasets (0% corruption). On the modified datasets (with 20% and 40% corruption) $F_1$ drops quite drastically with the number of parties. The reason is that when records with modifications occur in each dataset the number of missed true matching record sets increases. The filtering approach (MPAM-F) only affects the quality of the linkage slightly, as we achieved similar results to MPAM. On the non-modified datasets the filtering approach performs comparatively well. This is because the precision improves by removing false matching sets, and thus leads to higher $F_1$ results. Though the baseline approach performs well on the non-modified datasets, $F_1$ is significantly lower on the modified datasets (as the baseline approach by Lai et al. supports only exact matching).

Finally, the privacy of our protocol (as well as Lai et al.’s approach [13]), as measured by DR measures [27] (mean disclosure risk and marketer disclosure risk), for a frequency linkage attack on Bloom filter segments in the NCVR-10,000 datasets to the known values in the global database $G$ (in the worst case setting of $G \equiv$ NCVR-10,000) for different number of parties is shown in Fig. 12 (c). As discussed in Section 4.2, disclosure risk decreases (i.e. privacy increases) with an increasing number of parties $P$ as the Bloom filter segments ($l/P$) become shorter and are therefore matched to a larger number of global records (i.e. $n_g$ increases). This results in lower probability of suspicion of segments ($p_s = 1/n_g$) with larger $n_g$ and provides lower values for the disclosure risk measures [27].

6 Conclusions and Future Work

We have presented an efficient and approximate private comparison and classification protocol for multi-party PPRL based on Bloom filter encoding and distributed secure summation. Our protocol efficiently identifies sets of records that have a high Dice coefficient similarity across all the parties. The protocol has a communication complexity that is linear in the number of parties and the size of the databases that are linked, making the protocol scalable to applications where data from multiple parties need to be linked. However, a main bottleneck of multi-party PPRL is the large number of candidate record sets.

In future work, we plan to improve the scalability of our protocol by reducing the number of candidate record
sets further using improved and advanced private blocking or filtering approaches, and by investigating different communication patterns. A second avenue of future work will be to conduct linkage attacks on the protocol with different Bloom filter encoding methods and different noise addition techniques to further evaluate the privacy of our approach. In terms of linkage quality, we also plan to investigate how to make our protocol more general and allow for different approximate string similarity functions [3] to be incorporated. Developing PPRL techniques for identifying matching record sets across sub-sets of multiple databases is another important research direction. Finally, we plan to investigate improved classification techniques for multi-party PPRL including relational clustering and graph-based approaches [3] which are successfully used in non-PPRL applications.

Our ultimate aim is to develop techniques that allow for large databases to be linked in secure, accurate, automatic, and scalable ways across many parties, thereby facilitating novel ways of data analysis and mining that currently are not feasible due to privacy and confidentiality concerns.

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