Preferred Keyword Search over Encrypted Data in Cloud Computing

Zhirong Shen, Jiwu Shu[†], Wei Xue
Department of Computer Science and Technology, Tsinghua University,Beijing 100084, China
Tsinghua National Laboratory for Information Science and Technology, Beijing 100084, China
[†]*Corresponding author:shujw@tsinghua.edu.cn*
czr10@mails.tsinghua.edu.cn,xuewei@tsinghua.edu.cn

***Abstract*—Cloud computing cuts down large capital outlays in facilities purchase and eliminates complex system management for users. To protect data confidentiality in cloud utilization, sensitive data are usually stored in encrypted form, making traditional search service on plaintext inapplicable. Thus, enabling keyword search over encrypted data becomes a paramount urgency. Given massive data users with various search preferences, it becomes necessary to support preferred keyword search and output the data files in the order of the user's preference. In this paper, for the first time, we investigate the challenging problem of preferred keyword search over encrypted data (PSED). We first establish a set of privacy requirements and utilize the appearance frequency of each keyword to serve as its "weight". A preference preprocessing mechanism is then explored to ensure that the search result will faithfully respect the user's preference and the Lagrange polynomial is introduced to express the user's preference formula. We further represent keyword weights of each file by using vectors, convert the preference polynomial into the vector form, and securely calculate their inner products to quantitatively characterize the relevance measure between data files and a query. Finally, an extensive performance evaluation demonstrates the proposed scheme can achieve acceptable efficiency.**

I. Introduction

Cloud computing centralizes a large amount of materials and offers pay-as-you-use service. However, the data hosted in the cloud may suffer from the unsolicited access from both of the cloud server and other unauthorized users. To protect confidentiality, sensitive data are hosted in encrypted form in the cloud, making it different from the traditional data service based on plaintext keyword search. The trivial solution of downloading all the data and decrypting them locally is extremely expensive. Thus, exploring an efficient search service over encrypted data becomes a paramount urgency.

On one hand, the scale of massive files in the cloud requires flexible search query to retrieve accurate search results without receiving the unneeded files. On the other hand, given the large amount of users in cloud environment, *different users may find different things relevant when searching because of different preferences* [14], indicating the necessity of *preferred search* support to cope with users' various preferences. Thus, exploring a flexible search service with preferred search support over encrypted data is extremely meaningful in cloud environment.

During last several years, *searchable encryption (SE)* [2]–[11] has been evolved in pursuit of search over encrypted data under different applications. For schemes [2], [8], [10] that realize the flexible search, they only support "Boolean keyword search" and pay limited attention to the relevance between files and a query. For schemes [9], [11] that enable ranked keyword search, they either just support single keyword search [9] or may return inaccurate results [11]. Even more important, most of the existing works ignore the user's preference, easily leading to the following drawbacks. First, a user who does not have any pre-understanding about the encrypted data has to endure the labor-intensive task of manually picking out their interested files. Secondly, the naive search output without preference consideration will easily cause network congestion because of the transmission for all the matching files. Meanwhile, in the branch of *information retrieval (IR)* and *database (DB)*, some search schemes with preference [13]–[17] have been proposed to quantify the retrieved files, however, they cannot be directly applied in the context of encrypted cloud data retrieval due to the limited attention on security and privacy for both queries and files. In short, the absence of preferred search with privacy preserved and flexible search query support is still a typical shortage in existing SE schemes.

In this paper, we study the problem of preferred keyword search over encrypted data (PSED) for the first time. We first specify a set of privacy requirements and use the appearance frequency of each keyword to a file to act as its weight. A flexible search query (e.g., the query over multiple keyword fields) is converted into polynomial form and the Lagrange polynomial is utilized to characterize the user's preference query. Then we convert the search polynomial and the preference polynomial into vector forms, and propose a secure inner product computation mechanism to capture the correlation of files to the query. Thorough the analysis investigating efficiency and privacy is given, and the intensive evaluations on a real-world dataset demonstrate the efficiency of the proposed solution.

II. Problem Formulation

A. System Model and Threat Model

Figure 1 presents the system model. The *data owner* hosts a collection of encrypted files $\mathcal{C} = \{F_1, \ldots, F_{|C|}\}$ in the cloud and allows authorized users to search through them. The *data user* is the entity who wishes to fetch the files according to his interest. He should generate a search query $\mathcal{Q}$ and a search preference $\mathcal{P}$, and request for the search trapdoor $T_{\mathcal{Q},\mathcal{P}}$. The *cloud server* keeps data files and responds users' search requests. When receiving $T_{\mathcal{Q},\mathcal{P}}$, the server will locate the matching files by scanning the indexes $\mathcal{I}$, calculate corresponding relevance scores, and return the ranked result.

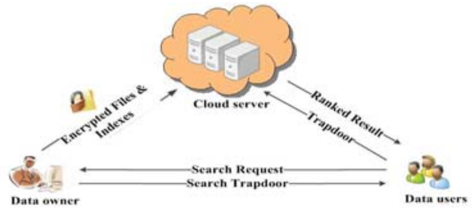

Fig. 1. The system model of PSED.

Like many previous works [9], [11] of SE, the cloud server is treated as ”honest but curious”, meaning the server will ”honestly” execute the designed protocol, but he is also ”curious” to learn the search query and the preferences.

B. Design Goals

Flexible search query with preferences. PSED should support preferred search over multiple keyword fields, including equality, range, and subset query over each keyword field, such as *conjunctive normal form (CNF)* policy.

Index privacy. The index privacy generally means the keywords (resp. keyword weights) should be kept secret against the server to prevent it from learning the keywords in the query and the file content (resp. the characteristics) of the files.

Trapdoor privacy. Trapdoor privacy can be partitioned into query privacy and preference privacy. Query privacy means the server cannot guess whether two trapdoors are generated from the same query, while preference privacy denotes the server should be unaware of the user’s preference for each keyword.

Relevance privacy. Though the cloud server knows the ranked order according to the calculated scores, it is forbidden to sense the actual relevance of each file to a query, otherwise it can deduce the file content based on the actual relevance.

Efficiency The proposed scheme should introduce lightweight operations to the user/owner, and promise the search efficiency.

C. Variables and Notations

Preference and Relevance score. Users can specify some numbers called *preferences* to characterize his different levels of interests for keywords. The larger preference generally means the higher priority order. Since keywords and their frequencies are practical tools to characterize the file content and their significance, the relevance of a file to a query can be divided into many ”sub-relevances” to represent the ”correlation” of the file to keywords in the query. We adopt the product of the preference and the keyword weight to server as this ”sub-relevance”, and take the accumulated ”sub-relevances” to act as the *relevance score* of the file to the query. Therefore, we can express the keyword weight and the keyword preference in vector form (see Section III-A2), so that their inner product can achieve this kind of effect. Compared to the ”inner product similarity” [11] model which ignores the importance of keyword frequency, we argue our model is quite more practical and reasonable.

Secure inner-product calculation. It means a user can specify a third party to compute the inner-product of two encrypted vectors $E(\vec{p})$ and $E(\vec{q})$ without learning the actual values in $\vec{p}$ and $\vec{q}$ by using random asymmetric splitting, so that $E(\vec{p})^T \cdot E(\vec{q}) = \vec{p}^T \cdot \vec{q}$. The reader can refer [12] for more detail.

TABLE I
THE FREQUENTLY USED VARIABLES AND NOTATIONS.

Variables	Notations
$\mathcal{C}$,u	The file collection, the number of keyword fields
$\mathcal{W}$, $\mathcal{W}_i$	The keyword space of $\mathcal{C}$, the keyword space of F_i
$W_i, w_{i,j}$	The i-th keyword field, the j-th keyword of W_i
n_i, n	The number of keywords in W_i, $\sum_{i=1}^{u} n_i$
$\mathcal{Q}, \mathcal{P}$	a search query, a search preference
$h_{i,j}, p_{i,j}$	The weight of $w_{i,j}$, the preference of $w_{i,j}$
$n_{\mathcal{Q}}$	The number of keywords in $\mathcal{Q}$
$\mathcal{W}_{i,p_j}$	The keyword set in F_i whose preferences are p_j
$h_{\mathcal{W}_{i,p_j}}$	The sum of weights for the keywords in $\mathcal{W}_{i,p_j}$
$\vec{Q}, \vec{P}$	A search query vector, a preference vector
$T_{\mathcal{Q},\mathcal{P}}$	The trapdoor derived from $\mathcal{Q}$ and $\mathcal{P}$
$F_{\mathcal{Q},\mathcal{P}}$	The search output of $T_{\mathcal{Q},\mathcal{P}}$
$\lvert\mathcal{W}\rvert$, $\lvert\mathcal{C}\rvert$	The number of keywords in $\mathcal{W}$, the number of files in $\mathcal{C}$

III. THE DESIGN OF PSED

In this section, we start with the preference preprocessing. Then the transformation from the preference query (resp., the search query) to the preference vector (resp., the search vector) will be presented. We will further give the detailed design of PSED and provide an analysis on security and efficiency.

A. Algorithm description

To characterize the matching equality among different files to a query, we first define the concept of *”Priority order of files to a search trapdoor”*.

Definition 1 (**Priority order of files to a search trapdoor**). *For files F_i and F_j, F_i is prior to F_j to $T_{\mathcal{Q},\mathcal{P}}$ if either of following two conditions establishes:*

(1)F_i matches with the query $\mathcal{Q}$ and F_j is rejected;

(2)Both F_i and F_j match with $\mathcal{Q}$. There exists a preference p_m, and two keyword sets $\mathcal{W}_{i,p_m} \subset \mathcal{W}_i$ and $\mathcal{W}_{j,p_m} \subset \mathcal{W}_j$, such that $h_{\mathcal{W}_{i,p_m}} > h_{\mathcal{W}_{j,p_m}}$. For other preferences, if there is $p_z \in \mathcal{P}$ such that $p_z > p_m$, then there exist two keyword sets $\mathcal{W}_{i,p_z} \subset \mathcal{W}_i$ and $\mathcal{W}_{j,p_z} \subset \mathcal{W}_j$, such that $h_{\mathcal{W}_{i,p_z}} = h_{\mathcal{W}_{j,p_z}}$.

Here, we denote the preference p_m in case (2) as a *”critical preference value (CPV)”* between F_i and F_j.

1) Preference Preprocessing: Adding the product of every keyword weight and its preference together to serve as the relevance score may not output the results that strictly follow the user’s search priority.

For example, there are two files F_1 and F_2 containing $w_{1,1}$ and $w_{1,2}$ in the field W_1 respectively and the corresponding keyword weights are $h_{1,1} = 10$ and $h_{1,2} = 4$, then for a query $(w_{1,1} \vee w_{1,2})$ with a preference $(p_{1,1} = 8 \vee p_{1,2} = 10)$, the relevance score of F_1 is $p_{1,1} \times h_{1,1} = 80$ which is larger than that of F_2 (i.e., $p_{1,2} \times h_{1,2} = 40$), resulting in the unexpected deviation of ranked order. Therefore, the owner needs to preprocess the search preference when deriving the trapdoor, ensuring the search results will faithfully adhere to the user’s search preference.

To preprocess the preference, besides secret keys, the owner can keep some additional secret information, i.e., $\zeta_i = Max\{h_{i,j}\}$, which represents the maximum keyword weight of the field W_i among the collection $\mathcal{C}$. The preferences of the keywords which do not appear in the query are assumed to be 0. Meanwhile, to represent the keywords by numbers, we can construct a hash function $H(\cdot)$ from the keyword set $\mathcal{W} := \{w_{i,j}\}_{i\in[1,u],j\in[1,n_i]}$ to $[1,|\mathcal{W}|]$ without collision, where u and n_i denote the number of keyword fields and the number of keywords in the filed W_i respectively. Without loss of generality, a multi-field search query can be expressed as

$$\mathcal{Q} := (w_{1,1} \vee ... \vee w_{1,d_1}) \wedge \cdots \wedge (w_{u,1} \vee ... \vee w_{u,d_u}) \quad (1)$$

where $d_i \leq n_i$ and $w_{i,j}$ denote the *j*-th keyword of W_i. Assume that the preference of keyword $w_{i,j}$ in the query is $p_{i,j}$, the search preference of $\mathcal{Q}$ can be expressed as

$$\mathcal{P} := (p_{1,1} \vee \cdots \vee p_{1,d_1}) \wedge \cdots \wedge (p_{u,1} \vee \cdots \vee p_{u,d_u}) \quad (2)$$

The owner preprocesses the search preferences by taking the following steps. Firstly, the preference of each keyword in $\mathcal{P}$ would be sorted in an ascending order and be converted into the vector form, for instance, the formula (2) can be sorted as $(p_1, \ldots, p_{|d|})$, where $|d| = \sum_i^u d_i$ and a bijective function $\phi(\cdot) : \{i,j\}_{i\in[1,u],j\in[1,d_i]} \to \{t\}_{t\in[1,|d|]}$ can be established. Then, we set $p'_1 := p_1$. For p_j, if $p_{j-1} < p_j$, suppose $\phi^{-1}(z) = \{i_z, j_z\}$ where i_z denotes the keyword field that the keyword w_{i_z,j_z} belongs to, then $p'_j := 1 + \sum_{z=1}^{j-1} p'_z \zeta_{i_z}$; else if p_{j-1} equals to p_j, then $p'_j := p'_{j-1}$. Finally, we resort the preprocessed preferences back to the original CNF formula and get the updated preference

$$\mathcal{P}' := (p'_{1,1} \vee \cdots \vee p'_{1,d_1}) \wedge \cdots \wedge (p'_{u,1} \vee \cdots \vee p'_{u,d_u}) \quad (3)$$

An example. Suppose a original preference formula is $(2 \vee 1) \wedge (4 \vee 3)$, where $\{\zeta_i\}_{1\leq i \leq 2}$=3. The formula will be transformed into the vector $(2, 1, 4, 3)$ firstly and then be sorted into $(1, 2, 3, 4)$. In the stage of preprocessing, $p'_1 := p_1 = 1$, $p'_2 := 1 + p_1 \cdot \zeta_1 := 4$, $p'_3 := 1 + \sum_{z=1}^{2} p'_z \cdot \zeta_{i_z} := 16$, $p'_4 := 1 + \sum_{z=1}^{3} p'_z \cdot \zeta_{i_z} := 64$. Finally, the updated vector $(1, 4, 16, 64)$ will be flushed back into the original formula form $(4 \vee 1) \wedge (64 \vee 16)$ according to the function $\phi^{-1}(\cdot)$.

After the preprocessing, the file containing the larger preference will always be ranked higher without being affected by the keyword weight, which is proved by the Theorem 1 and Lemma 1 (The detailed proofs are shown in the Appendix). Meanwhile, the preprocessing obeys "*order preserving*" rule, i.e., $p'_i < p'_j$ (resp., $p'_i = p'_j$) will still establish in $\mathcal{P}'$ if $p_i < p_j$ (resp., $p_i = p_j$) holds in $\mathcal{P}$.

Theorem 1. *The original priority of each file will not be affected after the preprocessing of preference formula $\mathcal{P}$.*

Lemma 1. *If F_i is prior to F_j to $\mathcal{P}$, then the relevance score of F_i is larger than that of F_j to $\mathcal{P}$ if both of them match $\mathcal{Q}$.*

2) Preference Transformation: After producing the processed preference formula (3), we first transform it into the Lagrange polynomial, ensuring the actual preference $p'_{i,j}$ will be activated to involve in the calculation of "sub-relevance" with $h_{i,j}$, only when the keyword $w_{i,j}$ meets the condition over the keyword field W_i in the query. During the transformation, the owner will invoke a hash function $H(\cdot)$ to map keyword $w_{i,j}$ to the number $\lambda_{i,j}$ and employ Lagrange coefficients to obtain the polynomials as $\sum_{i=1}^{u} \varphi_i(x_i)$ for the keyword field W_i, where $\varphi_i(x_i)$ is

$$\sum_{j=1}^{d_i} \frac{(x_i-\lambda_{i,1})\ldots(x_i-\lambda_{i,j-1})(x_i-\lambda_{i,j+1})\ldots(x_i-\lambda_{i,d_i})}{(\lambda_{i,j}-\lambda_{i,1})\ldots(\lambda_{i,j}-\lambda_{i,j-1})(\lambda_{i,j}-\lambda_{i,j+1})\ldots(\lambda_{i,j}-\lambda_{i,d_i})} p'_{i,j} \quad (4)$$

If $w_{i,j}$ meets the requirement over the field W_i, the "sub-relevance" will be correctly calculated as $p'_{i,j}h_{i,j}$; otherwise, an incorrect "sub-relevance" $\varphi_i(\lambda'_{i,j})h_{i,j}$ will be produced, and the cloud server will fail to learn the relevance between the unsatisfied files and the query even it stealthily computes their relevance scores to the query. Then, the owner can draw out the coefficients of x_i^j from equation (4) to denote the preference vector

$$\vec{P}' := (b_{1,n_1}, \cdots, b_{1,0}, \cdots, b_{u,n_u}, \cdots, b_{u,0})^T$$

where $b_{i,j}$ is the coefficient of x_i^j and please notice that $b_{i,j} := 0$ for $d_i \leq j \leq n_i$. Suppose the keyword of file F_s is $\{W_1 = w_{1,s(1)}, \ldots, W_u = w_{u,s(u)}\}$, then the corresponding keyword weight vector of F_s can be denoted as

$$\vec{W}_s := (t_{1,n_1}, \cdots, t_{1,0}, \cdots, t_{u,n_u}, \cdots, t_{u,0})^T$$

where $t_{i,j} := h_{i,s(i)} \cdot \lambda^j_{i,s(i)}$, so that the relevance score of F_s to $\mathcal{P}$ is $\vec{W}_s^T \vec{P}' := \sum_{i=1}^{u} h_{i,s(i)} \cdot \varphi_i(\lambda_{i,s(i)}) := \sum_{i=1}^{u} h_{i,s(i)} \cdot p'_{i,s(i)}$ if F_s matches the search query.

To mess the real relevance scores against the cloud server, we introduce random numbers r_p, r_q and ε_i, expand $\vec{P}'$ as $\hat{P} := (r_p\vec{P}', r_q)$, and enlarge $\vec{W}_i$ as $\hat{W}_i := (\vec{W}_i, \varepsilon_i)$, so that the calculated relevance score will be $\hat{W}_i^T \hat{P} := r_p \vec{W}_i^T \vec{P}' + r_q \varepsilon_i$. Here, we denote $\vec{W}_i^T \vec{P}'$ and $\hat{W}_i^T \hat{P}$ as the "*actual relevance score*" and the "*calculated relevance score*" respectively. The random value $r_q\varepsilon_i$ is used to blind $r_p \vec{W}_i^T \vec{P}'$, otherwise r_p could be acquired simply through "greatest common divisor" computation if the cloud server obtains enough calculated relevance scores.

To achieve the accurate order even when the random values ε_i is introduced, we can narrow the range of ε_i to [-1/2,1/2] and make $r_q \leq r_p$. Since the relevance score $\vec{W}_i \vec{P}'$ is represented by the integer, so that the disturbance of $r_q\varepsilon_i$ is still within the minimum distances r_p and the relative ranking between the matching files will be preserved.

3) Flexible search query support: To improve the storage efficiency, the weight vector can be directly reused to support the flexible search query just by taking the following steps.

For the search query as formula (1), the owner can choose a set of random values $\{r_i\}_{i=1}^{u}$, invoke the hash function $H(\cdot)$ to map keyword $w_{i,j}$ to the numeral $\lambda_{i,j}$, and transform the query into the polynomial form as follows: $r_1(x_1 - \lambda_{1,1}) \ldots (x_1 - \lambda_{1,d_1}) + \ldots + r_u(x_u - \lambda_{u,1}) \ldots (x_u - \lambda_{u,d_u})$.

Then the vector $(a_{1,d_1}, \cdots, a_{1,0}, \cdots, a_{u,d_u}, \ldots, a_{u,0})$ can be derived, where $a_{i,j}$ is the coefficient of x_i^j and $a_{i,0} = r_i(-1)^{d_i} \prod_{j=1}^{d_i} \lambda_{i,j}$. Finally, the query vector is unified as

$$\vec{Q} := (a_{1,n_1}, \cdots, a_{1,0}, \cdots, a_{u,n_u}, \cdots, a_{u,0})^T$$

where n_i is the number of keywords on the field W_i and is larger than d_i. Notice that $a_{i,j} := 0$ for $(d_i + 1) \leq j \leq n_i$.

For the file F_s that is labeled with the keywords $\{W_1 = w_{1,s(1)}, \ldots, W_u = w_{u,s(u)}\}$, so when testing whether F_s matches a query, then the server will calculate

$$\vec{W}_s^T \cdot \vec{Q} := h_{1,s(1)} \sum_{j=0}^{d_1} a_{1,j} \lambda^j_{1,s(1)} + \cdots + h_{u,s(u)} \sum_{j=0}^{d_u} a_{u,j} \lambda^j_{u,s(u)}$$

The outputs will equal to 0 with overwhelming probability if the file really matches the search query. The random values

Algorithm 1: The detailed description of PSED

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Setup$(n, u)$:
  1. generate two invertible $(n+u+1)\times(n+u+1)$ matrices $M_1, M_2$, initiate a $(n+u+1)$-dimension binary vector $\vec{S}$ and outputs $SK := \{M_1, M_2, S\}$;
BuildIndex$(\{M_1, M_2\}, \{\vec{S}\}, \mathcal{C})$:
  1. For $F_i \in \mathcal{C}$
     i) generate the keyword weight vector $\vec{W}_i$;
     ii) expand $\vec{W}_i$ to $\hat{W}_i := (\vec{W}_i, \varepsilon_i)$, create two random shares of $\hat{W}_i$, i.e., $\hat{W}_{i,1}$ and $\hat{W}_{i,2}$ to meet the following conditions;
     iii) For $j$=1 to $(n+u+1)$
          if $\vec{S}[j] = 1$, then $\hat{W}_{i,1}[j] + \hat{W}_{i,2}[j] := \hat{W}_i[j]$;
          else, $\hat{W}_{i,1}[j] := \hat{W}_{i,2}[j] := \hat{W}_i[j]$;
     iv) run $\widetilde{W_{i,1}}$=$M_1^T\hat{W}_{i,1}$,$\widetilde{W_{i,2}}$=$M_2^T\hat{W}_{i,2}$, and set $I_i := \{\widetilde{W}_{i,1}, \widetilde{W}_{i,2}\}$;
  2. upload the encrypted files $\{F_i\} \in \mathcal{C}$ and $\mathcal{I} := \{I_i\}$ to the cloud server;
GenTrapdoor$(\mathcal{Q}, \mathcal{P}, \{M_1, M_2\}, \{\vec{S}\})$:
  1. preprocess the preference $\mathcal{P}$ to $\mathcal{P}'$, transform the query $\mathcal{Q}$ and the preference $\mathcal{P}'$ into $\vec{Q}$ and $\vec{P}'$;
  2. expand $\vec{Q}$ to $\hat{Q} := (\vec{Q}, 0)$, randomly choose $r_p$, $r_q$ ($r_q \le r_p$), and create $\hat{P} := (r_p\vec{P}', r_q)$;
  3. create two random shares of $\hat{Q}$ and $\hat{P}$, i.e., $\hat{Q}_1$ and $\hat{Q}_2$, $\hat{P}_1$ and $\hat{P}_2$ respectively;
  4. For $i$=1 to $(n+u+1)$
     if $\vec{S}[i] = 0$, then $\hat{Q}_1[i] + \hat{Q}_2[i] = \hat{Q}[i]$, $\hat{P}_1[i] + \hat{P}_2[i] = \hat{P}[i]$;
     else, $\hat{Q}_1[i] := \hat{Q}_2[i] := \hat{Q}[i]$, $\hat{P}_1[i] := \hat{P}_2[i] := \hat{P}[i]$;
  5. compute $T_{Q[1]} = M_1^{-1}\hat{Q}_1$, $T_{Q[2]} = M_2^{-1}\hat{Q}_2$, $T_{P[1]} = M_1^{-1}\hat{P}_1$, $T_{P[2]} = M_2^{-1}\hat{P}_2$;
  6. return search trapdoor $T_{\mathcal{Q},\mathcal{P}}$:=$\{T_Q = (T_{Q[1]}, T_{Q[2]}), T_P = (T_{P[1]}, T_{P[2]})\}$ to the user.
SearchIndex$(\mathcal{I}, T_{\mathcal{Q},\mathcal{P}})$
  1. For $F_i \in \mathcal{C}$, compute $\widetilde{W}_{i,1}^T \cdot T_{Q[1]} + \widetilde{W}_{i,2}^T \cdot T_{Q[2]}$;
     i) If the calculated result is zero, calculate the relevance score $\widetilde{W}_{i,1}^T \cdot T_{P[1]} + \widetilde{W}_{i,2}^T \cdot T_{P[2]}$;
  2. rank the satisfied files and return $F_{\mathcal{Q},\mathcal{P}}$;
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$\{r_i\}_{i=1}^u$ can mess the distribution of the query vector, so that even $\vec{Q}$ and $\vec{Q}'$ are derived from the same search query $\mathcal{Q}$, $\vec{W}_s^T \cdot \vec{Q}$ and $\vec{W}_s^T \cdot \vec{Q}'$ will differentiate as long as F_s is excluded both by $\mathcal{Q}$ and $\mathcal{Q}'$. In addition, we can expand $\vec{Q}$ to $\hat{Q} = (\vec{Q}, 0)$, so that $\hat{W}_s^T \cdot \hat{Q} = (\vec{W}_s^T, \varepsilon_s)^T \cdot (\vec{Q}, 0) = \vec{W}_s^T \cdot \vec{Q}$

B. PSED: Privacy-Preserving Scheme

As an summary of the designs above, our proposed preferred keyword search scheme is shown in Algorithm 1 as detail.

Setup. The owner initiates the secret keys, including a binary vector and two invertible matrices, where $n = \sum_{i=1}^u n_i$ and u is the number of keyword fields.

BuildIndex. The owner generates the keyword weight vector $\vec{W}_i$ (step 1-i), expands $\vec{W}_i$ to $\hat{W}_i$ (step 1-ii), divides the vectors (step 1-iii), and encrypts them (step 1-iv).

GenTrapdoor. Given a query $\mathcal{Q}$ and its preference $\mathcal{P}$, the owner converts $\mathcal{Q}$ into the query vector $\vec{Q}$ and preprocess the preference (step 1). Then the owner enlarges $\vec{P}'$ (resp.,$\vec{Q}$) to $\hat{P}$ (resp.,$\hat{Q}$)(step 2), splits the vectors (step 3, step 4), and encrypts them with the secret matrices (step 5).

SearchIndex. The server calculates the relevance score for matching files and returns the ranked results.

C. The Analysis

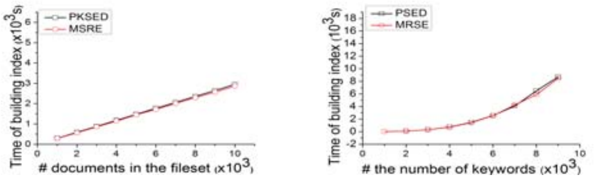
1) Efficiency Analysis: The stage of $BuildIndex$ (resp.$GenTrapdoor$) calls for multiplications between two $(n+u+1)\times(n+u+1)$ matrices and one (resp. two) $(n+u+1)$-dimension vector for each file (resp. each query with preference). In $SearchIndex$, the cloud server will only compute two inner-products between four $(n+u+1)$-dimension vectors for each mismatched files. For the matching files, extra two inner-products between four $(n+u+1)$-dimension vectors are needed. With respect to storage overhead, the owner should only keep two $(n+u+1)\times(n+u+1)$ secret matrices (i.e., M_1, M_2), a vector whose lengths is $(n+u+1)$ (i.e., $\vec{S}$), and some secret information (i.e., $\{\zeta_i\}_{1\le i\le u}$). The user should store the trapdoor which is constituted by four $(n+u+1)$-dimension vectors, while the cloud server is required to keep the encrypted collection as well as the encrypted indexes $\mathcal{I}$.

2) Privacy Analysis: As for the *index privacy*, because keywords and their corresponding weights are hashed by the secret hash function and then be encrypted by the secret matrices, the cloud server will find it difficult to deduce the meaning of every item in the index; this security is guaranteed by the computation complexity of secure kNN [12]. Based on the same principle, the requested keywords and the corresponding preferences will be invisible to the cloud server, thus the *query privacy* can be achieved.

Because of the randomized splitting and the introduction of some random values (e.g., $\{r_i\}_{1\le i\le u}$, r_p, and r_q), the produced trapdoors will be various even to the same query. This non-deterministic property will also make the cloud server have trouble mining the relationship between two trapdoors by comparing them directly. Though the cloud server can compare the matching files and ranked results to judge whether the targeted queries have internal correlation, this attack will fail if some puppet files to mess the search outputs are introduced.

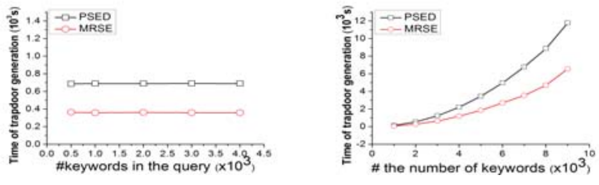
3) Relevance privacy: With the protection of random values, the calculated scores of the matching file F_i will be $(r_p\vec{W}_i^T\vec{P}' + r_q\varepsilon_i)$, which blinds the actual relevance score $\vec{W}_i^T\vec{P}'$ against the cloud server. Even the cloud server may try to collect some actual relevance scores $\vec{W}_i^T\vec{P}'$ to construct the linear equations $\{\widetilde{W}_i^T T_{P[1]} + \widetilde{W}_i^T T_{P[2]} = r_p\vec{W}_i^T\vec{P}' + r_q\varepsilon_i\}_{1\le i\le t}$, it will be difficult to recover $\{\vec{W}_i^T\vec{P}'\}_{1\le i\le t}$ by solving *t* equations, since there are *(t+2)* variables.

For the unsatisfied files to a query, $\vec{W}_i^T\vec{P}'$ will produce incorrect relevant scores, because the weight of the excluded keyword will participate in the calculation and roil the final result, increasing the hardness for the server to learn the relevance of the unsatisfied files to a query.



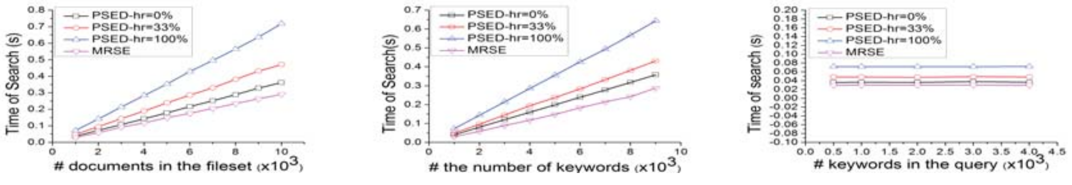
(a) (b)

Fig. 2. The time cost of building index. (a) For the different amount of files in the whole collection, when n=5000,n_Q=100. (b) For the different number of keywords in the collection,when n_Q=100,$|\mathcal{C}|$=5000.



(a) (b)

Fig. 3. The time cost of trapdoor generation. (a) For the different number of keywords in the query, when n=5000,$|\mathcal{C}|$=1000. (b) For the varying number of keywords in the whole collection,when n_Q=100,$|\mathcal{C}|$=5000.



(a) (b) (c)

Fig. 4. The time cost of query search.(a) For the different number of files in the collection, when n=5000,n_Q=100.(b) For the different amount of keywords in the collection,when n_Q=100,$|\mathcal{C}|$=5000.(c) For the varying number of keywords in the query, when n=5000,$|\mathcal{C}|$=1000.

IV. Performance evaluation

We utilize the "Connectionist Bench (Nettalk Corpus) Data Set" from UCI Machine Learning Repository [1] which has 4 keyword fields to evaluate the performance of PSED. We fully realize PSED on the modern server equipped with 2.10GHZ Intel ® Core 2 Duo CPU and 4GB RAM. The OS running on the server is Ubuntu (version: 11.04) and the kernel is Linux Ubuntu 2.6.38-8-generic. We choose MRSE_II [11] to act as the reference, where U in MRSE_II is chosen to be 40.

A. Index Building

Figure 2(a) indicates the time to build indexes is linear with the number of files in the collection, since PSED has to generate an encrypted index for each file. Meanwhile, when n varies, the time to generate indexes in PSED scales as $O(n^2)$, because it is usually required to implement $O(n^2)$ multiplications and $O(n^2)$ addition operations per index generation when u is fixed. From the comparison, the time to generate an encrypted index in PSED is nearly the same with that in MRSE. Since it is a one-time cost to build indexes for the fileset, we argue that the efficiency is quite reasonable. In Table II, we compare the storage space of every index in PSED with that in MRSE and indicate they are approximately same.

B. Trapdoor generation

In Figure 3(a), the number of keywords in the query will not affect the performance of trapdoor generation very much. Figure 3(b) indicates the time to generate a trapdoor will be greatly affected by the total number of keywords in the collection, since it is required to encrypt the query vector and the preference vector, involving $O(n^2)$ multiplications and $O(n^2)$ addition calculations when u is fixed. Meanwhile, the performance of PSED is a bit slower than that of MRSE for the following reasons. Firstly, PSED has to preprocess the preferences before generating the corresponding trapdoor, while MRSE only produces the trapdoor by encrypting the query vector. Secondly, PSED has to afford additional encryption of $\mathcal{P}$ to support the preferred search when compared to MRSE.

TABLE II
Size of an index and a trapdoor in MRSE and PSED

n	1000	3000	5000	8000
MRSE-Index(/Trapdoor) (KB)	8.13	23.76	39.38	62.82
PSED-Index (KB)	7.85	23.48	39.10	62.54
PSED-Trapdoor (KB)	15.70	46.96	78.20	125.08

Moreover, the owner can either distribute the secret matrices to authorized users or delegate the job of trapdoor generation to a *Trusted Third Party* to mitigate the computation burden at the own's side. In addition, a trapdoor of PSED takes up nearly double the amount of storage space than that of MRSE as shown in Table II, since both the query vector and the preference vector should be encrypted in PSED.

C. Query

The time in $SearchIndex$ can be divided into the time to test whether an index matches the query and the time of relevance score calculation. We use "hit rate" to serve as the rate that an index matches the query and consider the search time under different "hit rates". We run three different performance tests as illustrated in Figure 4. In Figure 4(a), the search time is linear to the number of files in the fileset, since it is required to scan every file to test whether it matches the query conditions. Figure 4(b) indicates the search time is linear to the number of keywords n among the whole collection, since $O(n)$ multiplications and $O(n)$ addition operations are performed in the steps of both matching test and relevance score calculation when u is fixed. Figure 4(c) shows the number of keywords in the query will not affect the performance of query search. Meanwhile, the query time of PSED is a bit larger than that of MRSE and the gap will narrow as the hit rate drops, because it usually incurs four inner-products calculation if the query "hits" a index in PSED, while in MRSE the inner-product computation only happens twice.

D. Complexity analysis

From Table III, the computation complexity of PSED is close to that of MRSE. Different from MRSE which provides multi-keyword similar search and may return inaccurate search

TABLE III
THE COMPARISON OF COMPLEXITY BETWEEN MRSE AND PSED.

Comparison Metrics	MRSE [11]	PSED
Time of BuildIndex(/GenTrapdoor)	$O((n+U)^2)$	$O((n+u)^2)$
Time of SearchIndex	$O(n+U)$	$O(n+u)$
Flexible query support	No	Yes
Preferred keyword search	No	Yes
Accurate search result	No	Yes

outputs, PSED focuses on preferred search over multiple fields, which aims to locate the accurate matching files and rank them according to the calculated scores. The performance difference between PSED and MRSE lies in the change of U and u, where u is introduced in keyword weight vector generation in PSED and U is used to resist know-background attack in MRSE. Compared to MRSE, PSED is more suitable to applied in the environment with both preference consideration and high-accuracy requirement.

V. RELATED WORK

A. Searchable Encryption

Song et al. [3] proposed the first practical scheme of searchable encryption. Goh et al. [4] presented a scheme that supports secure indexed over encrypted data by employing Bloom Filter. Boneh et al. [5] proposed the first searchable encryption scheme based on public key. Water et al. [7] proposed a scheme to fulfill searchable audit log. Golle et al. [8] developed two searchable encryption schemes to realize conjunctive keyword search. Wang et al. [9] and Cao et al. [11] investigated secure ranked keyword search on single keyword and multiple keywords over encrypted data respectively. Shi et al. [10] presented their method to realize multi-dimensional range query over encrypted data. However, most of the existing SE works missed users' preferences when performing search.

B. Keyword Search with Preference

Leubner et al. [13] showed prioritization would be explained as the subspace preferences in vector space model. Koutrika et al. [14] established a preference model and presented progressive personalized answers. Chomicki et al. [15] presented the framework for formulating preferences. Kiessling et al. [16] proposed strictly partial order semantics for preferences. Georgiadis et al. [17] defined the preorders over attributes and explored the semantics of preferences expression. However, most of existing search schemes with preference are inapplicable on ciphertext.

VI. CONCLUSION

In this paper, we address the problem of preferred keyword search over encrypted data. We first establish a set of designed goals and use the occurrence of each keyword to characterize its significance to the file. Then we represent the query and index in the vector form, and employ secure inner-product computation to calculate the inner-product of the weight vector and the preference vector to quantitatively characterize the correlation of files to the query. Thorough analysis concerning privacy and efficiency is presented, and the intensive evaluation of PSED on a modern server demonstrates its suitability when deployed in real application.

ACKNOWLEDGMENTS

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APPENDIX

Proof of Theorem1. If F_i is prior to F_j to $T_{\mathcal{Q},\mathcal{P}}$, then we will prove F_i is still prior to F_j to $T_{\mathcal{Q},\mathcal{P}'}$. In the case of Definition1.(1), the conclusion is obviously established. In the case of Definition1.(2), because the keyword weights of F_i and F_j are unchanged, so $h_{\mathcal{W}_{i,p'_m}} = h_{\mathcal{W}_{i,p_m}} > h_{\mathcal{W}_{j,p_m}} = h_{\mathcal{W}_{j,p'_m}}$ still holds, where p_m is the original critical preference value (CPV) and p'_m is the preprocessed preference of p_m. According to the order-preserving rule of the preprocessing, if there exists a value $p'_z > p'_m$, then we have $h_{\mathcal{W}_{i,p'_z}} = h_{\mathcal{W}_{i,p_z}} = h_{\mathcal{W}_{j,p_z}} = h_{\mathcal{W}_{j,p'_z}}$, thus p'_m will be the CPV of $\mathcal{P}'$. Since $h_{\mathcal{W}_{i,p'_m}} > h_{\mathcal{W}_{j,p'_m}}$, then F_i is still prior to F_j to $T_{\mathcal{Q},\mathcal{P}'}$.$\square$

Proof of Lemma1. If both of F_i and F_j match $\mathcal{Q}$, assume the CPV between F_i and F_j is p_m. Suppose $\phi^{-1}(z) = \{s_z, t_z\}$, since $\{h_{\mathcal{W}_{i,p_z}}\}$ will be integers, then the difference of the relevance score between F_i and F_j will be $\sum_{p'_z} h_{\mathcal{W}_{i,p'_z}} p'_z - \sum_{p'_z} h_{\mathcal{W}_{j,p'_z}} p'_z = \sum_{p'_z > p'_m} (h_{\mathcal{W}_{i,p'_z}} - h_{\mathcal{W}_{j,p'_z}}) p'_z + (h_{\mathcal{W}_{i,p'_m}} - h_{\mathcal{W}_{j,p'_m}}) p'_m + \sum_{p'_z < p'_m} (h_{\mathcal{W}_{i,p'_z}} - h_{\mathcal{W}_{j,p'_z}}) p'_z \geq p'_m - \sum_{p'_z < p'_m} h_{\mathcal{W}_{j,p'_z}} p'_z > 0$ $\square$