ARM: Authenticated Approximate Record Matching for Outsourced Databases

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Abstract

In this paper, we consider the outsourcing model in which a third-party server provides data integration as a service. Identifying approximately duplicate records in databases is an essential step for the information integration processes. Most existing approaches rely on estimating the similarity of potential duplicates. The service provider returns all records from the outsourced dataset that are similar according to specific distance metrics. A major security concern of this outsourcing paradigm is whether the service provider returns sound *and* complete *near-duplicates. In this paper, we design ARM, an authentication system for the outsourced record matching. The key idea of ARM is that besides the similar record pairs, the server returns the* verification object *(VO) of these similar pairs to prove their correctness. First, we design an authenticated data structure named MB-tree for VO construction. Second, we design a lightweight authentication method that can catch the service provider's various cheating behaviors by utilizing VOs. We perform an extensive set of experiment on real-world datasets to demonstrate that ARM can verify the record matching results with cheap cost.*

***Keywords*—**authentication, outsourcing, approximate string matching, verification object, MB-tree

1 Introduction

Big data analytics offers the promise of providing valuable insights of knowledge. However, many companies, especially the small- and medium-sized ones, lack the computational resources, in-house knowledge and experience of big data analytics. A practical solution to this dilemma is that the data owner outsources the data to a computational powerful third-party service provider (e.g., the cloud) for cost-effective data analytics solutions.

In this paper, we consider *approximate record matching*, an important data analytics operation for information integration, as the outsourced computations. Generally speaking, the data owner (client) outsources a record database D to a third-party service provider (server). The server identifies the similar record pairs in D that may refer to the same entity, where the similarity is measured by a specific string distance function and user-defined threshold values.

For all the benefits of outsourcing and cloud computing, though, the outsourcing paradigm deprives the data owner of direct control over her data. This poses numerous security challenges. One of the challenges is that the server may cheat on the record matching results. For example, the server is incentivized to improve its revenue by computing with less resources (e.g., only search a portion of D) while charging for more. Therefore, it is important to authenticate whether the service provider has performed the matching faithfully, and returned the correct results to the client. A naive method is to execute the record matching locally, and compare the results with the matching results returned by the server. Apparently this method is prohibitively costly. We aim to design efficient methods that enable the client to authenticate that the server returned *sound* and *complete* similar record pairs. By soundness we mean that the returned record pairs are indeed similar. By completeness we mean that all similar records are returned.

Most existing work (e.g. [2, 7, 21]) solve the *data privacy* issue in the outsourced record matching computations, aiming to prevent the server from possessing the original data while still enabling the server to perform accurate record matching. Previous work (e.g. [13, 19, 26]) on *authentication* mainly focus on the SQL aggregation queries and similarity search for Euclidean points. To our best knowledge, ours is the first to consider the authentication of *approximate record matching* on outsourced data.

In this paper, we design ARM, an Authentication mechanism of outsourced Record Matching. The key idea of ARM is that besides returning the similar record pairs, the server returns a verification object (VO) that can prove the soundness and completeness of the returned record matching results. In particular, we make the following contributions. First, we design an authentication tree structure named *MB-tree*. MB-tree is constructed by integrat-

ing Merkle hash tree [22], a popularly-used authenticated data structure, with B^{ed}-tree [28], a compact index for efficient string similarity search based on edit distance. We pick B^{ed}-tree because compared with other data structures for string similarity measurement [25, 12], it is not limited to main memory usage and incurs minimal I/O time when there is limited memory in the system. Besides, B^{ed}-tree supports incremental updates in the dataset. Second, based on MB-tree, we design a lightweight authentication method named VS^2 for the approximate record matching. VS^2 constructs the verification object VO from the MB-tree. The VO consists of certain MB-tree entries that can be later utilized by the client to verify the completeness and soundness of results. Third, we formally prove that the VO enables to catch the server's cheating behaviors such as tampered records, soundness violation, and completeness violation. Fourth, we complement the theoretical investigation with a rich set of experiment study on two real-world datasets. The experiment results show that ARM incurs cheap cost at the client side. It requires no more than 11 seconds to construct the VO. Furthermore, the data owner can save up to 87% computational efforts if she outsources record matching to the server, while only performing verification locally. This shows that ARM is suitable for the outsourcing setting.

The rest of the paper is organized as follows. Section 2 discusses the preliminaries. Section 3 defines the problem. Section 4 and 5 present our verification approach. Section 6 analyzes the security guarantee of our approach. The experiment results are shown in Section 7. Sections 8 discusses the related work. Section 9 concludes the paper.

2 Preliminaries

2.1 Record Similarity Measurement

Record matching is a fundamental problem in many research areas, e.g., information integration, database joins, and more. In general, the evaluation that whether two records match is mainly based on the string similarity of the attribute values. There are a number of string similarity functions, e.g., Hamming distance, n-grams, and edit distance (see [11] for a good tutorial). In this paper, we mainly consider *edit distance*, one of the most popular string similarity measurement that has been used in a wide spectrum of applications. Informally, the edit distance of two strings s_1 and s_2, denoted as $DST(s_1, s_2)$, measures the minimum number of insertion, deletion and substitution operations to transform s_1 to s_2. We say two strings s_1 and s_2 are *similar*, denoted as $s_1 \approx s_2$, if $DST(s_1, s_2) \leq \theta$, where θ is a user-specified similarity threshold. Otherwise, we say s_1 and s_2 are *dissimilar* (denoted as $s_1 \not\approx s_2$). Without loss of generality, we assume that the dataset D only contains a single attribute. Thus, in the following sections, we use record and string interchangeably. Our methods can be easily adapted to the datasets that have multiple attributes.

2.2 Authenticated Data Structure

To enable the client to authenticate the correctness of mining results, the server returns the results along with some supplementary information that permits result verification. Normally the supplementary information takes the format of *verification object* (VO). In the literature, VO generation is usually performed by an authenticated data structure (e.g., [13, 26, 19]). One of the popular authenticated data structures is *Merkle tree* [22]. In particular, a Merkle tree is a tree T in which each leaf node N stores the digest of a record r: $h_N = h(r)$, where $h()$ is a one-way, collision-resistant hash function (e.g. SHA-1). For each non-leaf node N of T, it is assigned the value $h_N = h(h_{C_1}||\ldots||h_{C_k})$, where $C_1, \ldots, C_k$ are the children of N. The root signature sig is generated by signing the digest h_{root} of the root node using the private key of a trusted party (e.g., the data owner). The VO enables the client to re-construct the root signature sig.

2.3 B^{ed}-Tree for String Similarity Search

A number of compact data structures (e.g., [1, 4, 12]) are designed to handle edit distance based similarity measurement. In this paper, we consider *B^{ed}-tree* [28] due to its support for external memory and dynamic data updates. B^{ed}-tree is a B^+-tree based index structure that can handle arbitrary edit distance thresholds. The tree is built upon a *string ordering* scheme which is a mapping function φ to map each string to an integer value. To simplify notation, we say that $s \in [s_i, s_j]$ if $\varphi(s_i) \leq \varphi(s) \leq \varphi(s_j)$. Based on the string ordering, each B^{ed}-tree node N is associated with a string range $[N_b, N_e]$. Each leaf node contains f strings $\{s_1, \ldots, s_f\}$, where $s_i \in [N_b, N_e]$, for each $i \in [1, f]$. Each intermediate node contains multiple children nodes, where for each child of N, its range $[N'_b, N'_e] \subseteq [N_b, N_e]$, as $[N_b, N_e]$ is the range of N. We say these strings that stored in the sub-tree rooted at N as the strings that are *covered* by N.

We use $DST_{min}(s_q, N)$ to denote the *minimal* edit distance between a string s_q and any string s that is covered by a B^{ed}-tree node N. A nice property of the B^{ed}-tree is that, for any string s_q and node N, the string ordering φ enables to compute $DST_{min}(s_q, N)$ efficiently by computing $DST(s_q, N_b)$ and $DST(s_q, N_e)$ only, where N_b, N_e refer to the string range values of N. Then:

Definition 2.1 *Given a string s_q and a similarity threshold θ, a B^{ed}-tree node N is a* candidate *if $DST_{min}(s_q, N) \leq \theta$. Otherwise, N is a* non-candidate. ∎

B^{ed}-tree has an important monotone property.

Property 2.1 Monotone Property of B^{ed}-tree : Given a node N_i in the B^{ed}-tree and any child node N_j of N_i,

for any string s_q, it must be true that $DST_{min}(s_q, N_i) \leq DST_{min}(s_q, N_j)$. Therefore, for any non-candidate node, all of its children must be non-candidates. This monotone property enables early termination of search on the branches that contain non-candidate nodes.

For any given string s_q, the string similarity search algorithm starts from the root of the B^{ed}-tree, and iteratively visits the candidate nodes, until all candidate nodes are visited. The algorithm does not visit those non-candidate nodes as well as their descendants. An important note is that for each candidate node, some of its covered strings may still be dissimilar to s_q. Therefore, given a string s_q and a candidate B^{ed}-tree node N, it is necessary to compute $DST(s_q, s)$, for each s that is covered by N.

3 Problem Formulation

In this section, we define our authentication problem.

3.1 System Model

We consider the outsourcing model that involves two parties - a data owner (client) who possesses a dataset D that contains n records, and a third-party service provider (server) that executes the record matching on D. The data owner outsources D and the similarity threshold θ to the server. The server provides storage and record matching as services. To facilitate authenticated record matching, the data owner generates some auxiliary information of D, and sends D together with the auxiliary information. Upon finishing record matching on D, the server returns the matching result M^S to the client.

3.2 Threat Model

We assume that the third-party server is not fully trusted as it could be compromised by the attacker (either inside or outside). The server may alter the received dataset D and return any matching result that does not exist in D. It also may tamper with the matching results. For instance, the server may return *incomplete* results that omit some legitimate similar pairs in the matching results [16]. Note that we do not consider privacy protection for the outsourced data. This issue can be addressed by privacy-preserving record linkage [7] and is beyond the scope of this paper.

3.3 Verification Goal of Result Integrity

To catch the cheating on the matching results, we formally define the integrity of the record matching result from two perspective: *soundness* and *completeness*. Let M be the set of matching pairs in the outsourced database D, and M^S be the result returned by the server. We define the *precision* pre of M^S as $pre = \frac{|M \cap M^S|}{|M^S|}$ (i.e., the percentage of returned pairs that are similar to each other), and the *recall* rec of M^S as $rec = \frac{|M \cap M^S|}{|M|}$ (i.e., the percentage of matching pairs that are returned). We say the result M^S is incorrect if $pre < 1$ and incomplete if $rec < 1$. The soundness verification is straightforward. For each record pair $(s_i, s_j) \in M^S$, the data owner checks whether $s_i \approx s_j$. On the other hand, the completeness verification requires to verify for each record pair $(s_i, s_j) \notin M^S$, it is true that $s_i \not\approx s_j$. A naive method for the data owner to verify the result integrity (for both soundness and completeness) is to re-compute the similarity of all record pairs, which is prohibitively costly. In this paper, we design an efficient verification approach for the client to verity both the soundness and completeness of matching results.

3.4 Overview of Our Approach

Given a dataset D, the server finds all similar pairs in the format (s_i, s_j). The pairs that have the same first record s_i (called *target*) are assigned to the same group. For instance, given a set of similar pairs $M = \{(s_1, s_2), (s_1, s_3), (s_2, s_3), (s_2, s_5)\}$, the similar pairs are grouped into $G_1 = \{(s_1, s_2), (s_1, s_3)\}$ and $G_2 = \{(s_2, s_3), (s_2, s_5)\}$. Intuitively, G_1 (G_2, resp.) contains the records that are similar to its target s_1 (s_2, resp.). Then for each group, the server constructs a verification object VO. The VO of G_1 (G_2, resp.) can be used to verify the soundness and completeness of records that are similar to its target s_1 (s_2, resp.). We require that by utilizing VO, the client only needs to perform a small number of string similarity calculations. This is enabled by using the monotone property of the B^{ed}-tree (Property 2.1). In particular, for a given target record s_q and its B^{ed}-tree T, the VO only includes the non-candidate nodes N in T but not all children strings that are covered by N. Therefore, the client is certain that all children strings of N are dissimilar to s_q, and avoids a large number of edit distance calculations.

4 VO Construction for A Single Target Record

In this section, we consider a set of similar record pairs $\{(s_q, s_1), (s_q, s_2), \ldots, (s_q, s_t)\}$ for a single target record s_q. We design a verification method of similarity search (VS^2) approach. VS^2 constructs a *proof* that proves $S = \{s_1, s_2, \ldots, s_t\}$ include all strings (records) that are similar to s_q (completness), and all strings (records) in S is indeed similar to s_q (correctness), where θ is the similarity threshold. VS^2 consists of three phases: (1) the *preprocessing* phase in which the data owner constructs the authenticated data structure T of the dataset D. Both D and the root signature sig of T are outsourced to the server; (2) the *matching* phase in which the server executes the approximate matching on D to find similar strings for s_q, and constructs the *verification object* (VO) of the search results M^S. The server returns both M^S and VO to the data owner; and (3) *verification* phase in which the data owner verifies the integrity of M^S by leveraging VO. Next we explain the details of these three phases.

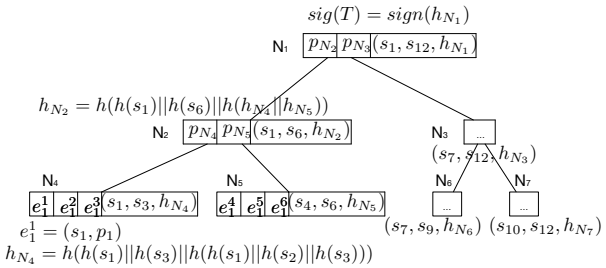


Figure 1: An example of Merkle B^{ed} tree

4.1 Pre-Processing

In this one-time phase, the data owner constructs the authenticated data structure of the dataset D before outsourcing D to the server. We design a new authenticated data structure named the *Merkle B^{ed} tree* (MB-tree). Next, we explain the details of MB-tree.

The MB-tree is constructed on top of the B^{ed} tree by assigning the digests to each B^{ed} node. In particular, every MB-tree node contains a triple (N_b, N_e, h_N), where N_b, N_e correspond to the string range values associated with N, and h_N is the digest value computed as $h_N = h(h(N_b)||h(N_e)||h^{1\to f})$, where $h^{1\to f} = h(h_{C_1}||\dots||h_{C_f})$, with $C_1, \dots, C_f$ being the children of N. If N is a leaf node, then $C_1, \dots, C_f$ are the strings $s_1, \dots, s_f$ covered by N. Besides the triple, each MB-tree node contains multiple entries. In particular, for any leaf node N, assume it covers f strings. Then it contains f entries, each of the format (s, p), where s is a string that is covered by N, and p is the pointer to the disk block that stores s. For any intermediate node, assume that it has f children nodes. Then it contains f entries, each entry consisting of a pointer to one of its children nodes.

The digests of the MB-tree T can be constructed in the bottom-up fashion, starting from the leaf nodes. After all nodes of T are associated with the digest values, the data owner signs the root with her private key. The signature can be created by using a public-key cryptosystem (e.g., RSA). An example of the MB-tree structure is presented in Figure 1. The data owner sends both D and T to the server. The data owner keeps the root signature of T locally, and sends it to any client who requests for it for authentication purpose.

Following [6, 13], we assume that each node of the MB-tree occupies a disk page. For the constructed MB-tree T, each entry in the leaf node occupies $|s| + |p|$ space, where $|p|$ is the size of a pointer, and $|s|$ is the maximum length of a string value. The triple (N_b, N_e, h_N) takes the space of $2|s| + h$, where $|h|$ is the size of a hash value. Therefore, a leaf node can have $f_1 = [\frac{P-2|s|-|h|}{|p|+|s|}]$ entries at most, where P is the page size. Given n unique strings in the dataset, there are $[\frac{n}{f_1}]$ leaf nodes in T. Similarly, for the internal nodes, each entry takes the space of $|p|$. Thus each internal node can have at most $f_2 = [\frac{P-2|s|-|h|}{|p|}]$ entries (i.e., $[\frac{P-2|s|-|h|}{|p|}]$ children nodes). Therefore, the height h of T $h \geq log_{f_2}[\frac{n}{f_1}]$.

4.2 VO Construction

For each target string s_q, the server constructs a verification object VO to show that the matching result M^S is both sound and complete.

First, we define *false hits*. Given a target string s_q and a similarity threshold θ, the *false hits* of s_q, denoted as F, are all the strings that are dissimilar to s_q. In other words, $F = \{s | s \in D, s_q \not\approx s\}$. Intuitively, to verify that M^S is sound and complete, the VO includes both similar strings M^S and false hits F. Apparently including all false hits may lead to a large VO, and thus high network communication cost and the verification cost at the data owner side. Therefore, we aim to reduce the VO size of F.

Before we explain how to reduce VO size, we first define C-strings and NC-strings. Apparently, each false hit string is covered by a leaf node of the MB-tree T. Based on whether a leaf node in MB-tree is a candidate, the false hits F are classified into two types:

- **C-strings**: the strings that are covered by *candidate* leaf nodes; and
- **NC-strings**: the strings that are covered by *non-candidate* leaf nodes.

Our key idea to reduce VO size of F is to include *representatives* of NC-strings instead of individual NC-strings. The representatives of NC-strings take the format of *maximal false hit subtrees* (MFs). Formally, given a MB-tree T, we say a subtree T^N that is rooted at node N is a *false hit subtree* if N is a *non-candidate* node. We say the false hit subtree T^N rooted at N is *maximal* if the parent of N is a candidate node. The MFs can root at leaf nodes. Apparently, all strings covered by the MFs must be NC-strings. And each NC-string must be covered by a MF node. Furthermore, MFs are disjoint (i.e., no two MFs cover the same string). Therefore, instead of including individual NC-strings into the VO, their MFs are included. As the number of MFs is normally much smaller than the number of NC-strings, this can effectively reduce VO size. Now we are ready to define the VO.

Definition 4.1 *Given a dataset D, a target string s_q, let M^S be the returned similar strings of s_q. Let T be the MB-tree of D, and NC be the strings that are covered by non-candidate nodes of T. Let $\mathcal{M}$ be a set of MFs of NC. Then the VO of s_q consists of: (i) string s, for each $s \in D - NC$; and (ii) a pair $(N, h^{1\to f})$ for each $MF \in \mathcal{M}$ that is rooted at node N, where N is represented as $[N_b, N_e]$, with $[N_b, N_e]$ the string range associated with N, and $h^{1\to f} = h(h_{C_1}||\dots||h_{C_f})$, with $C_1, \dots, C_f$ being the children of N. If N is a leaf node, then $C_1, \dots, C_f$ are the strings $s_1, \dots, s_f$ covered by N. Furthermore, in VO, a pair of*

brackets is added around the strings and/or the pairs that share the same parent in T. ∎

Intuitively, in VO, the similar strings and C-strings are present in the original string format, while NC-strings are represented by the MFs (i.e., in the format of $([N_b, N_e], h_N)$).

Example 4.1 *Consider the MB-tree T in Figure 1, and the string s_1 to construct VO. Assume the similar strings are $M^S = \{s_3, s_5\}$. Also assume that node N_3 of T is the only non-candidate node. Then NC-strings are $NC = \{s_7, s_8, \ldots, s_{12}\}$, and C-strings are $\{s_2, s_4, s_6\}$. The set of MFs $\mathcal{M}$ =$\{N_3\}$. Therefore,*

$VO = \{(((s_1, s_2, s_3), (s_4, s_5, s_6)), ([s_7, s_{12}], h^{7\rightarrow 12}))\}$,
where $h^{7\rightarrow 12} = h(h_{N_6}||h_{N_7})$,
$h_{N_6} = h(h(s_7)||h(s_9)||h(h(s_7)||h(s_8)||h(s_9)))$,
and $h_{N_7} = h(h(s_{10})||h(s_{12})||h(h(s_{10})||h(s_{11})||h(s_{12})))$.

For each MF, we do not require that $h(N_b)$ and $h(N_e)$ appear in VO. However, the server must include both N_b and N_e in VO. This is to prevent the server to cheat on the non-candidate nodes by including insound $[N_b, N_e]$ in VO. More details of the robustness of our authentication procedure can be found in Section 6.

4.3 Authentication Phase

For a given target string s_q, the server returns VO together with the matching set M^S to the client. The verification procedure consists of three steps. In Step 1, the client re-constructs the MB-tree from VO. In Step 2, the client re-computes the root signature sig', and compares sig' with sig. In Step 3, the client re-computes the edit distance between s_q and a *subset* of strings in VO. Next, we explain the details of these steps.

Step 1: Re-construction of MB-tree: First, the client sorts the strings and string ranges (in the format of $[N_b, N_e]$) in VO by their mapping values according to the string ordering scheme. String s is put ahead of the range $[N_b, N_e]$ if $s < N_b$. It returns a total order of strings and string ranges. If there exists any two ranges $[N_b, N_e]$ and $[N'_b, N'_e]$ that overlap, the client concludes that the VO is not sound. If there exists a string $s \in M^S$ and a range $[N_b, N_e] \in VO$ such that $s \in [N_b, N_e]$, the client concludes that M^S is not sound, as s indeed is a dissimilar string (i.e., it is included in a non-candidate node). Second, the client maps each string $s \in M^S$ to an entry in a leaf node in T, and each pair $([N_b, N_e], h_N) \in VO$ to an internal node in T. The client re-constructs the parent-children relationships between these nodes by following the matching brackets () in VO.

Step 2: Re-computation of root signature: After the MB-tree T is re-constructed, the client computes the root signature of T. For each string value s, the client calculates $h(s)$, where $h()$ is the same hash function used for the construction of the MB^{ed}-tree. For each internal node that corresponds to a pair $([N_b, N_e], h^{1\rightarrow f})$ in VO, the client computes the hash h_N of N as $h_N = h(h(N_b)||h(N_e)||h^{1\rightarrow f})$. Finally, the client re-computes the hash value of the root node, and rebuilds the root signature sig' by signing h_{root} using the data owners's public key. The client then compares sig' with sig. If $sig' \neq sig$, the client concludes that the server's results are not sound.

Step 3: Re-computation of necessary edit distance: First, for each string $s \in M^S$, the client re-computes the edit distance $DST(s_q, s)$, and verifies whether $DST(s_q, s) \leq \theta$. If all strings $s \in M^S$ pass the verification, then the client concludes that M^S is *sound*. Second, for each C-string $s \in VO$ (i.e., those strings appear in VO but not M^S), the client verifies whether $DST(s_q, s) > \theta$. If it is not (i.e., s is a similar string indeed), the client concludes that the server fails the completeness verification. Third, for each range $[N_b, N_e] \in VO$, the client verifies whether $DST_{min}(s_q, N) > \theta$, where N is the corresponding MB-tree node associated with the range $[N_b, N_e]$. If it is not (i.e., node N is indeed a candidate node), the client concludes that the server fails the completeness verification.

Phase	Measurement	VS^2
Pre-processing	Time	$O(n)$
	Space	$O(1)$
VO construction	Time	$O(n)$
	VO Size	$O((n_C + n_R)\sigma_S + n_{MF}\sigma_M)$
Verification	Time	$O((n_R + n_{MF} + n_C)C_{Ed})$

Table 1: Complexity analysis of VS^2
(n: # of strings in D; σ_S: AVG. length of string;
σ_M: AVG. size of MB-tree node; n_{MF}: # of MF nodes;
n_R: # of strings in M^S; n_C: # of C-strings;
C_{Ed}: the complexity of an edit distance computation)

Example 4.2 *Consider the MB-tree in Figure 1 as an example, and the target string s_1. Assume the similar strings $M^S = \{s_3, s_5\}$. Consider the VO shown in Example 4.1. The C-strings are $C = \{s_2, s_4, s_6\}$. After the client reconstructs the MB-tree, it re-computes the hash values of strings $M^S \cup C$. It computes the root signature sig' from these hash values. It also performs the following distance computations: (1) for $M^S = \{s_3, s_5\}$, compute the edit distance between s_1 and string in M^S, (2) for $C = \{s_2, s_4, s_6\}$, compute the edit distance between s_1 and any C-string in C, and (3) for the pair $([s_7, s_{12}], h_{N_3}) \in VO$, compute $DST_{min}(s_q, N_3)$.* ∎

4.4 Complexity Analysis

We formally analyze the time and space complexity of the three phases of VS^2, and present the result in Table 1.

In the pre-processing phase, the data owner needs to hash all the records to construct the leaf nodes of the MB-tree,

which results in $O(n)$ time complexity, where n is the number of records in the dataset D. As the total number of nodes in the MB-tree is $O(\frac{n}{f})$, where f is the fanout of the nodes, the total time complexity of the pre-processing phase is $O(n)$. Regarding the space complexity, as the data owner only needs to keep the root signature of the MB-tree locally, the storage overhead is only $O(1)$.

Regarding the VO construction phase, the server traverse the MB-tree to construct the VO. In the worst case, the server scans all the MB-tree nodes to find C-strings and MF nodes. Thus, the time complexity is $O(n)$. The VO size of the VS^2 approach is calculated as the sum of two parts: (1) the total size of the similar strings and C-strings (in string format), which is $O((n_R + n_C)\sigma_S)$ and (2) the size of MF nodes, which is $O(n_{MF}\sigma_M)$. Note that $\sigma_M = 2\sigma_S + |h|$, where $|h|$ is the size of a hash value. In our experiments, it turned out that $\sigma_M/\sigma_S \approx 20$.

Regarding the authentication phase, in order for the client to authenticate the matching results based on the VO, the main time complexity comes from calculating the string edit distance, as it is very efficient to compute the hash values and the root signature of the MB-tree. Specifically, for each similar string and C-string, the client calculates its edit distance to the target string. Besides, the completeness verification requires to compute the edit distance $DST_{min}(s_q, N)$, for each MF node N. Thus, the complexity of VO verification is $O((n_R + n_{MF} + n_C)C_{Ed})$.

5 VO Construction for Multiple Target Records

So far we discussed the authentication of record matching of a single target string (record). To authenticate the matching result for multiple target strings (records) $S = \{s_1, \ldots, s_\ell\}$, a straightforward solution is to create VO for each string $s_i \in S$ and its similarity result $M^S(s_i)$. Apparently this solution may lead to VO of large sizes in total. Thus, we aim to reduce the size of VOs. Our VO optimization method consists of two main strategies: (1) optimization by triangle inequality; and (2) optimization by overlapping dissimilar strings.

5.1 Optimization by Triangle Inequality

It is well known that the string edit distance satisfies the *triangle inequality*, i.e. $|DST(s_i, s_k) - DST(s_j, s_k)| \leq DST(s_i, s_j) \leq DST(s_i, s_k) + DST(s_j, s_k)$. Therefore, consider two strings s_i, $s_j \in D$, assume the the server has executed the approximate matching of s_i and prepared the VO of the results. Then consider the authentication of the search results of string s_j, for any string $s \in D$ such that $DST(s, s_i) - DST(s_i, s_j) > \theta$, there is no need to prepare the proof of s showing that it is a false hit for s_j. A straightforward method is to remove s from the MB-tree T for VO construction for the string s_j. Now the question is whether removing s always lead to VO of smaller sizes. We have the following theorem.

Theorem 5.1 Given a string s and a MB-tree T, let $N \in T$ be the corresponding node of s, and N_P be the parent of N in T. Let $C(N_P)$ be the set of children of P in T, and N'_P be the node constructed from $C(N_P)\backslash N$ (i.e., the children nodes of N_p excluding N). Then if N_P is a non-candidate, it must be true that N'_P must be a non-candidate.

Let $[N_b, N_e]$ be the range of N_P. The proof of Theorem 5.1 considers two cases: (1) $s \neq N_b$ and $s \neq N_e$. Removing s will not change N_b and N_e, which results in that both N'_p and N_p have the same range $[N_b, N_e]$. (2) $s = N_b$ or $s = N_e$. Removing s from $C(N_P)$ changes the range of N_P to be $[N'_b, N'_e]$. Note that it must be true $[N'_b, N'_e] \subseteq [N_b, N_e]$. Therefore, N'_P must be a non-candidate.

Based on Theorem 5.1, removing the MB-tree nodes that correspond to any dissimilar string does not change the structure of the MB-tree. Therefore, we can optimize the VO construction procedure by removing those strings covered by the triangle inequality from the MB-tree.

Another possible optimization is that for any two target strings s_i and s_j, for any string $s \in D$ such that $DST(s, s_i) + DST(s_i, s_j) \leq \theta$, the client does not need to re-compute $DST(s, s_j)$ to prove that s_i is a similar string in the results. We omit the details due to the space limit.

5.2 Optimization by Overlapped Dissimilar Strings

Given multiple target records (strings), the key optimization idea is to merge the VOs of various target strings. This is motivated by the fact that any two strings s_i and s_j may share a number of dissimilar strings. These shared dissimilar strings can enable to merge the VOs of s_i and s_j. Note that simply merging all similar strings of s_i and s_j into one set and constructing MB-tree of the merged set is not correct, as the resulting MB-tree may deliver non-leaf MFs that are candidates to both s_i and s_j. Therefore, given two target strings s_i and s_j such that their false hits overlap, let NC_i (NC_j, resp.) be the NC-strings of s_i (s_j resp.), the server finds the overlap of NC_i and NC_j. Then the server constructs VO that shares the same data structure on these overlapping strings. In particular, given the overlap $O = NC_i \cap NC_j$, the server constructs the non-leaf MFs from O, and include the constructed MFs in the VOs of both s_i and s_j.

6 Security Analysis

Given a target string s_q and a similarity threshold θ, let M (F, resp.) be the similar strings (false hits, resp.) of s_q. Let M^S be the similar strings of s_q returned by the server. An untrusted server may perform the following cheating behaviors the real results M^S: (1) *tampered values*: some

strings in M^S do no exist in the original dataset D; (2) *soundness violation*: the server returns $M^S = M \cup FS$, where $FS \subseteq F$; and (3) *completeness violation*: the server returns $M^S = M - SS$, where $SS \subseteq M$.

The tampered values can be easily caught by the authentication procedure, as the hash values of the tampered strings are not the same as the original strings. This leads to that the root signature of MB-tree re-constructed by the client differet from the root signature of original dataset before outsourcing. The client can catch the tampered values by Step 2 of the authentication procedure. Next, we mainly focus on the discussion of how to catch soundness and completeness violations.

Soundness. The server may deal with the VO construction of $M^S = M \cup FS$ in two different ways:

Case 1. The server constructs the VO of the correct result M, and returns $\{M^S, VO\}$ to the client;

Case 2. the server constructs the VO of M^S, and returns $\{M^S, VO\}$ to the client. Note that the strings in FS can be either NC-strings or C-strings. Next, we discuss how to catch these two types of strings for both Case 1 and 2.

For Case 1, for each NC-string $s \in FS$, s must fall into a MF-tree node in VO. Thus, there must exist an MF-tree node whose associated string range overlaps with s. The client can catch s by Step 1 of the authentication procedure. For each C-string $s \in FS$, s must be treated as a C-string in VO. Thus the client can catch it by computing $DST(s, s_q)$ (i.e., Step 3 of the authentication procedure).

For Case 2, the C-strings in FS will be caught in the same way as Case 1. Regarding NC-strings in FS, they will not be included in any MF-tree in V'. Therefore, the client cannot catch them by Step 1 of the authentication procedure (as Case 1). However, as these strings are included in M^S, the client still can catch these strings by computing the edit distance of s_q and any string in M^S (i.e., Step 3 of the authentication procedure).

Completeness. To deal with the VO construction of $M^S = M - SS$, we again consider the two cases as for the discussion of soundness violation.

For Case 1 (i.e., the server returns $\{M^S, VO\}$), where VO is constructed from the correct result M, any string $s \in SS$ is a C-string. These strings can be caught by re-computing the edit distance between the target string and any C-string (i.e., Step 3 of the authentication procedure).

For Case 2 (i.e., the server returns $\{M^S, VO\}$), where VO is constructed from the M^S, any string $s \in SS$ is either a NC-string or a C-string in V'. For any C-string $s \in SS$, it can be caught by re-computing the edit distance between the target string and the C-strings (i.e., Step 3 of the authentication procedure). For any NC-string $s \in SS$, it must be included into a non-candidate MB-tree node. We have the following theorem.

Theorem 6.1 Given a target string s_q and a non-candidate node N of range $[N_b, N_e]$, including any string s' into N such that $s' \approx s_q$ will change N to be a candidate node.

The proof is straightforward. It is easy to see that $s' \notin [N_b, N_e]$. Therefore, including s' into N must change the range to be either $[s', N_e]$ or $[N_b, s']$, depending on whether $s' < N_b$ or $s' > N_e$. Now it must be true that $DST_{min}(s_q, N) \leq \theta$, as $DST(s', s_q) \leq \theta$.

Following Theorem 6.1, for any string $s \in SS$ that is considered a NC-string in VO, the client can easily catch it by verifying whether $DST_{min}(s_q, N) > \theta$, for any non-candidate node (i.e., Step 3 of the authentication procedure).

7 Experiments

In this section, we report the experiment results.

7.1 Experiment Setup

Datasets and queries. We use two real-world datasets : (1) the *Actors* dataset from IMDB [1] that contains 260K last names. The maximum length of a name is 63, while the average is 14.627; and (2) the *Authors* dataset from DBLP [2] including 1,000,000 researcher names. The maximum length of a name is 99 while the average length is 14.732. As both datasets are very large, it is too time-consuming to execute approximate matching for all records in these two datasets. Thus, we picked 10 target strings for approximate matching. For the following results, we report the average performance of matching of the 10 target strings.

Experimental environment. We implement the VS^2 approach in C++. The hash function we use is the *SHA256* function from the OpenSSL library. We execute the experiments on a machine with 2.4 GHz CPU and 48 GB RAM, running Linux 3.2.

Baseline. As the baseline method, we implement the brute-force approximate string matching algorithm that calculates the edit distance between every string in the dataset and the target string s_q.

Parameter setup. The parameters include: (1) string edit distance threshold θ, and (2) the fanout f of MB-tree nodes (i.e., the number of entries that each node contains). The details of the parameter settings can be found in Table 2.

Parameter	setting
Similarity threshold θ	2,3,4,5,6,7
MB-tree fanout f	10, 100, 1000, 10000

Table 2: Parameter settings

In the discussions, we use the following notations: (1) n: the number of strings in the dataset, (2) n_R: the number of similar strings, (3) n_{MF}: the number of MFs, and (4) n_C: the number of C-strings. We use σ_S to indicate the average string size, and σ_M as the size of MB-tree node.

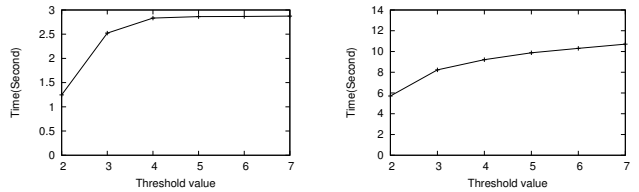
[1] http://www.imdb.com/interfaces

[2] http://dblp.uni-trier.de/xml/

7.2 VO Construction Time

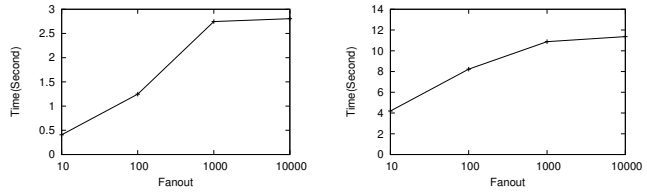
We measure the VO construction time at the server side.

The impact of θ. In Figure 2, we show the VO construction time with regard to different θ values on both datasets. First, in all our experiments, the VO construction time is very short; it never exceeds 11 seconds for both datasets. It only needs around 3 seconds for the *Actor* dataset. Second, we observe that the VO construction time grows when θ increases. This is because n_{MF} reduces with the increase of θ. When θ is small, a node N may be a MF, because $DST_{min}(s_q, N) > \theta$. While with a larger θ values, the node N becomes a candidate. Thus, the server needs to search deep in the MB-tree to find the MF nodes, if there is any. Third, we observe the dramatic increase in VO construction time when θ changes from 2 to 3. With further analysis, we discover that the change in VO construction time is consistent with how n_{MF} varies. For example, on the *Actors* dataset, when $\theta = 2$, $n_{MF} = 2,958$. However, n_{MF} decreases to 649 when $\theta = 3$. The abrupt reduction in n_{MF} leads to the immense increment effort that the server devotes to traverse the MB-tree to find MFs. Fourth, the VO construction time on the *Authors* dataset is larger than that on the *Actors* dataset. This is because with the same fanout f, the MB-tree's size of the *Authors* dataset is larger, due to the greater data size.



(a) The *Actors* dataset (b) The *Authors* dataset

Figure 2: VO construction time w.r.t. θ ($f = 100$)



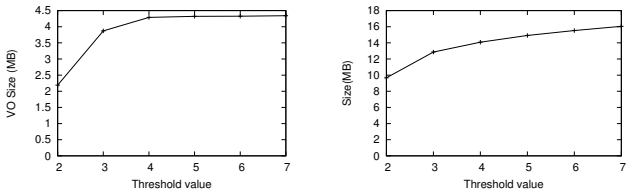
(a) The *Actors* dataset ($\theta = 2$) (b) The *Authors* dataset ($\theta = 3$)

Figure 3: VO construction time w.r.t. f

The impact of f. From Figure 3, we observe that the VO construction time increases with the fanout value f. Even though the total number of nodes in the MB-tree decreases with larger fanout values, the decrease in the number of MFs n_{MF} is more intense. For example, on the *Authors* dataset, when $f = 100$, $n_{MF} = 5,420$; while when $f = 1,000$, $n_{MF} = 57$. The reason behind the significant reduction in n_{MF} is that when f is large, $DST_{min}(s_q, N)$ becomes a loose lower-bound for any MB-tree node N. This leads to a significant portion of the MB-tree nodes to become candidates. The observation from Figure 3 suggests that small fanout values fit our VS^2 method better.

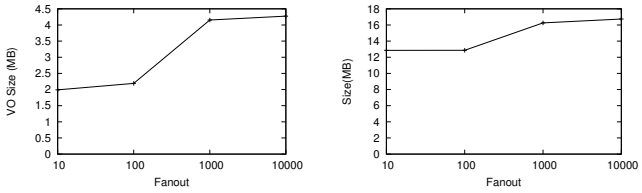
7.3 VO Size

We measure the size of the VO constructed by VS^2.



(a) The *Actors* dataset (b) The *Authors* dataset

Figure 4: VO size w.r.t. θ ($f = 100$)



(a) The *Actors* dataset ($\theta = 2$) (b) The *Authors* dataset ($\theta = 3$)

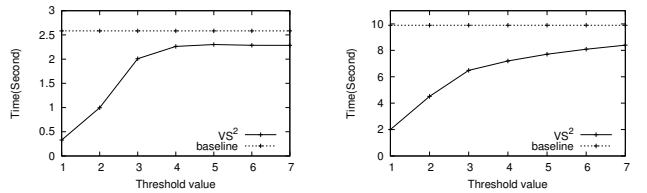
Figure 5: VO size w.r.t. f

The impact of θ. The results are shown in Figure 4. The observation is that the VO size increases with the growth of θ value. Apparently, larger θ values lead to more similar strings (i.e., larger n_R), fewer MFs (i.e., smaller n_{MF}), and fewer C-strings (i.e., smaller n_C). The VO size is decided by $(n_R + n_C)\sigma_S + n_{MF}\sigma_M$, where $\frac{\sigma_M}{\sigma_S} \approx 20$. When we increase θ, even though n_{MF} reduces, the intensive growth of n_R and n_C leads to the increase of VO size. For example, on the *Actors* dataset, when $\theta = 2$, $n_R + n_C = 126,858$, $n_{MF} = 2,958$. While when $\theta = 3$, $n_R + n_C = 230,821$, $n_{MF} = 649$.

The impact of f. As shown in Figure 5, the VO size increases with the growth of the fanout f. Recall that the VO size is $(n_R + n_C)\sigma_S + n_{MF}\sigma_M$. When f increases, n_R is unchanged. Meanwhile, n_C dramatically increases with f (e.g., on the *Actors* dataset, when f increases from 100 to $1,000$, n_C increases by $122,515$). Furthermore, when f increases, n_{MF} decreases by a small degree (when f changes from 100 to $1,000$, n_{MF} decreases by $2,937$). Consider that $\frac{\sigma_M}{\sigma_S} \approx 20$. The intensive increase of n_C leads to a larger VO size. We observe the sharp increase in VO size when f increases from 100 to $1,000$. This is because at this point, n_C experiences the maximum extent of growth.

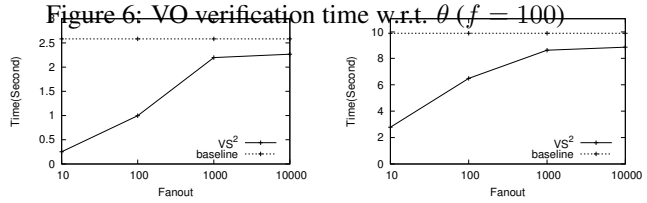
7.4 VO Verification Time

In this section, we measure the VO verification time at the data owner side. We compare the VO verification time with the performance of our baseline algorithm, aiming to show that the client's verification effort is less than by doing string matching locally.



(a) The *Actors* dataset (b) The *Authors* dataset

Figure 6: VO verification time w.r.t. θ ($f = 100$)



(a) The *Actors* dataset ($\theta = 2$) (b) The *Authors* dataset ($\theta = 3$)

Figure 7: VO verification time w.r.t. f

The impact of θ. In Figure 6, we report the VO verification time of VS^2. First, we observe that the VO verification time is always smaller than the baseline. In particular, VS^2 can save up to 87% computational effort at the data owner side if she outsources the string matching to the server and does verification locally. This proves that our verification method is suitable for the outsourcing setting. Second, the VO verification time increases when θ increases. Recall that the complexity of VO verification is $O((n_R+n_C+n_{MF})C_{Ed})$. This is because when θ increases, n_{MF} decreases, while both n_R and n_C increase. As n_R and n_C increase faster than the decrease of n_{MF}, it leads to more edit distance calculations for the verification. Therefore, the total verification time increases.

The impact of f. We also measure the VO verification time of VS^2 with various fanout values. On both datasets, the VO verification is always more efficient than the baseline method. When the fanout is 10, VS^2 can save up to 90% computational effort at the client side. Besides, the verification time increases when f grows. This is straightforward as larger f results in the growth of the number of C-strings. This requires more calculations for the edit distance between C-strings and the target string.

In sum, the experiment results suggest that VS^2 is an efficient authentication approach to verify the result of outsourced record matching computations. In particular, VS^2 is more suitable for the setting in which the similarity threshold is small and the MB-tree's fanout is small.

8 Related Work

The security problem of outsourced computations caught much attention in recent years. Based on the the perspective to enforce security and the type of computations that are executed on the data, we classify these techniques into the following types: (1) authentication of outsourced SQL query evaluation, (2) authentication of keyword search, and (3) privacy-preserving record linkage. There are also other work on authentication of data integration [5] and in-network aggregation in distributed systems (e.g. [18, 27]). None of these work considered the authentication of outsourced approximate string matching .

Authentication of outsourced SQL query evaluation. The issue of providing authenticity for outsourced database was initially raised in the database-as-a-service (DaS) paradigm [10]. The aim is to assure the correctness of SQL query evaluation over the outsourced databases. The proposed solutions include Merkle hash trees [13, 15], signatures on a chain of paired tuples [17], and authenticated B-tree and R-tree structures for aggregated queries [14]. The key idea of these techniques is that the data owner outsources not only data but also the endorsements of the data being outsourced. These endorsements are signed by the data owner against tampering with by the service provider. For the cleaning results, the service provider returns both the results and a proof, called the *verification object* (VO), which is an auxiliary data structure to store the processing traces such as index traversals. The client uses the VO, together with the answers, to reconstruct the endorsements and thus verify the authenticity of the results. An efficient authentication technique should minimize the size of VO, while requiring lightweight authentication at the client side. In this paper, we follow the same VO-based strategy to design our authentication method.

Authentication of keyword search. Pang et al. [16] targeted at search engines that perform similarity-based document retrieval, and designed a novel authentication mechanism for the search results. The key idea of the authentication is to build the Merkle hash tree (MHT) on the inverted index, and use the MHT for VO construction. Though effective, it has several limitations, e.g., the MHT cannot deal data updates efficiently [9]. To address these limitations, Goodrich et al. [9] designed a new model that considered conjunctive keyword searches as equivalent with a set intersection on the underlying inverted index data structure. They use the authenticated data structure in [20] to verify the correctness of set operations.

Privacy-preserving record linkage. The privacy of sensitive information in the outsourced record matching has been the focus of research for two decades. Schnell et al. [23] and Durham et al. [8] propose to store the q-grams in the Bloom Filters (BFs); the BFs of two similar strings (i.e., many q-grams in common) have a large number of identical bit positions set to 1. However, Schnell et al. [23] observed that the BFs are still open to the frequency attack. Storer et al. [24] consider the duplicates as exact identical contents. They use convergent encryption that uses a function of the hash of the plaintext of a chunk as the encryption key, so that any identical plaintext values will be encrypted to identical ciphertext values. However, the convergent encryption

disables the approximate matching on outsourced records. Bonomi et al. [3] propose a new transformation method that integrates embedding methods with differential privacy. Its embedding strategy projects the original data on a base formed by a set of frequent variable length grams. The privacy of the gram construction procedure is guaranteed to satisfy differential privacy. Atallah et al. [2] design a SMC protocol based on homomorphic encryption for record linkage based on edit distance similarity.

9 Conclusion

In this paper, we designed an efficient authentication method, namely ARM, for outsourced approximate record matching. ARM is based on a novel authentication data structure named MB-tree that integrates both B^{ed}-tree and Merkle hash tree. Experimental results show that our methods can authenticate the record matching result efficiently. In the future, we will investigate how to reduce the VO size as well as the verification time.

10 Acknowledgment

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