Assignment: 3-Achieving Usable and Privacy-assured Similarity Search over Outsourced Cloud Data

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Overview

Introduction of the Paper

C. Wang, K. Ren, S. Yu, and K. M. R. Urs, "Achieving usable and privacy-assured similarity search over outsourced cloud data," in *INFOCOM, 2012 Proceedings IEEE*, pp. 451–459, IEEE, 2012.

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Purpose

Solve the problem of secure and efficient fuzzy search over encrypted outsourced cloud data

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Performance

Correctly achieves the defined similarity search functionality with **constant** searching time!

System and Threat Model

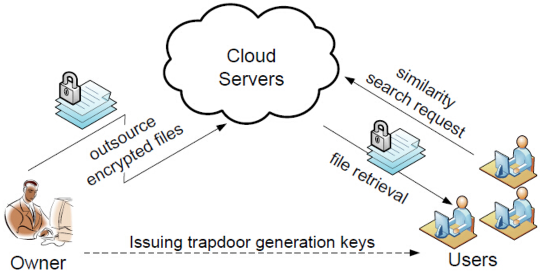

Figure: Architecture of similarity keyword search over outsourced cloud data

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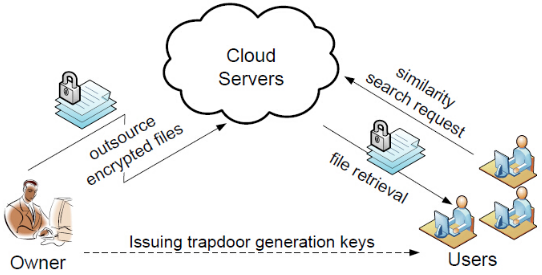

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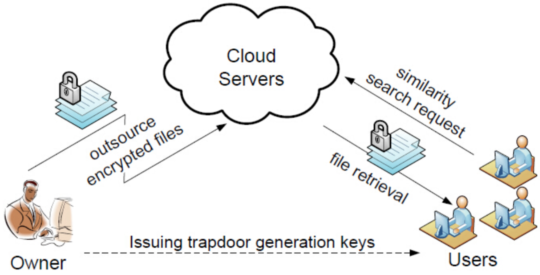

Figure: Architecture of similarity keyword search over outsourced cloud data

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- $W = \{w_i, w_w, \ldots, w_p\}$ is denoted as a predefined set of distinct keywords in C

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- At last, the user decrypts files they received from the cloud.

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We follow the security definition deployed in the traditional searchable symmetric encryption(SSE)

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- $f(key, \cdot), g(key, \cdot)$ pseudorandom function (PRF), defined as: $\{0,1\}^* \times key \to \{0,1\}^\ell$.
- $Enc(key, \cdot), Dec(key, \cdot)$ symmetric key based semantic secure encryption/decryption function.

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Quantitative measurement

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Example

Consider the keyword $w_0 = CENSOR$
a words set W $= \{CESOR, CENSER, CEANSOR\}$
for any $w' \in W, ed(w_0, w') \leq 1$ holds,
i.e. $w' \in S_{w_0,1}$ and $W \subseteq S_{w_0,1}$

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For the keyword $w_0 = CENSOR$, consider just one substitution operation with charaters on first character.
There are 26 items $\{AENSOR, BENSOR, \ldots, YENSOR, ZENSOR\}$
So $S_{w_0,1}$ will be
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Now,
$S_{SENSOR,1} = \{SENSOR, *SENSOR, *ENSOR, S*ENSOR, S*NSOR, \ldots, SENSO*R, SENSO*, SENSOR*\}$.
Size can be reduced to $S_{w_0,1}$ will be $[6 + (6 + 1)] \times 1 + 1$

Building Similarity Keyword Sets

Algorithm 1: CreateSimilaritySet(w_i, d)

Data: keyword w_i and threshold distance d
Result: similarity keyword set $S_{w_i,d}$
begin
    if $d > 1$ **then**
        CreateSimilaritySet(w_i, $d-1$);
    if $d = 0$ **then**
        set $S_{w_i,d} = \{w_i\}$;
    else
        for $k \leftarrow$ *1 to* $|S_{w_i,d-1}|$ **do**
            for $j \leftarrow$ *1 to* $2 \times |S_{w_i,d-1}[k]| + 1$ **do**
                if *j is odd* **then**
                    Set *variant* as $S_{w_i,d-1}[k]$;
                    Insert $\star$ at position $\lfloor (j+1)/2 \rfloor$;
                else
                    Set *variant* as $S_{w_i,d-1}[k]$;
                    Replace $\lfloor j/2 \rfloor$-th character with $\star$;
                if *variant is not in* $S_{w_i,d-1}$ **then**
                    Set $S_{w_i,d} = S_{w_i,d} \cup \{variant\}$;

The size of $S_{w_i,d}$ will be $\mathcal{O}(\ell^d)$,opposing to $\mathcal{O}(\ell^d \times 26^d)$ obtained in the straightforward approach.

Generating Searching Request

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Theorem

The intersection of the similarity sets $S_{w_i,d}$ *and* $S_{w,d}$ *for keyword* w_i *and search input* w *is not empty if and only if* $ed(w, w_i) \leq d$.

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- Completeness(i.e. $ed(w, w_i) \leq d \rightarrow S_{w_i,d} \cap S_{w,d} \neq \emptyset$):

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  - $w \rightarrow w_i$ need at most d primitive operations.
    the result after these operations is marked as w^*
  - w^* is naturally in $S_{w,d}$
  - w^* can be transformed into w_i, so it must be in $S_{w_i,d}$
  - $w^* \in S_{w_i,d} \cap S_{w,d}$

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  1. w^* does not contain any wildcard *,
     then $w^* = w = w'$,and $ed(w, w') = 0 \leq d$
  2. w^* does contain some wildcard *(at most d *'s),
     change * in w^* back to the character in w and w_i,
     denote the result as w'^* and $w_i'^*$ with both sharing $d-1$ different *'s.
     $w'^* \rightarrow w_i'^*$ need at most one primitive operation.
     So, $ed(w'^*, w_i'^*) \leq 1$
     $\Rightarrow ed(w, w_i) \leq d$

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1. picks random key x,y,and builds index $\mathcal{I} = \left\{ f(x, w_i'), Enc(sk_{w_i'}, FID_{w_i}) \right\}_{w_i' \in S_{w_i,d}, 1 \leq i \leq p}$, where secret key $sk_{w_i'} = g(y, w_i')$

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3. randomly shuffles $\mathcal{I}$, outsources $\mathcal{I}$, encrypted C to cloud.

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Improvement

Storage and search cost is $\mathcal{O}(\tau\,|W|)$.
Bloom Filters can be introduced in to reduce the searching cost to $\mathcal{O}(|W|)$

All similar words in the trie can be found by a depth-first search

Construct a multi-way tree for storing the similarity keyword elements over a finite symbol set. All trapdoors sharing a common prefix have a common node. The root is associated with an empty set.

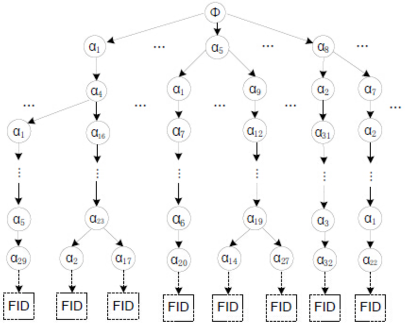

Figure: The depth of the tree is l/θ

The Symbol-based Trie-Traverse Searching Schema

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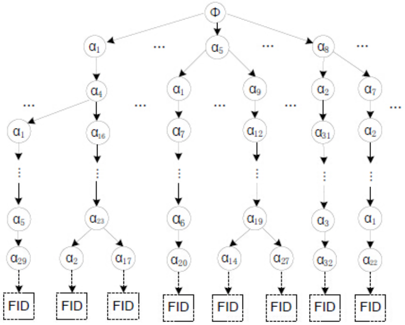

Figure: The depth of the tree is l/θ

- Assume $\Delta = \{\alpha_i\}$ is a predefined symbol set.
- $|\Delta| = 2^\theta$
- each symbol $\alpha_i \in \Delta$ is denoted by a θ-bit binary vector.
- l is the output length of one-way function $f(key, \cdot)$.

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1. sends a set of τ trapdoors(research request): $\{T_{w'}\}_{w' \in S_{w,d}}$ and $\tau - |w' \in S_{w,d}|$ dummy trapdoors.

The Symbol-based Trie-Traverse Searching Schema

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1. computes $f(x, w'_i)$ for each $w'_i \in S_{w_i,d}$,$1 \leq i \leq p$ together with dummy entries.
2. divides them into symbols as $\alpha_{i_1} \cdots \alpha_{i_{l/\theta}}$ from Δ.
3. builds up a trie G_W covering all $w_i \in W$.
4. attaches $\left\{Enc(sk_{w'_i}, FID_{w_i})\right\}_{w'_i \in S_{w_i,d}, 1 \leq i \leq p}$ to G_W,
   outsourced it
   with encrypted collection C to the cloud.

Searching phase(the user)

1. sends a set of τ trapdoors(research request): $\{T_{w'}\}_{w' \in S_{w,d}}$ and $\tau - |w' \in S_{w,d}|$ dummy trapdoors.
2. the cloud server divides each $f(x, w')$ into a sequence of symbols from Δ. Perform the search over the trie G_W.

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2. the cloud server divides each $f(x, w')$ into a sequence of symbols from Δ. Perform the search over the trie G_W.
3. decrypts matches entries via $g(y, w')$ and returns $\{FID_{w_i}\}_{ed(w,w_i) \le d}$ to the user.

The Symbol-based Trie-Traverse Searching Schema

Algorithm 2: SearchingTree($\{T'_w\}, G_w$)

Data: Searching Trapdoor set $\{T'_w\}$ and G_w
Result: Result ID set
begin
  for $i \leftarrow 1$ *to* $|\{T'_w\}|$ **do**
    set $currentnode$ as $root$ of G_w;
    for $j \leftarrow 1$ *to* l/θ **do**
      Set α as α_j in $f(x, w')$ within the i-th T'_w;
      if *no child of* $currentnode$ *contains* α **then**
        break;
      Set $currentnode$ as $child$ containing α;
    if $currentnode$ is $leafnode$ **then**
      Append $currentnode.FIDs$ to $resultIDset$;
      if $i = 1$ **then**
        return $resultIDset$;
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The search cost at the server side is only $\mathcal{O}(1)$ (a colorredconstant related to l/θ).

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The non-adaptive semantic security guarantee

The non-adaptive attack model only considers adversaries (i.e., the cloud server) that cannot choose search requests based on the trapdoors and search outcomes of previous searches. (Since only users with authorized secret keys can generate search trapdoors.)

Notations

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History an interaction between the user and the cloud server, determined by a file collection C and a set of keywords searched by the user, denoted as $H_q = (C, w^1, \ldots, w^q)$.

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View given a history H_q under some secret key K, the cloud server can only see an encrypted version of the history, i.e., the view $V_K(H_q)$, including: the index $\mathcal{I}$ of C; the trapdoors of the queried keywords $\{T_{w'}\}_{w' \in \{S_{w^1,d}, \ldots, S_{w^q,d}\}}$; and the encrypted file collection of C, denoted as $\{e_1, \ldots, e_n\}$.

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Trace given a history H_q and an encrypted file collection C, the trace of $Tr(H_q)$ captures the precise information to be learned by cloud server, including: the size of the encrypted files $\{|F_1|, \ldots, |F_n|\}$; the outcome of each search, $\{FID_{w_i}\}_{ed(w_i, w^j) \leq d}$ for $1 \leq j \leq q$; and the pattern $\prod_q$ for each search. Here $\prod_q$ is a symmetric matrix where the entry $\prod_q[i,j]$ stores the intersection $\{T_{w'}\}_{w' \in S_{w^i,d} \cap S_{w^j,d}}$.

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Given two histories with the identical trace, the cloud server is not able to distinguish the views of the two histories.
In other words, the cloud server cannot extract additional knowledge beyond the information we are willing to leak (i.e., the trace) and thus our mechanism is secure.

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Our similarity keyword search schemes meet the non-adaptive semantic security.

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Theorem

Our similarity keyword search schemes meet the non-adaptive semantic security.

Due to space limitation, we only give the proof for the basic approach. The proof of other schemes follow similarly.

Proof

Definition (Simulator $\mathcal{S}$)

Given $Tr(H_q)$, it can simulate a view V_q^* indistinguishable from cloud server's view $V_K(H_q)$ with probability negligibly close to 1, for any $q \in \mathbb{N}$, any H_q and randomly chosen K.

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- l: the security parameter of the RBF $f(key, \cdot)$ (output length)
- $\tau = \max\{|S_{w_i,d}|\}_{w_i \in W}$
- $|W|$, and size of padded FID_{w_i} are known to $\mathcal{S}$

Proof

- For $q = 0$, $\mathcal{S}$ builds $V_0^* = \{e_1^*, e_2^*, \ldots, e_n^*, \mathcal{I}^*\}$ such that e_i^* is randomly chosen from $\{0,1\}^{|F_i|}$ for $1 \leq i \leq n$.

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- Also due to the pseudo-randomness of the trapdoor function, no P.P.T. adversary can distinguish between $f(x, w_i')$ and a random string t_i^*.
- Thus, $V_K(H_0)$and V_0^* are indistinguishable.

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- For $q \geq 1$, $\mathcal{S}$ builds
  $V_q^* = \left\{ e_1^*, e_2^*, \ldots, e_n^*, \mathcal{I}^*, \left\{ T_{w'}^* \right\}_{w' \in \left\{ S_{w^1,d}, \ldots, S_{w^q,d} \right\}} \right\}$
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  - Set remaining $\tau - \alpha_1$ trapdoors as random value pairs $(t^*_{1,k}, \rho^*_{1,k}) \in \{0,1\}^l \times \{0,1\}^l$ for $\alpha_1 \leq k \leq \tau$.

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- For trapdoor simulation of w^j for $2 \leq j \leq q$, if $\left|\prod_q[i,j]\right| = 0$ for all $i < j$, the simulator repeats the same process as simulating trapdoors for w^1.

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- For trapdoor simulation of w^j for $2 \leq j \leq q$, if $\left|\prod_q[i,j]\right| = 0$ for all $i < j$, the simulator repeats the same process as simulating trapdoors for w^1.
- Otherwise, let β_j denotes the number of file identifier list in $\left\{FID_{w_j,k}\right\}_{1 \leq k \leq \alpha_j}$, which have been assigned already in $\left\{FID_{w_i,k}\right\}_{1 \leq k \leq \alpha_i, i<j}$.

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- Choose β_j trapdoors from existing $\left\{ T^*_{w'} \right\}_{w' \in \left\{ s_{w^i,d} \right\}, i<j}$ that match to the common β_j file identifier list of $\left\{ FID_{w_j,k} \right\}_{1 \leq k \leq \alpha_j} \cap (\bigcup_{i=1}^{j-1} \{FID_{w_i,k}\}_{1 \leq k \leq \alpha_i})$, and assign them to trapdoor simulation of w^j.

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- Set remaining $\tau - \alpha_j - \gamma_j$ trapdoors as random value pairs from $\{0,1\}^l \times \{0,1\}^l$.

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- The indistinguishability of index and trapdoors is based on the indistinguishability of the pseudorandom function output and a random string.

□

	SSE	Basic	Trie-traverse
Preprocessing	$\mathcal{O}(\|W\|)$	$\mathcal{O}(\tau\,\|W\|)$	$\mathcal{O}(\tau\,\|W\|)$
Index size	$\mathcal{O}(\|W\|)$	$\mathcal{O}(\tau\,\|W\|)$	$\mathcal{O}(\tau\,\|W\|)$
Search cost	$\mathcal{O}(1)$	$\mathcal{O}(\tau\,\|W\|)$	$\mathcal{O}(1)$
Similarity search	No	Yes	No

Table: Comparison of SSE schemes

Experiment

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Experiment Design

- A real data set: RFC, 5,731 plaintext files, 277MB
- C programming language
- Local workstation
- Cloud side:Amazon Elastic Computing Cloud(EC2)

Experiment Design

- A real data set: RFC, 5,731 plaintext files, 277MB
- C programming language
- Local workstation
- Cloud side:Amazon Elastic Computing Cloud(EC2)

Note

In our experiment the dominant factor affecting the performance is th number of unique keywords to be indexed, not the file collection size.

Cost for Generating Similarity Keyword Set

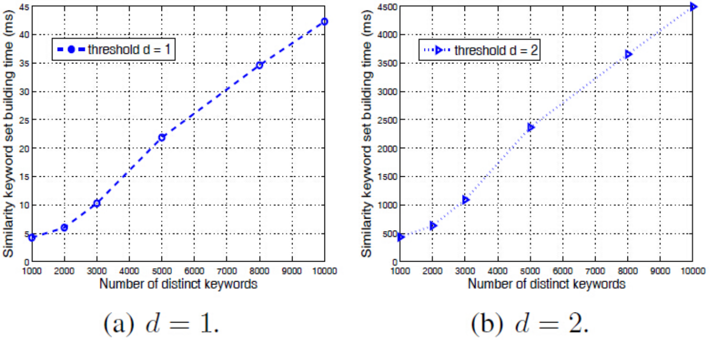


Figure: Similarity set construction time using wildcard-based approach with different choices of edit distance *d*

Cost for Generating Similarity Keyword Set

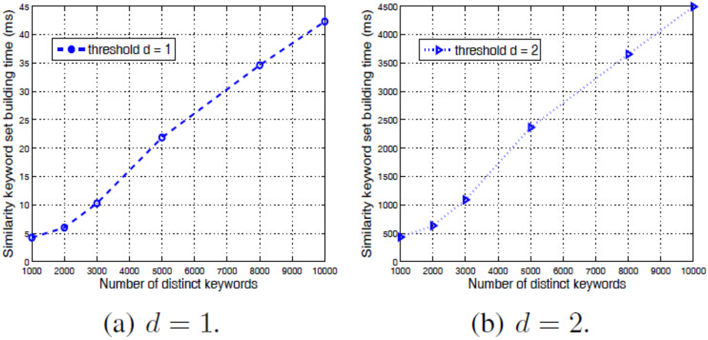
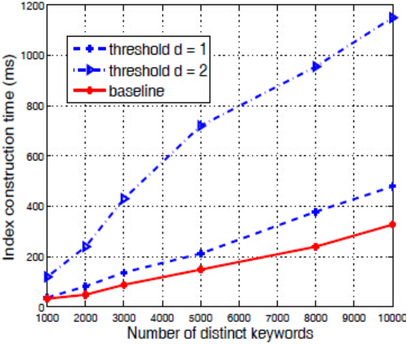


Figure: Similarity set construction time using wildcard-based approach with different choices of edit distance d

The construction time increases linearly with the number of keywords.

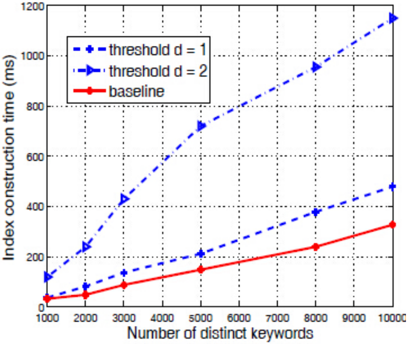
Cost For Building Searchable Index



(a) Index construction time.

Figure: Time cost for searchable index construction with different choices of edit distance d

Cost For Building Searchable Index



(a) Index construction time.

Figure: Time cost for searchable index construction with different choices of edit distance *d*

For completeness, we also include the index building time of existing SSE as a baseline for comparison here.

Cost For Building Searchable Index

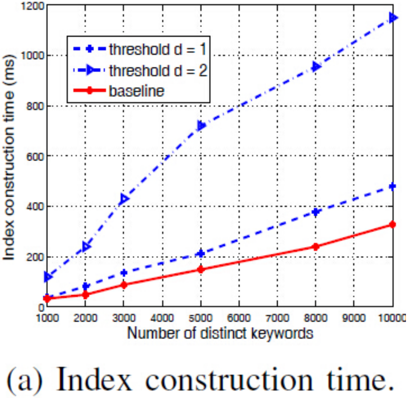


Figure: Time cost for searchable index construction with different choices of edit distance *d*

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The whole index construction is just a one-time cost and can be conducted off-line

Cost For Building Searchable Index

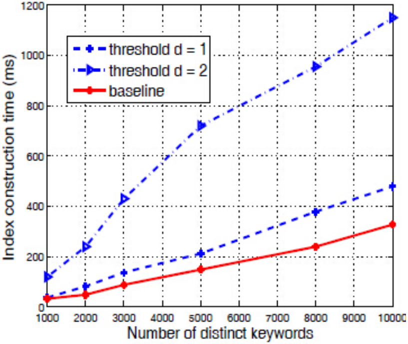

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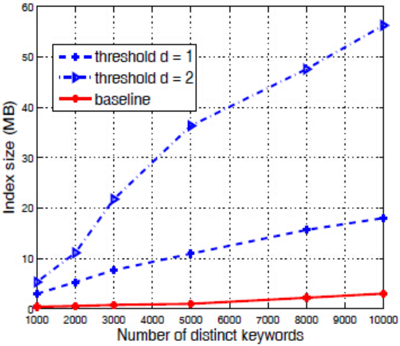
Figure: Time cost for searchable index construction with different choices of edit distance *d*

For completeness, we also include the index building time of existing SSE as a baseline for comparison here.

The whole index construction is just a one-time cost and can be conducted off-line

Similar to the similarity keyword set construction, the index construction time increases linearly with the number of distinct keywords.

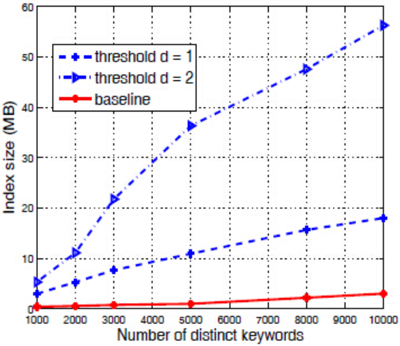
Cost For Building Searchable Index



(b) Index storage size.

Figure: Storage cost for searchable index construction with different choices of edit distance *d*

Cost For Building Searchable Index



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Again, our approach consumes more storage space than the baseline due to the multi-way tree structure and the additional entries in the index corresponding to the similarity keywords

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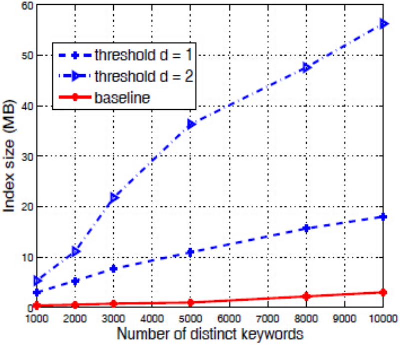

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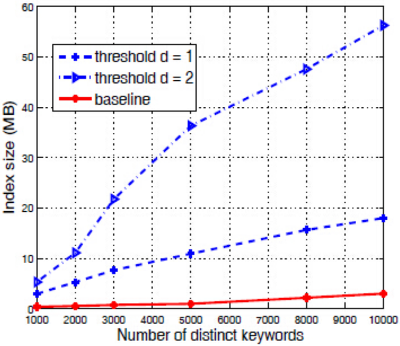

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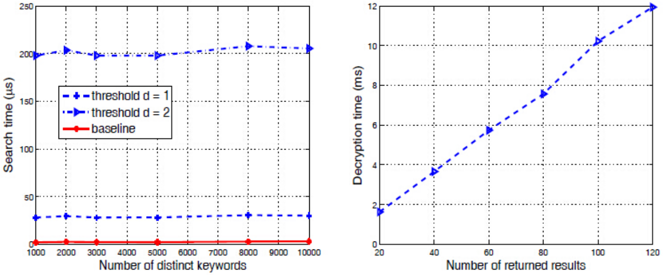
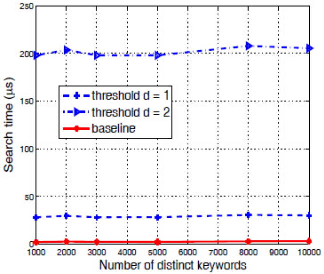
"Average keyword length" also sightly influence the time and space cost of building searchable index.

Cost For Searching the Index



(a) Cloud side search time. (b) User side decryption cost.

Cost For Searching the Index



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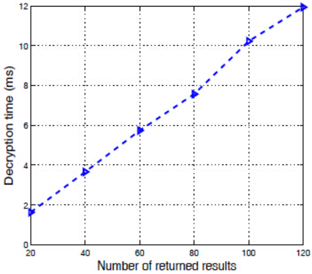
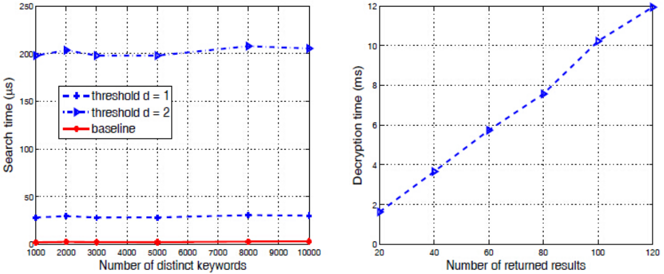


(b) User side decryption cost.

The proposed mechanism cost constant search time.

Cost For Searching the Index



(a) Cloud side search time. (b) User side decryption cost.

The proposed mechanism cost constant search time.

Cost for results retrieval and decryption is plainly determined by the number of retrieved results

Thanks