ShieldDB: An Encrypted Document Database with Padding Countermeasures

Viet Vo, Xingliang Yuan, Shi-Feng Sun, Joseph K. Liu, Surya Nepal, and Cong Wang

Abstract—Cloud storage systems have seen a growing number of clients due to the fact that more and more businesses and governments are shifting away from in-house data servers and seeking cost-effective and ease-of-access solutions. However, the security of cloud storage is underestimated in current practice, which resulted in many large-scale data breaches. To change the status quo, this paper presents the design of ShieldDB, an encrypted document database. ShieldDB adapts the searchable encryption technique to preserve the search functionality over encrypted documents without having much impact on its scalability. However, merely realising such a theoretical primitive suffers from real-world threats, where a knowledgeable adversary can exploit the leakage (aka access pattern to the database) to break the claimed protection on data confidentiality. To address this challenge in practical deployment, ShieldDB is designed with tailored padding countermeasures. Unlike prior works, we target a more realistic adversarial model, where the database gets updated continuously, and the adversary can monitor it at an (or multiple) arbitrary time interval(s). ShieldDB's padding strategies ensure that the access pattern to the database is obfuscated all the time. We present a full-fledged implementation of ShieldDB and conduct intensive evaluations on Azure Cloud.

Index Terms—Data Security and Privacy, Management and Querying of Encrypted Data, Padding Strategies.

1 INTRODUCTION

The adaptation of cloud storage by various governments and businesses is rapid and inexorable. It has brought many benefits to the economy and user productivity improvements, and caused a huge upheaval in the data center infrastructure development. However, data breaches in cloud stores are happening quite frequently in recent time, affecting millions of individuals [1]-[3]. This phenomenon calls for increased control and security for private and sensitive data [4]-[7]. To combat against such "breach fatigue", encrypted database systems recently receive wide attention [8]–[13]. Their objective is to preserve the query functionality of databases over encrypted data; that is, the server can process a client's encrypted query without decryption. The first generation of encrypted databases [8], [9], [14], [15] implements property-preserving encryption (PPE) in a way that a ciphertext inherits equality and/or order properties of the underlying plaintext. However, inference attacks can compromise these encryption schemes by exploiting the above properties preserved in the ciphertexts [16], [17].

In parallel, dedicated privacy-preserving query schemes are investigated intensively in the past decade. Among others, searchable symmetric encryption (SSE) [18], [19] is well known for its applications to ubiquitous keyword based search. In general, SSE schemes utilise an encrypted index to enable the server to search over encrypted documents. The server is restricted such that only if a query token (keyword ciphertext) is given, the search operation against the index will be triggered to output the matched yet encrypted documents. This ensures that an adversary with a full image of the encrypted database learns no useful information about the documents. In that sense, SSE outperforms PPE in terms of security. Apart from security, SSE is scalable, because it is realised via basic symmetric primitives.

In this paper, we design an encrypted document database system based on SSE, for which the client can add encrypted documents to the database and query encrypted keywords against it. However, deploying SSE in practice is non-trivial. With recent emerging inference attacks against SSE [20]-[22] introduced, it raises doubts whether SSE achieves an acceptable tradeoff between the efficiency and security. As a noteworthy threat, the count attack [21] demonstrates that an adversary with extra background knowledge of a dataset can analyse the size of the query result set to recover keywords from the query tokens. The above information is known as access pattern, and can be monitored via the server's memory access and communication between the server and client. If SSE is deployed to a database, access patterns can also be derived from database logs [23]. This situation further reduces the security claim of SSE, since the adversary does not have to stay online for monitoring.

Using oblivious-RAM (ORAM) is an quintessential approach to enable encrypted search without exposing access pattern [24], [25], but it is shown as an expensive tool [20], [26]–[28]. Alternatively, using padding (bogus documents) for inverted index solution [19] is proven as a conceptually simple but effective countermeasure to obfuscate the access pattern against the aforementioned attacks [20], [21], [29]. Unfortunately, existing padding countermeasures only consider a static database, where padding is only added at

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the setup [27], [29]. They are not sufficient for real-world applications. In practice, the states of database change over the time. Specifically, the updates of documents change the access pattern for a given keyword, and new keywords can be introduced randomly at any time. Hence, exploring to what extend adversaries can exploit such changes to compromise the privacy of data and how padding countermeasures can be applied in a dynamic environment are essential to make SSE deployable in practice.

Contributions: To address the above issues, we propose and implement an encrypted document database named ShieldDB, in which the data and query security in realistic and dynamic application scenarios is enhanced via effective padding countermeasures. Our contributions are as follows:

- ShieldDB is the first encrypted database that supports encrypted keyword search, while equipping with padding countermeasures against inference attacks launched by adversaries with database background knowledge.
- We define two new types of attack models, i.e., *nonpersistent* and *persistent* adversaries, which faithfully reflect different real-world threats in a continuously updated database. Accordingly, we propose padding countermeasures to address these two adversaries.
- ShieldDB is designed with a dedicated system architecture to achieve the functionality and security goals. Apart from the client and server modules for encrypted keyword search, a *Padding Service* is developed. This service leverages two controllers, i.e., *Cache Controller* and *Padding Controller*, to enable efficient and effective database padding.
- ShieldDB implements advanced features to further improve the security and performance. These features include: 1) forward privacy that protects the newly inserted document, 2) flushing that can reduce the load of the padding service, and 3) re-encryption that refreshes the ciphertexts while realising deletion and reducing padding overhead.
- We present the implementation and optimization of ShieldDB, and deploy it in Azure Cloud. We build a streaming scenario for evaluation. In particular, we implement an aggressive padding mode (*high* mode) and a conservative padding mode (low mode), and compare them with padding strategies against nonpersistent and persistent adversaries, respectively. We perform a comprehensive set of evaluations on the load of the cache, system throughput, padding overhead, and search time. Our results show that the *high* mode results in much larger padding overhead than the *low* mode does, while achieving lower cache load. In contrast, the *low* mode results in higher system throughput (accumulated amount of real data) but requiring a higher cache load. The evaluations of flushing and re-encryption demonstrate the effective reduction of the cache load and padding overhead.

Organisation: We present important related works in Section 2. Section 3 overviews the design of ShieldDB and demonstrates *non-persistent* and *persistent* adversaries. Section 4 demonstrates padding countermeasures and other optimisation features supported in ShieldDB. Section A

analyses the security of the system. Sections 6 and 7 present system deployment and evaluations. Conclusion is in Section 9.

2 BACKGROUND

In this section, we introduce the background knowledge related to the design of our system.

Dynamic symmetric searchable encryption. Considering a client *C* and a server *S*, the client encrypts documents in a way that the server can query keywords over the encrypted documents. Functions included in an SSE scheme are **setup** and **search**. If the scheme is dynamic, update functions (data addition and deletion) are also supported. Let DB represent a database of documents, and each document is a variable length set of unique keywords. We use $\Delta = \{w_1, ..., w_m\}$ to present all keywords occurred in DB, DB(*w*) to present documents that contain *w*, and |DB(w)| to denote the number of those documents, i.e., the size of the query result set for *w*. In SSE, the encrypted database, named EDB, is a collection of encrypted keyword and document id pairs (w, id)'s, aka an encrypted searchable index.

In setup, client encrypts DB by using a cryptographic key k, and sends EDB to server. During search, client takes k and a query keyword w as an input, and outputs a query token tk. S uses tk to query EDB to get the pseudo-random identifies of the matched documents, so as to return the encrypted result documents. In update, C takes an input of k, a document D_i parsed as a set of (w, id) pairs, and an operation $op \in \{add, del\}$. For addition, the above pairs are inserted to EDB. For deletion, the server no longer returns encrypted documents in subsequent search queries. As an output, the server returns an updated EDB. We refer readers to [30], [31] for more details about dynamic SSE.

The security of dynamic SSE can be quantified via a tuple of stateful leakage functions $\mathcal{L} = (\mathcal{L}^{Setup}, \mathcal{L}^{Search}, \mathcal{L}^{Update})$. They define the side information exposed in setup, search, and update operations, respectively. The detailed definitions can be referred to Section A.

Count Attack. Cash et al. [27] propose a practical attack that exploits the leakage in the search operation of SSE. It is assumed that an adversary with full or partial prior knowledge of DB can uncover keywords from query tokens via access pattern. Specifically, the prior knowledge allows the adversary to learn the documents matching a given keyword before queries. Based on this, she can construct a keyword co-occurrence matrix indicating keyword coexisting frequencies in known documents. As a result, if the result length |DB(w)| for a query token tk is unique and matches with the prior knowledge, the adversary directly recovers w. For tokens with the same result length, the co-occurrence matrix can be leveraged to narrow down the candidates. In this work, we extend the threat model of the count attack to the dynamic setting, which will be introduced in Section 3.2.

Forward Privacy. Forward privacy in SSE prevents the adversary from exploiting the leakage in update (addition) operations. Given previously collected query tokens, this security notion ensures that these tokens cannot be used to match newly added documents. As our system considers the scenario, where the documents are continuously

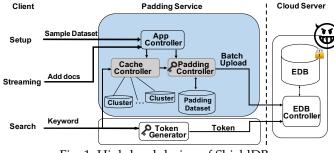


Fig. 1: High-level design of ShieldDB

inserted, we adapt an efficient scheme with forward privacy [32] proposed by Song et al. This scheme follows Bost's scheme [33] that employs trapdoor permutation to secure states associated to newly added (w, id)'s. Without being given new states, the server cannot perform search on the new data, and those states can be used to recover old states via trapdoor permutation. Specifically, we optimise the adapted scheme in the context of batch insertion and improve the efficiency, which will be introduced in Section 4.3.

3 OVERVIEW

3.1 System Overview

ShieldDB is a document-oriented database, where semistructured records are modeled and stored as documents, and can be queried via keywords or associated attributes.

Participants and scenarios: As illustrated in Figure 1, ShieldDB consists of a query client *C*, a trusted padding service *P* and an untrusted storage server *S*. In our targeted scenario, new documents are continuously inserted to *S*, and required to be encrypted. Meanwhile, *C* expects *S* to retain search functionality over the encrypted documents. To enhance the security, *P* adapts padding countermeasures during encryption. In this paper, we consider an enterprise that utilises outsourced storage. *P* is deployed at the enterprise gateway and in the same network with *C*, and *P* encrypts and uploads the documents created by its employees, while *C* is deployed for employees to search the encrypted documents at *S*. Note that the deployment of *P* is flexible. It can be separated from or co-located with *C*.

Overview: ShieldDB supports three main operations, i.e., setup, streaming, and search. The full protocols of ShieldDB is presented in Figure 4. Apart from the main functions, ShieldDB also supports optimisation features deletion and re-encryption, and flushing operations (Section 4.3).

During Setup, *P* receives a sample training dataset Δ_{stp} from *C*, and then it groups keywords into clusters $L = \{L_1, \dots, L_m\}$ based on keyword frequencies. After that, the module *App Controller* in *P* notifies *L* to the module *Cache Controller* to initialise a cache capacity L_i for each keyword cluster. *App Controller* also notifies *L* to the module *Padding Controller* to generate a padding dataset *B*.

During streaming, *P* receives an input, in = {(doc, id)} containing a collection of documents, each element is a document doc with identifier *id*, sent from *C*. Then, *P* parses them into a set of keyword and document identifier (*w*, *id*) pairs, i.e., index entries for search. Then, *Cache Controller* stores these pairs to the caches of the corresponding keyword clusters. Based on the targeted attack model, *Cache Controller* applies certain constraints in PaddingCheck to

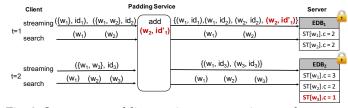


Fig. 2: Strawman padding against non-persistent adversary

flush the cache (Algorithm 1). Once the constraints on a cluster are met, *Cache Controller* notifies the satisfied cluster to *Padding Controller* for padding. In particular, *Padding Controller* adds bogus (w, id) pairs extracted from the padding dataset to make the keywords in this cluster have equal frequency. Then, *P* encrypts and inserts all those real and bogus index entries as a data collection in a batch to EDB (see streaming lines 7 - 30 in Figure 4).

During search, for a given single query keyword w, Cwants to retrieve documents matching that keyword from S and P. First, C retrieves the local results from Cache Controller in P, since some index entries might have not been sent to EDB yet. After that, C sends a query token generated from this keyword to *S* to retrieve the rest of the encrypted results. After decryption, C filters padding and combines the result set with the local one. For security, C will not generate query tokens against the data collection which is currently in streaming; this constraint enforces S to query only over data collections which are already inserted to EDB. Following the setting of SSE [19], [34], search is performed over the encrypted index entries in EDB, and document identifiers are pseudo-random strings. In response to query, S will return the encrypted documents via recovered identifiers in the result set after search.

Apart from padding countermeasures, ShieldDB provides several other salient features. First, it realises forward privacy [33] (an advanced notion of SSE) for the streaming operation. Our realisation is customised for efficient batch insertion and can prevent S from searching the data collection in streaming. Second, ShieldDB integrates the functionality of re-encryption. Within this operation, index entries in a targeted cluster are fetched back to P and the redundant padding is removed. At the same time, deletion can be triggered, where the deleted index entries issued and maintained at *P* are removed and will not be re-inserted. After that, real entries combing with new bogus entries are re-encrypted and inserted to EDB. Third, Cache Controller can issue a secure flushing operation before meeting the constraints for padding. This reduces the overhead of P while preserving the security of padding.

Remark: ShieldDB assigns P for key generation and management, and P issues the key for C to query. In addition, C also gets the latest state of the query keyword from P, and together with the key, to generate query tokens and send them to S. In our current implementation, P and C use the same key for index encryption, just as most SSE schemes do. This is practical because SSE index only stores pseudorandom identifies of documents, and documents can separately be encrypted via other encryption algorithms. Advanced key management schemes of SSE [35], [36] can readily be adapted; yet, this is not relevant to our problem.

Like many other SSE works [29], [37]–[39] that focus

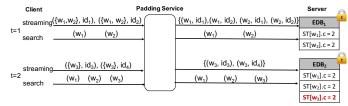


Fig. 3: Strawman padding against persistent adversary

on search document index, we only present that streaming in ShieldDB updates real/bogus document identifiers via (w, id) pairs to the index map EDB. Real and padding documents containing these pairs can be uploaded separately by *P* to *S* via other encryption algorithms. In search, once the identifiers of real/bogus documents matching the query keyword are uncovered, *S* retrieves the corresponding documents and returns them to *C*. Note that, we omit presenting the physical document management in *S* in the rest of the paper since it does not affect the security of ShieldDB against the non-persistent and persistent adversaries as proposed in Section 3.2.

3.2 Attack Models

ShieldDB mainly considers a passive adversary who monitors the server S's memory access and the communication between the *Server* and other participants. Following the assumption of the count attack [21], the adversary has access to the background knowledge of the dataset and aims to exploit this information with the access pattern in **Search** operations to recover query keywords. In this paper, we extend this attack model to the dynamic (streaming) setting.

Before elaborating the attack models, we define the streaming setting. In our system, **streaming** performs batch insertion on a collection of encrypted (w, id) pairs to *S*. Giving a number of continuous **streaming** operations, encrypted collections are added to a sequence over time. Accordingly, *S* orders the sequence of data collections by the timestamp. We define the gap between any two consecutive timestamps is a time interval *t*, and *C* is allowed to search at any time interval. Note that at a given *t*, *S* can only perform **search** operations against the collections that have been completely inserted to EDB.

In the dynamic setting, we observe two new attack models, which we refer to as non-persistent and persistent adversaries, respectively.

Non-persistent adversary: This adversary controls *S* within one single arbitrary time interval t_i , where *i* is a system parameter that monotonically increases and $i \ge 0$. During t_i , she observes query tokens that *C* issued to *S*, and the access patterns returned by *S*. She knows the accumulated (not separate) knowledge of the document sets inserted from t_0 to t_i .

Persistent adversary: This adversary controls *S* across multiple arbitrary time intervals, for example, from t_0 to t_i . She persistently observes query tokens and access patterns at those intervals, and knows the separate knowledge of the document sets inserted from t_0 to t_i .

For both attack models, *S* cannot obtain the query tokens against the encrypted data collections streamed in the current time interval. It is enforced by our streaming operation with forward privacy (see Section 4.3).

Strawman padding service against the adversaries: We note that a basic *Padding Service P* that only maintains one single cache for batch **streaming** cannot mitigate the proposed adversaries as presented in Figures 2 and 3.

In Figure 2, we show that the non-persistent adversary, capturing query tokens of w_1 , w_2 , and w_3 , and their corresponding access patterns (i.e., result lengths $ST[w_1].c$, $ST[w_2].c$, and $ST[w_3].c$) at time t = 2, can uncover which tokens used for what keywords if she has the corresponding background knowledge of DB at time t = 2 (i.e., DB₂). The reason is due to the unique result lengths introduced in EDB at time t = 2 (i.e., EDB₂) when *P* adds bogus pairs to equalise the number of pairs for keywords sent to EDB during every streaming operation.

In Figure 3, we demonstrate that the persistent adversary can detect when new keywords are inserted in EDB. For example, she might know the states of the database DB at time t = 1 and t = 2 as her background knowledge, and the query results of w_3 in EDB₁ and EDB₂ are different. Then, she knows the occurrence of a new keyword w_3 is introduced in EDB₂ at t = 2. Then, she is able to identify the query token of w_3 during search at t = 2.

Real-world implication of the adversaries: We note that the proposed attack models are new for leakage-abuse attacks, which have not been investigated and formalised in any of the prior works [20], [21], [40]. We stress that non-persistent adversary could be any external attackers, e.g., hackers or organised cyber criminals. They might compromise the server at a certain time window. We also assume that this adversary could obtain a snapshot of the database via public channels, e.g., a prior data breach [16]. Because the database is changed dynamically, the snapshot might only reflect some historical state of the database. On the contrary, the persistent adversary is more powerful and could be database administrators or insiders of an enterprise. They might have long term access to the server and could obtain multiple snapshots of the database via internal channels.

Other threats: Apart from the above adversaries, ShieldDB considers another specific rational adversary [22] who can inject documents to compromise query privacy. As mentioned, this threat can be mitigated via forward privacy SSE. Note that ShieldDB currently does not address an active adversary who sabotages the search results.

4 DESIGN OF SHIELDDB

In this section, we present the detailed design of ShieldDB in Setup, Stream, and Search. Then, we present some advanced features of ShieldDB to further improve the security and efficiency.

4.1 Setup

We consider $\Delta_{stp} = \{w_1, w_2, ..., w_l\}$ is the training dataset for the system. During Setup (Δ_{stp}) , *P* invokes *Cache Controller* to initialise the cache for batch insertion, and *Padding Controller* to generate bogus documents for padding.

To reduce padding overhead, ShieldDB implements cache management in a way that it groups keywords with similar frequencies together and performs padding at each individual keyword cluster. We denote $L = \{L_1, \dots, L_m\}$ as caching clusters managed by *Cache Controller*, where *m* is

setup $(1^{\lambda}, \Delta_{stp})$ 9: 10: Client: //let *b* is the current batch 1. Transfer dataset Δ_{stp} to *P*; 11: Padding Service: 12: 2: $\{k_1, k_2\} \xleftarrow{\$} \{0, 1\}^{\lambda};$ 13: 3: Initialise a map ST' and a tuple T; 14: 4: Run Setup (Δ_{stp}) (see Section 4.1); 15: Server: 16: 5: Initialise an index map EDB; 17: $i \leftarrow 0$; 18. streaming (in = {(doc, id)}) 19: 20: Client: 21: 1. Transfer in to *P*; 22: *Padding Service:* 23: 2: Parse in to $M = \{(w, id)\};$ 24: $c_{w_b} \leftarrow i;$ //cache and check padding con-25: straints 26: 3: $V \leftarrow \text{PaddingCheck}(M)$ (Algo-27: rithm 1); //if there is no real/bogus pairs re-28: $T \leftarrow T \cup (u_{w_b}, v_{w_b});$ turned by Padding Controller 29: end foreach 4: if $V = \{\emptyset\}$ then 30: Send T to Server; 5: return;//not sending to Server Server: 6: else: //perform encryption 31: foreach (u, v) in T do 7: foreach w in V do 32: EDB[u] = v;8: $k_e \stackrel{\$}{\leftarrow} \{0,1\}^{\lambda};$

search(w)

Client: //receive ST'[w] from *P* 1: if $ST'[w] \neq \bot$ then if $ST'[w] \neq \bot$ then 2: $k_w \leftarrow F(k_1, w);$ $(st_{w_{(b-1)}}, c_{w_{(b-1)}}) \leftarrow ST'[w];$ $k_{id} \leftarrow F(k_2, w);$ 3: 4: $(st_{w_b}, c_{w_b}) \leftarrow ST'[w];$ $st_{w_0} \stackrel{\$}{\leftarrow} \{0,1\}^{\lambda}$, $c_{w_0} \leftarrow 0$; 5: Send $(k_w, k_{id}, st_{w_b}, c_{w_b})$ to Server 6: else $st_{w_b} \leftarrow F(k_e, st_{w_{(b-1)}});$ 7: Search w in P, return R; 8: end if foreach *id* that matches *w* do Server: $u \leftarrow H_1(F(st_{w_b}, i) \parallel k_w);$ 9: $R \leftarrow \emptyset$, $st_i \leftarrow st_{w_b}$, $c_i \leftarrow c_{w_b}$; $v \leftarrow H_2(F(st_{w_b}, i) \parallel k_{id}) \oplus id;$ 10: while $c_i \neq 0$ do $T \leftarrow T \cup (u, v);$ for j = 0 to $(c_i - 1)$ do 11: $u \leftarrow H_1(F(st_i, j) \parallel k_w)$ 12: 13: $v \leftarrow \text{EDB}[u]$ $id \leftarrow v \oplus H_2(F(st_i, j) \parallel k_{id});$ 14: $ST'[w] \leftarrow (st_{w_b}, c_{w_b});$ 15: $R \leftarrow R \cup (u, v);$ $u_{w_b} \leftarrow H_1(F(st_{w_b}, c_{w_b}) \parallel k_w);$ 16: end for $v_{w_b} \leftarrow H_2(F(st_{w_b}, c_{w_b}) \parallel k_{id})$ 17: $u_k \leftarrow H_1(F(st_i, c_i) \parallel k_w);$ $\oplus (k_e \parallel c_{w_{(b-1)}});$ 18: $v_k \leftarrow \text{EDB}[u_k];$ 19: $(k_i \parallel c_{i-1}) \leftarrow v_k \oplus$ $H_2(F(st_i, c_i) \parallel k_{id})$ $st_{i-1} \leftarrow F^{-1}(k_i, st_i)$ 20: 21: $st_i \leftarrow st_{i-1}, c_i \leftarrow c_{i-1};$ 22: end while 23: send R to Client

Fig. 4: Forward-private SSE protocols in ShieldDB. In streaming, k_e is an ephemeral key generated for batch insertion. P maintains the master state $ST'[w] = (st_{w_b}, c_{w_b})$ for each keyword w, where st_{w_b} is the master key to derive entries for (w, id) pairs in the same latest batch b, and c_{w_b} presents the result length w (i.e., the number of real and bogus ids containing w) in that batch b. The result length of w in the previous batch $c_{w_{(b-1)}}$ is embedded in v_{w_b} (see streaming protocol line 26). In search, st_i and c_i present the state key and the result length of w in batch i. H_1 and H_2 are hash functions, and *F* is AES cipher.

 $k_w \leftarrow F(k_1, w);$

 $k_{id} \leftarrow F(k_2, w);$

else

end if

 $i \leftarrow i + 1;$

end foreach

33: end foreach

the number of cache clusters. This approach is inspired from existing padding countermeasures in the static setting [21], [29]. The idea of doing this in a static database is intuitive; the variance between the result lengths of keywords with similar frequencies is small, which can minimize the number of bogus entries added to the database. We note that it is also reasonable in the dynamic setting, where the keyword frequencies in specific applications can be stable in the long run. If a keyword is popular, it is likely to appear frequently during streaming, and vice versa. Therefore, we assume that the existence of the training dataset, where the keyword frequencies are close to the real ones during streaming is reasonble (see Section 7.2 for that distribution evaluation). We further suggest alternative training data collection approaches in Section 7.3.

Given Δ_{stp} , Cache Controller partitions keywords based on their frequencies by using a heuristic algorithm. The objective function in Eq. 1, such that the clustering can be formed as $[(w_1, \ldots, w_i), (w_{i+1}, \ldots, w_i), \ldots, (w_k, \ldots, w_l)].$ We note that the minimum size of each group α is subjected to $\alpha \geq 2$. For security, the keyword frequency in each cluster after padding should be the same, i.e., the maximum one, and thus *Cache Controller* computes the padding overhead γ

as follows:

$$\gamma = \left(i * f_{w_i} - \sum_{t=1}^{i} f_{w_t}\right) + \left((j-i) * f_{w_j} - \sum_{t=i+1}^{j} f_{w_t}\right) + \dots + \left((l-k-1) * f_{w_l} - \sum_{t=k}^{l} f_{w_t}\right)$$
(1)

This algorithm iterates evaluating γ for every combination of the partition. We denote by m the number of clusters. After that, the Cache Controller allocates the capacity of the cache based on the aggregated keyword frequencies of each cluster, i.e., $|L| \sum_{t=1}^{i} f_{w_t}$, $|L| \sum_{t=i+1}^{j} f_{w_t}$, ..., $|L| \sum_{t=k}^{l} f_{w_t}$, where |L| is the total capacity assigned for the local cache. We denote by $L_i.threshold()$ the function that outputs the caching capacity of cluster L_i .

After that, *Padding Controller* initialises a bogus dataset B with size |B|, where the number of bogus keyword/id pairs for each keyword w_i is determined via the frequency, i.e., $|B|(f_w - f_{w_i})$, where f_w is the maximum frequency in the cluster of w_i . The reason of doing so is that it still follows the assumption in cache allocation. If the keyword is less frequent in a cluster, it needs more bogus pairs to achieve the maximum result length after padding, comparing other keywords with higher frequency, and vice versa. Then the

```
Algorithm 1: Padding strategies
 1 function PaddingCheck()
   Input : M = \{(w, id)\}: entries for streaming,
             \{L_1, \cdots, L_m\}: cache clusters,
             ST: a map that tracks keyword states,
             B: bogus document set;
             mode: padding mode (high or low);
   Output: V: a set of real and bogus entries
 2 push entries in M to \{L_1, \dots, L_m\};
 V \leftarrow \{\emptyset\};
 4 if padding against non-persistent adversary then
       for cluster L_i \in \{L_1, \cdots, L_m\} do
 5
           if L_i.capacity() \ge L_i.threshold() then
 6
               for w \in L_i do
 7
                  if ST[w]. flag = false then
 8
                      skip padding for w when executing
 9
                       PaddingByMode(); //not
                        occurred yet
                  end
10
               end
11
               M_i \leftarrow \texttt{PaddingByMode}(L_i, ST, B, mode);
12
              add M_i to V;
13
           end
14
       end
15
16 end
   if padding against persistent adversary then
17
       for cluster L_i \in \{L_1, \cdots, L_m\} do
18
          if L_i.firstBatch=true & ST[w].flag = true for
19
            \forall w \in L_i then
               M_i \leftarrow \texttt{PaddingByMode}(L_i, ST, B, mode);
20
               add M_i to V;
21
22
           else if L_i.capacity() \ge L_i.threshold() then
               M_i \leftarrow \texttt{PaddingByMode}(L_i, ST, B, mode);
23
               add M_i to V;
24
25
           end
       end
26
27 end
28 return V;
```

controller generates bogus index pairs. Once the bogus pairs for a certain keyword w_i is run out, the controller is invoked again to generate padding for it through the same way.

Remark: We assume that the distribution of the sample dataset is close to the one of the streaming data in a running period. We acknowledge that it is non-trivial to obtain an optimal padding overhead in the dynamic setting due to the variation of streaming documents in different time intervals. Nevertheless, if the distribution of the database varies during the runtime, the setup can be re-invoked. Namely, keyword clustering algorithm can be re-activated based on the up-to-date streaming data (e.g., in a sliding window), and the cache can be re-allocated. Additionally, our proposed re-encryption operation can further reduce the padding overhead (see Section 4.3) if the streaming distribution only differs on particular keyword clusters. We discuss the distribution difference detection in Sections 7.2 and 7.3. We also note that there are applications and scenarios where the distribution does not vary much, like IoT streaming data for environment sensors. In such applications, the range of

| 1 function PaddingByMode($L_i, ST, P, mode$) Input : L_i : cluster for padding, ST: a map that tracks keyword states, |
|---|
| |
| ST: a map that tracks keyword states, |
| 1 , , , , , , , , , , , , , , , , , , , |
| B: bogus dataset; |
| <i>mode</i> : padding mode (<i>high</i> or <i>low</i>) |
| Output: M_i : a set of real and bogus entries |
| 2 $M_i \leftarrow \emptyset;$ |
| $s st_{max} \leftarrow \max\{ST[w].c\} \text{ for } \forall w \in L_i;$ |
| ⁴ let c_w is the length of the currently matching list of |
| w cached in L_i ; |
| 5 if $mode = high$ then |
| $6 \text{ let } c_{max} \text{ is } \max\{c_w, \forall w \in L_i\};$ |
| 7 $C \leftarrow st_{max} + c_{max};$ |
| s for $w \in L_i$ with $ST[w]$. $flag = true$ do |
| 9 add $(C - c_w)$ bogus entries from $B[w]$ to M_i ; |
| 10 add all c_w cached entries of w in L_i to M_i ; |
| 11 $ ST[w].c \leftarrow C;$ |
| 12 end |
| 13 else |
| 14 // mode is low 15 lot $a \rightarrow ic \min\{a \ge 0, \forall a \in L\}$ |
| 15 let c_{min} is $\min\{c_w > 0, \forall w \in L_i\}$; |
| 16 $C \leftarrow st_{max} + c_{min};$ 17 for $w \in L_i$ with $ST[w].flag = true$ do |
| $\begin{array}{c ccccccccccccccccccccccccccccccccccc$ |
| $\begin{array}{c c} $ |
| 20 $add (m - c_w)$ bogus entries from $B[w]$ to |
| $M_{i;}$ |
| 21 add all c_w cached entries of w in L_i to M_i ; |
| 22 else |
| 23 //do not add bogus entries for w ; |
| put (m) cached entries of w in L_i to M_i ; |
| 25 //the remaining $(c_w - m)$ entries of w are |
| still cached in L_i ; |
| 26 end |
| 27 $ ST[w].c \leftarrow C;$ |
| 28 end |
| 29 end |
| 30 return M_i ; |

numbers/indicators are already specified by the vendors.

4.2 Padding Strategies

During streaming, documents are continuously collected and parsed as $M = \{(w, id)\}$ in *P*. Then, *P* executes PaddingCheck(*M*) to cache and check padding constraints. In details, these (w, id) pairs are cached at their corresponding clusters by *Cache Controller*. Once a cluster L_i is full, *Padding Controller* adapts the corresponding padding strategy to the targeted adversary, encrypts and inserts all real and bogus pairs to EDB in a batch manner. We elaborate on the padding strategies against the non-persistent and persistent adversaries, respectively. The details are given in Algorithms 1 and 2.

Padding strategy against the non-persistent adversary: Recall that this adversary controls *S* within a certain time interval *t*. From the high level point of view, an effective padding strategy should ensure that all keywords occurred

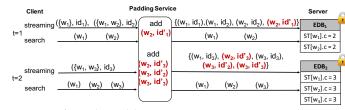


Fig. 5: *High* mode padding against non-persistent adversary

in EDB at t do not have unique result lengths. There are two challenges to achieve this goal. First, t can be an arbitrary time interval. Therefore, the above guarantee needs to be held at any certain time interval. Second, not all the keywords in the keyword space would appear at each time interval. It is non-trivial to deal with this situation to preserve the security of padding.

To address the above challenges, ShieldDB programs *Padding Controller* to track the states of keywords over the time intervals from the beginning. Specifically, each keyword state ST[w] includes two components, a flag ST[w].*flag* that indicates whether the keyword has existed before in the streamed documents, and a counter ST[w].c that presents the number of total real and bogus (w,id) pairs already uploaded in EDB of the keyword w. Note that ST[w].flag = true is kept permanently once w has existed in the documents streamed to the server. *Padding Controller* only pads the keywords in a cluster L_i if the number of cached real (w,id) pairs of the cluster, denoted by $L_i.capacity()$, exceeds $L_i.threshold()$ defined in setup (see Algorithm 1 line 6).

Based on the states of keywords, Padding Controller performs the following actions. If the keyword has not existed yet, the controller will not pad it even its cluster is full (see Algorithm 1 line 8). The reason is that the adversary might also know the information of keyword existence. If C queries a keyword which does not exist, S should return an empty set. Otherwise, the adversary can identify the token of this keyword if padded. Accordingly, only when a keyword wappears at the first time (i.e., ST[w].flag = true), padding over this keyword will be invoked (see Algorithm 2 lines 8 and 17). Once ST[w].flag = true, this keyword will always get padded later, as long as the cache of its cluster $L_i.capacity() > L_i.threshold()$, no matter it exists in a certain time interval or not. The padding ensures that all existing keywords in the cluster always have the same result length at any following time interval.

Padding strategy against the persistent adversary: Recall that this adversary can monitor the database continuously and obtain multiple references of the database across multiple time intervals. Likewise, the padding strategy against the persistent adversary should ensure that all keywords have no unique access pattern in all time intervals from the very beginning. However, directly using the strategy against the non-persistent adversary here does not address the leakage of keyword existence.

To address this issue, *Padding Controller* is programmed to enforce another necessary constraint to invoke padding. That is, all keywords in the cluster at the first batch have to exist before streaming. Formally, we let L_i .*firstBatch* be the constraint that evaluates the existence of all predefined keywords in L_i . Then, L_i .*firstBatch* = true implies

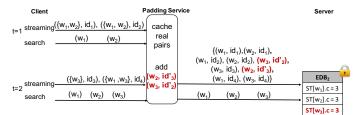


Fig. 6: High mode padding against persistent adversary

ST[w].flag = true for $\forall w \in L_i$. The constraint remains false if there is $\exists w_j \in L_i$, $ST[w_j] = false$. As a trade-off, *Cache Controller* has to hold all the pairs in the cluster even the cache is full, if there are still keywords yet to appear (see Algorithm 1 line 18). For subsequent batches of the cluster, the padding constraint follows the same strategy for the non-persistent adversary (see Algorithm 1 line 21).

Padding modes: ShieldDB implements two modes for padding, i.e., *high* and *low* modes. These two modes both are applicable to the above two padding strategies (see mode in Algorithm 1). The padding mechanism of these modes are described in Algorithm 2. In the high mode, once the constraint for the cache of a cluster is met, the keywords to be padded have the maximum result length of keywords in this cluster (see Algorithm 2 lines 9-11). Accordingly, the cache can be emptied since all entries are sent to *Padding Controller* for streaming. On the contrary, the *low* mode is invoked in a way that the keywords to be padded have the minimum result length of keywords in this cluster. Therefore, some entries of keywords might still be remained in the cache (see Algorithm 2 lines 24-25). Yet, this mode only introduces necessarily minimum padding for keywords which do not occur in random time intervals. The two modes have their own merits. The high mode consumes a larger amount of padding and execution time for padding and encryption, but it reduces the load of cache in *P*. In contrast, the *low* mode introduces relatively less padding overhead but heavier load of *P*.

Figure 5 demonstrates the padding strategy against the non-persistent adversary by using *high* padding mode. Given a cluster L_j containing three keywords $w_i, \forall i \in [1, 3]$, P tracks their keyword state $ST[w_i].c$ and $ST[w_i].flag$ and applies padding when real cached pairs exceed the capacity of the cluster. Then, P adds bogus pairs to ensure they have the same result length in EDB at t = 1 and t = 2. Note that, there is no padding applied for w_3 at time t = 1 due to $ST[w_3].flag = false$ at that time. At t = 2, P pads all the keywords to the maximum result length among them in the cluster (i.e., $ST[w_i] = 3, \forall i \in [1,3]$).

In Figure 6, we demonstrate the padding strategy against the persistent adversary by using *high* padding mode for a cluster $L_j = \{w_i\}, \forall i \in [1,3]$. *P* only performs padding and inserts encrypted real/bogus entries to EDB when all keywords in L_j have appeared (i.e., waiting for w_3 occurs at t = 1). Querying any w_i of the cluster prior this time does not make the client *C* send query tokens to *S*. The reason is because *C* only receives $ST'[w_i] = \bot$ sent by *P* to do search. We note that *P* only updates $ST'[w_i]$, (i.e., keyword state of w_i for encryption) (see ST'[w] in streaming and search in Figure 4) when w_i in the cluster is ready for encryption after padding applied. We note that L_j .*firstBatch* = *true* once all keywords in L_j have been

TABLE 1: Time complexity of Padding Service and Server

| Padding | Server | |
|------------------------|---------------------------|--------------------------|
| padding (streaming) | encryption (streaming) | update/search |
| $ B (f_w - f_{w_i})$ | $\mathcal{O}(n_r + n_b)$ | $\mathcal{O}(n_r + n_b)$ |

appeared. Then, subsequent batches at t > 1 of L_j does not need to check keyword occurrence. Instead, it follows the padding strategy addressing the non-persistent adversary. The reason is because w_i is always padded in the following batches once it had appeared at the first time. The strategy aims to ensure there is no new keyword introduced at any random time interval to address the persistent adversary.

Complexity analysis of padding: We note that during setup, the *Padding Service* initialises a padding (bogus) dataset *B* with size of |B|. Then, the total number of bogus pairs used for the keyword w_i during the streaming phase is $|B|(f_w - f_{w_i})$, where f_w is the maximum frequency in the cluster of w_i found in the setup. The asymptotic complexity to encrypt real/bogus pairs of w_i in the streaming is $O(n_r + n_b)$, where n_r and n_b present the total number of real and bogus pairs of w_i , respectively. In streaming (resp. search), upon receiving the update (resp. query) token(s) of w_i , the *Server* inserts (resp. retrieves) the entries (resp. search result) based on encrypted labels of w_i from the map EDB (i.e., $O(n_r + n_b)$) by following the forward-private SSE protocols (see Figure 4). The performance is summarised in Table 1.

Security guarantees: Our padding countermeasures ensure that no unique access pattern exists for keywords which have occurred in EDB. For the persistent adversary, the padding countermeasure also ensures that the keyword occurrence is hidden across multiple time intervals. Note that padding not only protects the result lengths of queries, but also introduces false counts in keyword co-occurrence matrix, which further increases the efforts of the count attack. Regarding the formal security definition, we follow a notion recently proposed by Bost et al. [29] for SSE schemes with padding countermeasures. This notion captures the background knowledge of the adversary and formalises the security strength of padding. That is, given any sequence of query tokens, it is efficient to find another same-sized sequence of query tokens with identical leakage. We extend this notion to make the above condition hold in the dynamic setting in Section A.

Remark: Our padding strategies are different from the approach proposed by Bost et al. [29], which merely groups keywords into clusters and pads them to the same result length for a static database. Directly adapting their approach for different batches of incoming documents will fail to address persistent or even non-persistent adversaries. The underlying reason is that the above approach treats each batch individually, while the states of database are accumulated. Effective padding strategies in the dynamic setting must consider the accumulated states of the database so that the adversaries can be addressed in arbitrary time intervals.

4.3 Other Features

ShieldDB provides several other salient features to enhance its security, efficiency, and functionality.

Forward privacy: In streaming and search, ShieldDB realises the notion of forward privacy [32], [33] to protect the newly added documents and mitigate the injection attacks [22]. In particular, our system customises an efficient SSE scheme with forward privacy [32] to our context of batch insertion. The detailed algorithm for encryption and search can be found in Figure 4. Our forward-private scheme is built on symmetric-key based trapdoor permutation and is faster than the public-key based solution [33]. The ephemeral key k_e of permutation is embedded inside the index entry to recover the state $(st_{w_{(b-1)}}, c_{w_{(b-1)}})$ of the previous entries in batch (b-1) (see Figure 4, lines 16-27 in streaming, and lines 17-21 in search protocol). To reduce the computation and storage overhead, we link a master state $ST'[w] = (st_{w_b}, c_{w_b})$ to a set of entries with the same keyword in the batch *b* (see streaming at lines 19-20).

Upon receiving ST'[w] of the query keyword w sent from P, C generates a query token and sends to S (see Figure 4 line 5 in search protocol). We note that ST'[w] is different from the state ST[w] used for padding in *Padding Controller*. The benefit of our forward-private design is that S can be enforced to perform search operations over the completed batches. The batches which are still transmitted on the fly cannot be queried without the latest keyword state ST'[w] from C.

Re-encryption and deletion: ShieldDB also implements the re-encryption operation. This operation is periodically conducted over a certain keyword cluster. *Padding Service P* first fetches all entries in this cluster stored in EDB from *S*. After that, *P* removes all bogus entries and re-performs the padding over this cluster of keywords. All the real and bogus entires are then encrypted via a fresh key, and inserted back to EDB. The benefits of re-encryption are two-fold: (1) redundant bogus entries in this cluster can be eliminated; and (2) the leakage function can be reset to protect the search and access patterns. During re-encryption, ShieldDB can also execute deletion. A list of deleted document ids is maintained at *P*, and the deleted entries are physically removed from the cluster before padding.

Cache flushing: During streaming, the keywords in some clusters might not show up frequently. Even the cache capacity of such clusters is set relatively small, the constraint might still not be triggered very often. To reduce the load of the cache at *P* and improve the streaming throughput, ShieldDB develops an operation called flushing to deal with the above "cold" clusters. In particular, *Cache Controller* monitors all the caches of clusters, and sets a time limit to trigger flushing. If a cluster is not full after a period of this time limit, all entries in this cluster will be sent to *Padding Controller*. Note that the padding strategies still need to be followed for security and the *high* mode of padding is applied to empty the cache.

5 SECURITY OF SHIELDDB

ShieldDB implements a dynamic searchable encryption scheme $\Sigma = (\text{setup, streaming, search})$, consisting of three protocols between a padding service P, a storage server S, and an querying client C. We note that a database $\text{DB}_t = (w_i, id_i)_{i=1}^{|DB_t|}$ is defined as a tuple of keyword and document id pairs with $w_i \subseteq \{0, 1\}^*$ and $id_i \in \{0, 1\}^l$ at the

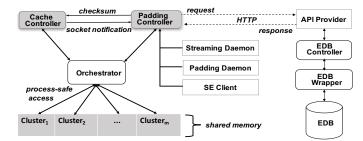


Fig. 7: Implementation of ShieldDB

time interval $t \ge 0$. DB_t presents the accumulated database up to time t. The security of ShieldDB can be quantified via a leakage function $\mathcal{L} = (\mathcal{L}^{Stp}, \mathcal{L}^{Stream}, \mathcal{L}^{Srch})$. It defines the information exposed in setup, streaming, and search, respectively. The security of ShieldDB ensures that it does not reveal any information beyond the one that can be inferred from $\mathcal{L}^{Stp}, \mathcal{L}^{Stream}$, and \mathcal{L}^{Srch} .

We adapt the notion of *constrained security* [29] to formalise the knowledge the information known by the non-persistent and persistent adversaries. Formally, we model the fact that the non-persistent adversary knows the database by considering the constraint set $\mathcal{C}^{\mathcal{DB}_t} = \{C^{\mathrm{DB}_t}, \mathrm{DB}_t \in \mathcal{DB}_t\}$, where \mathcal{DB}_t is a computable database set at the time t (see Appendix A-B and A-C). Then, with the knowledge of DB_t, the leakage function of Σ_{NP} is formally defined as $\mathcal{L}_{NP} = (\mathcal{L}^{Stp}, \mathcal{L}^{Srch}, \mathcal{L}^{\alpha-pad})$, where \mathcal{L}^{Stp} and \mathcal{L}^{Srch} reveals the leakage in Setup at t and Search against EDB_t, respectively, and the new leakage $\mathcal{L}^{\alpha-pad}$ reveals the minimum size of clusters induced by $\mathcal{L}^{\alpha-pad}$. We define the Ind_{SSE,A,L,NP,C} $\mathcal{DB}_{t,\alpha}$ game for the non-persistent in Definition 5 in the supplementary material.

We state the following theorem regarding the security of ShieldDB against the adversary as follows (full proof is provided in the supplementary material Section A-C).

Theorem 1. Let $\Sigma_{NP} = ($ **Setup, Search**) be our SSE scheme, and $\mathfrak{C}^{\mathcal{DB}_t}$ a set of knowledge constraints. If Σ_{NP} is \mathcal{L}_{NP} -constrainedadaptively-indistinguishable secure, and $\mathfrak{C}^{\mathcal{DB}_t}$ is $(\mathcal{L}_{NP}, \alpha)$ acceptable, then Σ_{NP} is $(\mathcal{L}_{NP}, \mathfrak{C}^{\mathcal{DB}_t}, \alpha)$ -constrained-adaptivelyindistinguishability secure.

Then, we generalise the knowledge of the non-persistent adversary over the time to be the persistent adversary's knowledge of databases. Namely, we denote by $(DB_{t=0}, \ldots, DB_{t=T})$ such knowledge, where T denotes the streaming period. We also make use of the constraint set $\mathfrak{C}^{\mathcal{DB}_t} = \{C^{DB_t}, DB_t \in \mathcal{DB}_t\}$ to formulate $\mathbf{C}^{[1,\ldots,T]} = \{\mathfrak{C}^{\mathcal{DB}_0}, \ldots, \mathfrak{C}^{\mathcal{DB}_T}\}$ the generalisation of constraint sets over the period such that we know every $\mathfrak{C}^{\mathcal{DB}_t}(\mathcal{L}_{NP}, \alpha)$ -acceptable, $\forall t \in [0, T]$.

The security of a scheme $\Sigma_P = (\text{Setup}, \text{Stream}, \text{Search})$ against the persistent adversary over a streaming period T. We start adding a padding mechanism against the persistent adversary in Algorithm 1 (i.e., Padding Strategies) to Σ_P such that, $\forall G_{i,t}$ in $\Gamma_t = \{G_{1,t}, \ldots, G_{m,t}\}$ induced by Search_t (i.e., searching at time t) against EDB_t, $G_{i,t}$ always has the same size $|G_{i,t}| = |G_{i,t'}|$, where $G_{i,t'}$ in $\Gamma_{t'} = \{G_{1,t'}, \ldots, G_{m,t'}\}, \forall t' \neq t$. Let $\mathcal{L}_{[1,\ldots,T]}^{Stream} = \{L_1^{Stream}, \ldots, L_T^{Stream}\}, \text{ and } \mathcal{L}_{[1,\ldots,T]}^{Search} = \{\mathcal{L}_{NP,i}^{Srch}\}, \text{ for } i \in [1,\ldots,T], \text{ where } \mathcal{L}_{NP,i}^{Srch} = (\mathcal{L}_i^{Srch}, \mathcal{L}_i^{\alpha-pad})$ is the search leakage at time i, where $\mathcal{L}_i^{\alpha-pad}$ reveals the sizes of clusters induced by $\mathcal{L}_{i}^{\alpha-pad}$. Then, the leakage function of Σ_{P} can be quantified via the leakage function $\mathcal{L}_{P} = (\mathcal{L}^{Stp}, \mathcal{L}_{[1,...,T]}^{Stream}, \mathcal{L}_{[1,...,T]}^{Search})$. The Ind_{DSSE}, $\mathcal{A}, \mathcal{L}_{P}, \mathbf{C}^{[1,...,T]}, \alpha, \mathcal{F}$ game is given in Definition 7.

We state the below theorem regarding the security of ShieldDB against the *persistent* adversary. Security proof is provided in the supplementary material in Section A-D).

Theorem 2. Let $\Sigma_P = (\text{Setup,Streaming,Search})$ be our DSSE scheme, and $\mathbf{C}^{[1,...,T]} = \{\mathbf{C}^{\mathcal{DB}_0}, \ldots, \mathbf{C}^{\mathcal{DB}_T}\}$ is a set of constraint sets. If Σ is \mathcal{L}_P -constrained-adaptivelyindistinguishable secure, and $\mathbf{C}^{[1,...,T]}$ is $(\mathcal{L}_P, \alpha, \mathcal{F})$ -acceptable, then Σ is $(\mathcal{L}_P, \mathbf{C}^{[1,...,T]}, \alpha, \mathcal{F})$ -constrained-adaptivelyindistinguishability secure.

6 SYSTEM IMPLEMENTATION

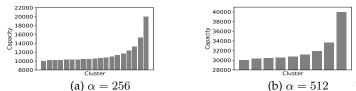
A simple way to implement the padding service P of ShieldDB is that *Cache Controller* and *Padding Controller* are maintained synchronously in a single process. That is, *Cache Controller* is idle while *Padding Controller* performs padding and encryption, and vice versa. Then, encrypted batches are uploaded to the server *S*. We observe that this single process becomes extremely slow in the long run because *Cache Controller* and *Padding Controller* cannot make use of CPU cores in parallel. As a result, there are a very few batches uploaded to *S*.

To address the above bottleneck, we propose Orchestrator, a component bridging data flow between Cache Controller and Padding Controller. Orchestrator enables ShieldDB to maximise the usage of CPU cores by splitting two controllers to process in parallel. Figure 7 depicts the implementation of the system. In details, Cache Controller and Padding Controller are spawned as separate system processes during setup. Orchestrator acts as an independent proxy manager managing the cache clusters in P's shared memory. It provides process-safe access methods of collecting, clearing, and updating data in a given cluster.

The communication between *Cache Controller* and *Padding Controller* is performed by sockets during the streaming operations. *Cache Controller* acts as a client socket, and notifies *Padding Controller* in the order of clusters that are ready for padding as per padding strategy. Then, *Cache Controller* awaits a checksum notified by *Padding Controller*. The checksum reports the number of keyword and document id pairs in the cached cluster. Note that *Padding Controller* only collects necessarily cached data for padding upon the *high* or *low* padding mode.

Apart from these components, ShieldDB contains *Padding Daemon, Streaming Daemon,* and *SE Client*. They are activated by *App Controller* during **setup**. *Padding Daemon* provides *Padding Controller* with the access to a bogus dataset, and maintains the track of remaining bogus entries for each keyword. It will generate a new bogus dataset if it is run out. *Streaming Daemon* allows *App Controller* to setup HTTP request/response methods to *S*'s address. *SE Client* deploys our encryption protocols at *C*, as presented in Figure 4. This service is separated so that later protocol updates are compatible to other components in the system.

At *S*, *API Provider* provides RESTful APIs to serve *C*'s HTTP requests. By calling streaming API requests, *API Provider* then passes collected batches in streaming to the



| TABLE 2: Batch processing results | | | | | | |
|-----------------------------------|----------------|----------------|----------------------|----------------|--|--|
| Setting | Batch In | sertions | Avg. time/batch (ms) | | | |
| Jetting | $\alpha = 256$ | $\alpha = 512$ | $\alpha = 256$ | $\alpha = 512$ | | |
| NH | 30 | 5 | 7047.2 | 51384.41 | | |
| NL | 1919 | 497 | 113.94 | 456.87 | | |
| PH | 45 | 6 | 5280.58 | 45734.16 | | |
| PL | 1916 | 549 | 138.34 | 465.09 | | |

EDB Controller. This component executes the insertion protocol as presented in Figure 4. ShieldDB introduces a component called *EDB Wrapper*, which separates *EDB Controller*'s protocols from any database storage technology.

7 EXPERIMENTAL EVALUATION

We evaluated ShieldDB to understand the applicability of the padding strategies by investigating (1) the streaming throughput, padding overhead, and local cache load of the *Padding Service* when using different padding strategies against the non-persistent and persistent adversaries, (2) the corresponding EDB size and search latency relating to the padding overhead, and (3) the efficiency of flushing in reducing the cache load and the padding overhead reduction when re-encryption is applied.

7.1 Setup and Overview

ShieldDB is developed using Python and the code is published online¹. We use standard packages of Pycrypto (2.6.1) to implement cryptographic primitives (SHA256 for cryptographic hash functions and AES-128 cipher for pseudorandom functions) and NLTK (3.3) for textual processing. We deploy ShieldDB in Azure Cloud and run on an isolated DS15 v2 instance (Intel Xeon E5-2673 2.4GHz CPU with 20 cores and 140G RAM), where Ubuntu Server 17.1 is installed. The controllers of the padding service are implemented by using Python multiprocessing package. For simplicity, we co-locate the *Client* and *Padding Service* at the same instance. At the server side. *API Controller* works on top of the Flask-a micro web framework, while EDB is realised by RocksDB, a key-value storage.

We select the Enron data set², and extract 2,418,270 keyword/document id pairs from the top 5,000 most frequent keywords in the dataset as the keyword space in our experiment. We group them and allocate the cache capacity for each keyword cluster based on their frequencies, as introduced in Section 4.1. Figure 8 presents the normalised cache capacities of these clusters at different values of α . Recalled that α indicates the minimum number of keywords in each cluster (see Section 4.1). During the setup, ShieldDB generates a padding dataset for the keyword set. In our experiments, the dataset is estimated empirically enough to be used in streaming data up to 175 seconds for both

 $\alpha = 256$ and $\alpha = 512$. In details, the dataset contains 1,859,877 bogus pairs (≈ 389 Kb).

To create the streaming scenario, the *Client* groups every 10 documents in the Enron data set as a batch (approx. 560 stemmed keyword/id pairs) and continuously inputs batches to the system. Note that we do not limit the processing capability of the *Padding Service P* and we let it continuously handle batches in a queue sent by the *Client*. In every batch, *P* performs the padding and encryption, and then continuously streams encrypted batches to the *Server*. To faithfully understand the performance of padding, we deploy the client and server to the same dedicated instance so that the impact of network I/O is minimised. Note that we begin to record the performance of ShieldDB after the cold start period of 75 seconds.

We experiment ShieldDB with different combinatorial settings of padding strategies and modes. They are denoted as *NH* (strategy against non-persistent adversary via *high* mode), *NL* (non-persistent padding strategy via *low* mode), *PH* (strategy against persistent adversary via *high* mode, and *PL* (strategy against persistent adversary via *low* mode). The performance of ShieldDB is evaluated via a set of measurements such as system throughput, local cache size, used bogus pairs, EDB size, and search time. Here, the system throughput represents the total accumulated number of real (w, id) pairs that have been encrypted and inserted to EDB.

Remark: Our focus is to analyse the system performance with different settings of padding strategies and modes related to the security as mentioned in Section 4.2. The empirical settings of 175 second streaming period and 10 documents per batch are used for the evaluation under a stable workload, not causing performance bottleneck, when the *Client* and *Padding Service* are co-located at the same Azure instance. Other parameters of a streaming period expects to result in the same observation as we obtained. The batch size can be adjusted empirically based on the application and client's resources.

7.2 Evaluation

We measure the performance of ShieldDB at both *Padding Service* and the untrusted server *S* over a 175-second streaming period. In details, Fig. 9 summarises the performance of *Padding Service* with the three different metrics of accumulated throughput, local cache size, and padding overhead when setting $\alpha = 256$ and $\alpha = 512$. Then, Fig. 11 describes the performance of *S* by observing EDB size, search time, and the average result length of query keywords.

System throughput: We first measure the accumulated throughput over time when ShieldDB is deployed with different padding modes of *NH* (<u>n</u>on-persistent using <u>high</u> padding mode), *NL* (<u>n</u>on-persistent using <u>low</u> padding mode), *PH* (persistent using <u>high</u> padding mode), and *PL* (persistent using <u>low</u> padding mode). We also monitor the number of batch insertions and the average batch processing time of *Padding Controller* to evaluate the throughput difference between these padding strategies.

Fig. 9 shows that these padding modes have similar throughput at a lower $\alpha = 256$. However, the overall throughput reduces nearly a half when setting $\alpha = 512$. It is explained that padding overhead and encryption cost are higher when more keywords are allocated in each cluster.

^{1.} https://github.com/MonashCybersecurityLab/ShieldDB

^{2.} Enron email dataset: https://www.cs.cmu.edu/~./enron/

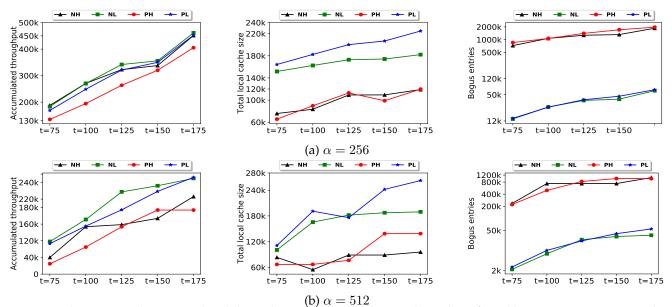


Fig. 9: Evaluations on the accumulated throughput, local cache size, and number of used bogus entries, respectively

Consequently, the throughput will be decreased. Table 2 also supports that finding when fewer batches are inserted to *S* and the average processing time per batch takes a longer time when setting $\alpha = 512$.

Furthermore, when setting $\alpha = 512$, Fig. 9 shows that *low* mode promotes more real keyword/id pairs to be inserted to EDB than *high* mode. In details, the throughput of *NL* is 1.23 times higher than the throughput of *NH*, and *PL*'s is about 1.51 timer higher than *PH*'s. Table 2 also supports this finding when it reports that *low* mode creates more batch insertions than *high* mode, while its average batch processing time is completely negligible compared to that value of the latter. This observation shows the efficiency of *low* mode since it only performs necessarily minimum padding for keywords in every batch. In contrast, *Padding Controller* takes longer time under *high* padding mode due to higher padding overhead and the longer encryption time taken by the large number of bogus pairs.

Cache size: To investigate the overhead at the padding service, we monitor the local cache as shown in Fig. 9. In general, *low* mode results in a larger number of cached pairs in cache clusters than *high* mode, regardless of padding constraints. The cache in *NL* consumes $150\% \sim 197\%$ larger space than the cache in *NH*. The load of cache in *PL* is $1.8 \sim 2.5 \times$ higher than the load of the cache in *PH*.

Padding Overhead: We rely on the number of used bogus entries reported in Fig. 9 to compute the padding overhead of different combinatorial settings of padding strategies and modes. The padding overhead is estimated as the ratio between the bogus and real (throughput) pairs. We see that although *high* padding mode achieves a lower load of cache than *low* mode, it utilises more bogus pairs from the generated padding dataset than the latter. In details, the padding overhead of *NH* ranges from $3.8 \sim 4.1$ and from $5.6 \sim 5.8$ for $\alpha = 256$ and 512, respectively. In contrast, the padding overhead of *NL* ranges is marginal, varying from $0.07 \sim 0.13$ and $0.06 \sim 0.16$ for $\alpha = 256$ and 512, respectively. The reason is that a portion of streamed keyword/id pairs are still cached at the padding service. It also demonstrates

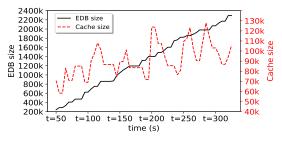


Fig. 10: Flushing operation with $\alpha = 256$

that when α is large, *PH* generates a larger padding overhead than *NH* does. Specifically, the padding overhead of *PH* is in the range of 6.4~8.9 for $\alpha = 512$. The reason is that *PH* will add bogus pairs for keywords that do not appear in the current time interval, while *NH* will not if the keywords have not existed.

EDB size: We report the number of real and bogus pairs in EDB over the time in Fig. 11. It demonstrates that *high* mode generates more data in EDB than *low* mode due to the selection of all cached pairs in clusters for padding and the large number of used bogus pairs.

Search time: To demonstrate the search performance, we configure the client to query 10% randomly selected keywords in EDB at timestamps, i.e, t = 75, 100, 125, 150, and 175. Fig. 11 shows that *high* mode makes querying a keyword take a longer time, because *S* decrypts more bogus pairs. In contrast, the search time in *low* mode is shorter due to the fewer used bogus pairs. The search time in *NH* and *PH* is fluctuated due to the change of the result lengths of keywords in EDB as given in Table 3 and Table 4.

Flushing: We select two largest cache clusters to simulate the flushing operation. In particular, we set a small time window, 20 seconds, to trigger flushing. If these clusters do not exceed up to 75% of their original capacities, then the flushing operation is invoked. Figure 10 reports EDB size and cache size over the time with a scanning window of 20 seconds. The operation occurs at t = 73, 45, 80, 121, 144, 189, 222, 272, and 331 seconds. We observe that the cache size drops significantly at these timestamps since *Cache*

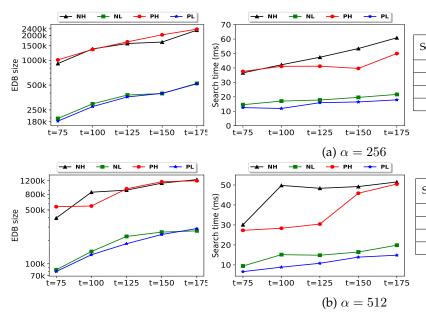


TABLE 3: Result length with $\alpha = 256$

| Betting | Time intervals | | | | | | |
|---------|----------------|---------|---------|---------|---------|--|--|
| etting | t = 75 | t = 100 | t = 125 | t = 150 | t = 175 | | |
| NH | 593.78 | 669.94 | 778.45 | 811.25 | 903.53 | | |
| NL | 109.856 | 144.66 | 164.40 | 171.56 | 186.04 | | |
| PH | 562.86 | 660.22 | 593.18 | 579.30 | 714.12 | | |
| PL | 89.25 | 82.38 | 107.92 | 110.57 | 126.43 | | |

TABLE 4: Result length with $\alpha = 512$

| Setting | Time intervals | | | | | | |
|---------|----------------|---------|---------|---------|---------|--|--|
| Jetting | t = 75 | t = 100 | t = 125 | t = 150 | t = 175 | | |
| NH | 668.02 | 843.22 | 837.01 | 840.85 | 861.44 | | |
| NL | 81.64 | 140.95 | 147.73 | 168.17 | 174.40 | | |
| PH | 577.06 | 610.02 | 614.34 | 857.73 | 879.63 | | |
| PL | 51.66 | 85.33 | 89.21 | 93.82 | 112.32 | | |

Fig. 11: Evaluation on the EDB size and search time

Controller flushes the cached pairs to *Padding Controller*. Note that the EDB and cache sizes are flat while *Padding Controller* performs padding and encryption. Empirically, we observe that flushing operation averagely reduced the cache load efficiently up to $1.9 \sim 2.8 \times$ across the padding strategies in the same streaming period.

Re-encryption: To investigate the performance of reencryption, we experiment ShieldDB after 175 seconds operated with NH at $\alpha = 256$. We select the keyword cluster that has the most entries stored in EDB for the reencryption. This keyword set is also re-used as the query set to benchmark the query performance before, during, and after re-encryption. There are 180,677 real entries associating with 256 keywords of this cluster. Table 7 demonstrates the performance of the re-encryption. This operation takes 131.3 seconds for fetching process, and 103.11 seconds for padding and re-insertion. During the operation, the average query time per keyword is the smallest due to the deletion of all entries in the selected cluster. Note that this query time takes into account the search over local cache clusters if the keyword is not available in EDB. After re-encryption, the number of bogus entries used for the cluster is nearly reduced by 64.1%, making the average search time shorter.

Overall performance: Table 5 summarises the performance of *Padding Service* regarding three critical measurements of throughput per second, average cache size at every second, and the overall padding overhead. As seen, there are no perfect padding strategies that can achieve a great balance. *Low* padding mode makes a higher throughput value and lightens padding overhead, but it incurs a significant cache load. In contrast, *high* padding mode makes the cache load lightweight, but it introduces a higher overhead.

Note that the padding strategies against the persistent adversary are also applicable to the non-persistent adversary. The *firstBatch* condition can theoretically make some clusters might be not achieved in a long time if some keywords never appear. However, this is not the case in our current experiments. Therefore, the throughput for *PH* and *NH*, and *PL* and *NL* is close, respectively.

The value α relates to the number of keywords in clusters. A higher value indicates that more keywords are co-located in the same cluster. Hence, they all will have the same result length after padded. From the results, ShieldDB shows the tradeoff when selecting a higher value of α . That is, the throughput is declined nearly double while padding overhead increases almost twice (see Table 5).

Comparison with baselines: We further investigate the security and performance trade-off between ShieldDB and two baselines. The first baseline (aka Baseline-I) is an insecure system for which batches of un-encrypted keyword/id pairs without padding are streamed to the server's storage. We define the batch size as 256 pairs. The second one (aka Baseline-II) is also the streaming system without padding, but it realises our searchable encryption scheme with forward privacy, presented in Figure 4, to encrypt the pairs of every batch insertion.

We measure the overall performance of these baselines by using the same streaming database and the measurement metrics as evaluated for ShieldDB (in Section 7.1). It is clear that Baseline-II brings $2.5 \times$ overhead in addition throughput compared to Baseline-I. The reason is because that the encrypted entries of keywords in the same batch indeed are generated from the ephemeral key of the batch and keyword's extracted state. We note that Baseline-I maintained a constant throughput and completed streaming within 55 seconds, while Baseline-II finished in 162 seconds (Table 6). The throughput overhead ShieldDB brought forward is about 6.04 \sim 6.5× (resp. 10.7 \sim 11.74×) lower than performance of Baseline-II when setting $\alpha = 256$ (resp. 512). We note that overhead is caused by the encryption of additional bogus pairs introduced in every batch insertion. The average result length for keywords streamed to the EDB of ShieldDB is about $1.8 \sim 2.3 \times$ (high padding mode used) greater than that value if Baseline-II is deployed. The search latency of ShieldDB is almost double $(1.7 \sim 2.1 \times)$, slower than Baseline-II. We observe that the security enhanced by the padding and forward privacy would overall bring the streaming throughput per second $\sim 16.3 \times$ (resp. $\sim 27 \times$)

TABLE 5: Overall performance of ShieldDB throughout a 175-second streaming period

| Setting | Adversary Target | Throughput per second | | Avg. cache load | | Padding overhead | |
|---------|------------------|-----------------------|----------------|-----------------|----------------|------------------|-----------------|
| Setting | Auversary larget | $\alpha = 256$ | $\alpha = 512$ | $\alpha = 256$ | $\alpha = 512$ | $\alpha = 256$ | $\alpha = 512$ |
| NH | Non-persistent | 2,634.27 | 1,459.62 | 99,347.8 | 82,267.8 | $3.8 \sim 4.12$ | $5.6 \sim 5.8$ |
| NL | Non-persistent | 2,779.77 | 1,515.74 | 168, 681.4 | 164,960 | $0.07 \sim 0.13$ | $0.06\sim 0.16$ |
| PH | Persistent | 2,702.05 | 1,289.64 | 97,351.6 | 97,557.6 | $4.8 \sim 6.3$ | $6.4 \sim 8.9$ |
| PL | Persistent | 2,833.46 | 1,590.46 | 195,702.2 | 196, 413.6 | $0.08 \sim 0.14$ | $0.08\sim 0.23$ |

TABLE 6: Overall performance of the insecure streaming system and the forward-private SSE streaming system

| | insecure system | Forward-private system | | | | |
|-----------------------------|----------------------|------------------------|----------------------|----------------------|----------------------|----------------------|
| | misecure system | t = 75 | t = 100 | t = 125 | t = 150 | t = 162 |
| Throughput (pairs/s) | 4.3×10^{4} | 1.73×10^{4} | 1.71×10^{4} | 1.71×10^{4} | 1.73×10^{4} | 1.74×10^{4} |
| Avg. result length (#pairs) | 483.66 | 281.5 | 384.8 | 476.53 | 513.61 | 483.61 |
| Search latency (ms) | 5.12 | 20.9 | 24.62 | 33.75 | 40.95 | 43.59 |
| Storage overhead (#pairs) | 2.41×10^{6} | 1.3×10^{6} | 1.7×10^{6} | 2.14×10^{6} | 2.17×10^{6} | 2.41×10^{6} |

TABLE 7: Re-encryption on the largest cluster

| | Before | During | After |
|--------------------|----------|---------|---------|
| Bogus entries used | 643, 131 | 230,715 | 230,715 |
| Search time (ms) | 379.37 | 0.03 | 210.18 |

slower than Baseline-I when setting $\alpha = 256$ (resp. 512). Empirical analysis of streaming distribution: Next, we investigate how the streaming distribution of real data outsourced by ShieldDB to EDB changes over the time. To do this, we consider the training distribution used to generate the padding dataset and cluster's caches extracted from the training dataset in the Setup, (in Section 4.1), as the baseline distribution. Note that the training distribution was different with respecting to α (i.e., the minimal number of keywords in every cache cluster) (see Equation 1). Then, we monitor the streaming distribution of real data at different times t when ShieldDB employs different combinatorial settings of padding strategies and modes. In particular, we use the Kullback–Leibler (KL) distance [41] to measure the difference between such streaming distributions and the baseline distribution (Figure 12).

Our observation shows that the streaming distribution was different compared to the baseline at the early streaming time (i.e., t = 75 - 150). Then, it tended to converge to the baseline when the streaming dataset was almost outsourced completely ($t \ge 175$). At this time, the padding dataset was also almost used. The reason for that is because the completed streaming dataset shares the same distribution with the training dataset. However, at the earlier time, the difference was large because there was some keywords in the training distribution that did not appear yet in these early streaming batches. We note that, with $\alpha = 256$, the persistent padding settings (i.e., PH and PL) have the largest distribution difference since it requires the existence of all keywords in the cluster at the *firstBatch* (in Algorithm 1). With $\alpha = 512$ (i.e., more keywords required in clusters), the distribution difference was double (i.e., $0.8 \sim 1.0$ KL unit) since the setting causes a longer waiting period before the padding strategies meet, under the same streaming rate.

7.3 Discussion on Deployment

We note that the above experiments consider the keyword frequency distribution in **setup** is similar to the one in a period of **streaming** operation. We deem that the assumption and the corresponding setting of ShieldDB for deployment can be practically held in practice.

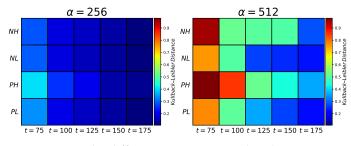


Fig. 12: The difference in streaming distribution

First, this setting is applicable to streaming applications for which the underlying distribution does not change much over time or it is known in advance, like the known data range of the IoT sensors [42], [43]. Second, in our observation (Figure 12), we show that the streaming distribution changes towards the training distribution over a streaming period, not requiring the exact matching between them for any particular interval. Therefore, the assumption can at least be hold for that duration, and better than assuming that the streaming and training distribution are close for any particular time interval. In addition, we note that the setup operation can be re-invoked again to re-cluster keywords based on up-to-date streaming data if the streaming distribution is different from the training distribution. In that way, the re-clustering can use that up-to-date streaming distribution as the training distribution.

We are aware that the keyword distribution difference can cause a long tail effect when applying the proposed padding strategies to low frequent keywords. For instance, if a keyword only occurs in the first batch of that keyword's cluster and disappears for all subsequent batches, *Padding Controller* still pads that keyword during subsequent batches when padding strategies NH and NL are used. As seen in the above experiments, such different distribution can happen at the early streaming stages. We also note that, when the streaming distribution differs from the training distributions, it may cause some "cold" clusters and/or the intensive usage of the padding datasets in some "hot" clusters. As a results, the overall streaming throughput can be slowed down.

To mitigate the above issues, ShieldDB offers flushing and re-encryption operations regarding the highly varied frequency of streaming keywords. As experimented, flushing could quickly reduce $1.9 \sim 2.8 \times$ the cache load to boost the "cold" clusters. In addition, re-encryption could lowered 64% the amount of bogus pairs used by re-padding all keywords in the "hot" cluster. The above result is obtained when we checked and applied the operations for every fixed time window. Nevertheless, it is non-trivial to optimise the padding overhead in the streaming setting and we leave it as future work.

8 RELATED WORKS

Searchable symmetric encryption: ShieldDB employs SSE [18] as an underlying building block to enable singlekeyword encrypted search. Curtmola et al. [19] and Kamara et al. [34] formalise the security of SSE for static and dynamic databases respectively, and devise concrete constructions with sublinear search time. A line of schemes [31], [36], [39], [44]–[46] (just to list a few) are proposed to improve performance and expressiveness of SSE. Driven by leakageabuse attacks [21], [22], [47], new schemes [33], [37], [38], [48] with less leakage in search and update are proposed to achieve forward and backward security. Note that, although oblivious RAM [49], [50] provides the highest protection for the Server's memory access pattern, we do not consider it for ShieldDB due its inefficient capability in the streaming setting. In details, the approach requires more computation and storage at the *Client*, and the communication between the *Client* and the *Server*. Also, ORAM does not hide the size of the query results, unless there is non-trivial padding.

In the meanwhile, padding countermeasures [20], [21], [29] are considered as an effective approach to obfuscate the leakage during search operations of SSE. In particular, Islam et al. [20] propose the first padding countermeasure for SSE; keywords are grouped into different clusters, where each keyword in a cluster matches a set of identical document ids. This requires another data structure to help the client to differentiate real and bogus document ids after search, since all bogus ids are selected from the real ones. After that, Cash et al. [21] propose another approach; the number of ids in each keyword matching list is padded up to the nearest multiple of an integer, aka padding factor. To guarantee effectiveness, this factor needs to be increased until no unique result size exists. However, this padding factor is a systemwide parameter, and incrementing it introduces redundant padding for all other padded matching lists. To reduce padding overhead, Bost and Fouque [29] propose to pad the keyword matching lists based on clusters of keywords with similar frequency. Their proposed clustering algorithm achieves minimised padding overhead while thwarting the count attack in the static setting. Very recently, Xu et al. [51] investigate the formal method to quantify the padding security strength, and propose a padding generation algorithm which makes the bogus and documents similar. Again, all the above padding countermeasures focus on the static setting, where the dataset remains unchanged after the setup. We note that the assumption in this setting is not always true in practice, and therefore ShieldDB is designed to embed padding countermeasures in the dynamic setting, where the keyword existence is a matter in online streaming.

Recent works [52], [53] propose volume-hiding encryption schemes to mitigate the leakage-abuse attacks. We note that those schemes are focused on the static setting, as they resort to specialised data structures and constructions. First, they are not dynamic friendly. Specifically, multihashing and cuckoo hashing techniques are adopted as the underlying data structures. It is not easy to insert new data into those data structures, and we are not aware any existing volume-hiding schemes support efficient updates. Second, volume hiding schemes may hide the size of the query result, but it is not clear whether they can protect the relationships between different query keywords when applying them into the context of keyword search.

Encrypted database systems: ShieldDB can also be fit into a line of research on designing encrypted database systems. Most of existing encrypted databases [8], [10]-[13], [54]-[56] focus on supporting rich queries over encrypted data in SQL and NoSQL databases. They mainly target on query functionality and normally integrate different primitives together to achieve the goal. Like the issues in SSE, inference attacks against encrypted databases [16], [57] are designed to compromise their claimed protection. To address this issue, one approach is to use advanced cryptographic tools such as secure multi-party computation [10], [12]. Note that padding can also be adapted to mitigate inference attacks. A system called Seabed [11] proposes a schema for RDBMS that introduces redundant data values in each attribute of data records to hide the frequency of the underlying data values. Compared with the above systems, ShieldDB focuses on the document-oriented data model and supports keyword search over encrypted documents.

9 CONCLUSIONS

ShieldDB is an encrypted database system that supports keyword search over encrypted documents with advanced security features. Our system employs the SSE framework to implement encrypted data structures for efficient queries. To defend against leakage-abuse attacks against SSE, ShieldDB includes effective padding countermeasures targeting adversaries in the dynamic setting. To demonstrate the performance of our system, we develop a prototype, and perform intensive evaluations on various metrics. We show that our proposed padding strategy is practical and deployable to real-world streaming applications/systems that require the privacy preservation on data stream.

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APPENDIX A SECURITY OF SHIELDDB

A.1 The leakage of dynamic searchable encryption scheme

ShieldDB implements a dynamic searchable encryption scheme (DSSE) $\Sigma = ($ Setup, Streaming, Search), consisting of three protocols between a padding service P, a storage server S, and an querying client C. A database $DB_t = (w_i, id_i)_{i=1}^{|DB_t|}$ is defined as a tuple of keyword and document id pairs with $w_i \subseteq \{0, 1\}^*$ and $id_i \in \{0, 1\}^l$ at the time interval $t \ge 0$. We first formalise the SSE-based leakage functions of ShieldDB as follows.

Setup(DB₀) is a protocol that takes as input a database DB₀, and outputs a tuple of $(k_1, k_2, \{L_1, \ldots, L_m\}, st, B, EDB_0)$, where k_1, k_2 are secret keys to encrypt keywords and document ids, a set $\{L_1, \ldots, L_m\}$ contains cache clusters, *st* maintains keyword states, and *B* is a bogus dataset to be used for padding, and EDB₀ is the encrypted database at t = 0.

Streaming($k_1, k_2, L_u, st, B, \{(w_i, id_i)\}; \text{EDB}_{t-1}, \{(u_i, v_i)\}$ is a protocol between P with inputs k_1, k_2 , and L_u $(1 \le u \le m)$ the cache cluster to be updated, the states st, the bogus dataset B, and the set of keyword and document id pairs $\{(w_i, id_i)\}$ to be streamed, and S with input EDB_{t-1} the encrypted database at time t - 1 ($t \ge 1$), and $\{(u_i, v_i)\}$ the set of encrypted keyword and document ider pairs for batch insertion. Once P uploads $\{(u_i, v_i)\}$ to S, st and B gets updated, L_u is reset. At S, once EDB_{t-1} gets updated by $\{(u_i, v_i)\}$, it changes to EDB_t .

Search $(k_1, k_2, q, st; EDB_t)$ is a protocol between C with the keys k_1, k_2 , the query q querying the matching documents of a single keyword w_i , and the state st, and S with EDB_t. Meanwhile, C queries P for retrieving cached documents of the query keyword.

The security of ShieldDB can be quantified via a leakage function $\mathcal{L} = (\mathcal{L}^{Stp}, \mathcal{L}^{Stream}, \mathcal{L}^{Srch})$. It defines the information exposed in Setup, Streaming, and Search, respectively. The function ensures that ShieldDB does not reveal any information beyond the one that can be inferred from \mathcal{L}^{Stp} , \mathcal{L}^{Stream} , and \mathcal{L}^{Srch} .

In Setup, $\mathcal{L}^{Stp} = |\text{EDB}_0|$ presenting the size of EDB₀, i.e., the number of encrypted keyword and document id pairs.

In Streaming, ShieldDB is *forward private* as presented in Streaming protocol. Hence \mathcal{L}^{Stream} can be written as

$$\mathcal{L}^{Stream}(\{(w, id)\}) = \mathcal{L}'(\{id\})$$

where $\{(w, id)\}$ denotes a batch of keyword and id pairs w, and \mathcal{L}' is a stateless function. Hence, \mathcal{L}^{Stream} only reveals the number of pairs to be added to EDB. ShieldDB does not leak any information about the updated keywords. In particular, S cannot learn that the newly inserted documents match a keyword that being previously queried.

In Search, \mathcal{L}^{Srch} reveals common leakage functions [19]: the *access pattern* ap and the *search pattern* sp as follows.

The ap reveals the encrypted matching document identifiers associated with search tokens. For instance, if an adversary controls EDB_t , she monitors the search query list $Q_t = \{q_1, \ldots, q_{n-1}\}$ by the time order. Then, $\text{ap}(q_i)$ (with $1 \le i \le n-1$) for a query keyword w_i is presented as

$$ap(q_i) = EDB(w_i) = \{(u_{w_i}, v_{w_i})\}$$

where u_{w_i} and v_{w_i} are an encrypted keyword and document id entry associated with w_i in EDB_t.

The **sp** leaks the repetition of search tokens sent by *C* to *S*, and hence, the repetition of queried keywords in those search tokens.

$$\mathsf{sp}(q_i) = \{ \forall j \neq i, q_j \in Q_t, w_j = w_i \}$$

Next, we detail the leakage during the interaction between *C* and *S* over Q_t on a given DB_t . We call an instantiation of the interaction as a *history* $H_t = (DB_t, q_1, \ldots, q_{n-1})$. We note that the states of keywords in DB_t do not change during these queries. The leakage function of H_t is presented as

$$\mathcal{L}(H_t) = (|\mathsf{EDB}(w_i)|, \dots, |\mathsf{EDB}(w_{n-1})|, \alpha(H_t), \sigma(H_t))$$

where $|\text{EDB}(w_i)|$ $(1 \le i \le n-1)$ is the number of matching documents associated with the keyword w_i mapping to the query q_i , $\alpha(H_t) = \{ \mathsf{ap}(q_1), \dots, \mathsf{ap}(q_{n-1}) \}$ is the *access pattern* induced by Q_t , and $\sigma(H_t)$ is a symmetric binary matrix such that for $1 \le i, j \le n-1$, the element at i^{th} row and j^{th} column is 1 if $w_i = w_j$, and 0 otherwise.

A.2 Constrained security in ShieldDB

We note that the database knowledge of non-persistent and persistent adversaries falls outside the traditional SSE formalisation [29]. The reason is because the notion is limited by the fact that knowing the DB, the query list is uniquely defined by the acceptable leakage of SSE. Namely, there is already the uniqueness of a *history* given the knowledge of the adversary. Therefore, we want to define new constrained security that can formalise the adversary's knowledge in H_t . But, given the constraint, there are multiple *histories* at time t satisfying the leakage function (i.e., making H_t no longer unique). In this way, one needs to find two different lists of queries generating the exact same leakage with the same DB_t. As a starting point, we extend the Definition 3.1 in [29] to formalise H_t satisfying the constraint C iff $C(H_t) = true$ as in Definition. 1.

Definition 1. A constraint $C = (C_0, C_1, \ldots, C_{n-1})$ over a database set \mathcal{DB}_t and a query set $Q_t = \{q_1, \ldots, q_{n-1}\}$, is a sequence of algorithms such that, for $\mathrm{DB}_t \in \mathcal{DB}_t$, $C_0(\mathrm{DB}_t) = (flag_0, st_0)$, where $flag_0$ is true or false and st_0 captures C_0 's state, and for $q \in Q_t$, $C_i(q, flag_{i-1}) = (flag_i), (i \ge 1)$. The constraint is consistent if $C_i(., \mathtt{false}, .) = (\mathtt{false}, .)$ (the constraint remains false if it once evaluates to false).

For a history $H_t = (DB_t, q_1, \dots, q_{n-1})$, we note $C(H_t)$ the evaluation of

$$C(H_t) := C_{n-1}(q_{n-1}, C_{n-2}(\dots, C_0(\mathsf{DB}_t))).$$

If $C(H_t) = true$, we say that H_t satisfies C. A constraint C is valid if there exists two different efficiently constructable histories H_t and H'_t satisfying C.

After defining the knowledge in H_t known by the adversary, we also formalise some elements (i.e., queries) in H_t that are unknown to the adversary. Namely, they are left *free* from the constraint *C*. We note that Bost et. al. [29] already defined *free* components in static database setting (i.e., not time interval *t*) for constraint security. Therefore, we extend

the Definition 3.2 in [29] to formalise *free* component in C regarding H_t in below Def. 2.

Definition 2. (Free history component) We say that C lets the *i*-th query free if for history $H_t = (DB_t, q_1, \ldots, q_{n-1})$ satisfying C, for every search (resp. update) query q if q_i is a search (resp. update) query, $H'_t = (DB'_t, q_1, \ldots, q_{i-1}, q, q_{i+1}, \ldots, q_{n-1})$ also satisfies C, where $DB'_t \in D\mathcal{B}_t$.

The idea behind of letting *i*-th query free is that there exists some other queries in the history H'_t such that H'_t still satisfies C (and both $\mathcal{L}(H_t) = \mathcal{L}(H'_t)$) without modifying the leakage $\mathcal{L}(H'_t)$.

Now, we also define the *acceptable* constraint notion, so that, given a constraint C, and a leakage function \mathcal{L} , for every history H_t , we are able to find another *history* satisfying C with the same leakage.

Definition 3. A constraint C is \mathcal{L} -acceptable for some leakage \mathcal{L} if, for every efficiently computable history H_t satisfying C, there exists an efficiently computable $H'_t \neq H_t$ satisfying C, for $H'_t = (DB'_t, q_1, \ldots, q_{n-1})$, such that $\mathcal{L}(H_t) = \mathcal{L}(H'_t)$.

A set of constraints \mathfrak{C} is said to be \mathcal{L} -acceptable if all its elements are \mathcal{L} -acceptable.

Now, after giving background definitions, we start to investigate the query at time t. We recall that the *Client* only triggers the search on completely outsourced data in EDB_t , where (t > 0) is a random interval upon receiving search query tokens. Therefore, we consider that the leakage function only depends on the query itself, and on the state of DB_t : $\mathcal{L}(q)$ can be presented as a stateless function of $f_{\mathcal{L}}(q, \mathsf{DB}_t)$. We make an observation on EDB_t that: let C be a constraint, $H_t = (DB_t, q_1, \ldots, q_{n-1})$ and history satisfying C, and q, q' be two queries such that $H_t = H_t ||q| = (DB_t, q_1, \dots, q_{n-1}, q)$ and $H'_t = H_t ||q'| =$ $(\mathsf{DB}_t, q_1, \ldots, q_{n-1}, q')$. Then, if $f_{\mathcal{L}}(q, \mathsf{DB}_t) = f_{\mathcal{L}}(q', \mathsf{DB}_t)$, then both \tilde{H}_t and \tilde{H}'_t with the same leakage satisfying C. This observation can be iterated to create multiple (i.e., more than 2) *histories* using the same DB_t and they are both satisfying C with the same leakage. Therefore, we can define a clustering $\Gamma_t = \{G_1, \ldots, G_m\}$ of queries induced by the leakage \mathcal{L} after history H_t is a partition of a query set Q_t , for which, in every cluster, queries share the same leakage after running the history H_t as below.

$$\bigcup_{i=1}^{m} G_i = Q_t$$
$$\forall i \neq j \ G_i \cap G_j = \emptyset$$
and $\forall q, q' \in G_i, \mathcal{L}(q, H_t) = \mathcal{L}(q', H_t)$

where $\mathcal{L}(H_t, q)$ is the output of $\mathcal{L}(q)$ after having been run on each element of H_t . Note that, we omit the subscript t in Γ_t in the clear context of H_t ; otherwise, we state it separately. We denote $\Gamma_{\mathcal{L}}(H_t)$ the clustering induced by \mathcal{L} after H_t . We can see that it is impossible to merge different clusters in $\Gamma_{\mathcal{L}}(H_t)$ with the same leakage. Therefore, formally, for $\Gamma_{\mathcal{L}}(H_t) = \{G_1, \ldots, G_m\}$, where m is the total number of clusters, we have:

$$\forall i \neq j, \forall q \in G_i, \forall q' \in G_j, \mathcal{L}(H_t, q) \neq \mathcal{L}(H_t, q')$$

We present $\Gamma_{\mathcal{L},C}(H_t)$ the \mathcal{L} -induced clustering applied on history H_t satisfying C such that a subset of queries Q_t in

queries q gives $C(H_t||q) = \text{true}$. We can see that, in the singular query q earlier, $\mathcal{L}(q)$ only depends on q and DB_t . Therefore, more generally, when q is a set of queries with $C(H_t||q) = \text{true}, \Gamma_{\mathcal{L},C}(H_t)$ only depends on DB_t . Indeed, the clustering $\Gamma_{\mathcal{L},C}(H_t)$ acquires at least two elements in every cluster. Otherwise, an *history* H_t can be constructed without any different *history* H'_t . Namely, we need at least $|G_i| > 2$ for $\forall i \in [1, m]$, to make sure that there are at least 2 constrained histories can be found. Therefore, we can extend Def. 3 to have an acceptable constraint C with α histories, where $|G_i| > \alpha$. We note that the notation α here is inline with the clustering algorithm in setup in ShieldDB (Section 4.1).

Definition 4. (Extended acceptable constraint) A constraint C is (\mathcal{L}, α) -acceptable for some leakage \mathcal{L} and integer $\alpha > 1$ if, for every efficiently computable history H_t^0 satisfying C (*i.e.*, $C(H_t^0) = \texttt{true}$), there exists $(\alpha - 1)$ efficiently computable $\{H_t^i\}_{1 \leq i \leq \alpha - 1}$ such that $H_t^i \neq H_t^j$ for $i \neq j$, that are all satisfying C, and $\mathcal{L}(H_t^0) = \cdots = \mathcal{L}(H^{\alpha - 1})$.

Now, we can see that when $|G_i| \ge \alpha$, for $\forall i \in [1, m]$, i.e., strictly more than one element in each cluster of $\Gamma_{\mathcal{L},C}(H_t)$, C is (\mathcal{L}, α) -acceptable, as formalised in below Proposition 1.

Proposition 1. Let C be a constraint, and \mathcal{L} a leakage function. If for every history H_t satisfying C, the clustering $\Gamma_{\mathcal{L},C}(H_t) = \{G_1, \ldots, G_m\}$ is such that $|G_i| \geq \alpha$ for all i, C is $(\mathcal{L}, \alpha) - acceptable$.

A.3 Security against Non-persistent Adversary

Prior knowledge of the database: Considering the adversary's knowledge of the database is DB_t when she captures $\mathcal{L}(H_t)$, we use the predicate C^{DB_t} to formalise this knowledge, by adapting the notion of server's knowledge in [29]. Formally, we have $C^{DB_t}(H_t) = \text{true}$ if the database of the input history is DB_t . As used in Definition 3, C^{DB_t} ensures that all challenge histories' database is the same, i.e., DB_t . That also leave all queries in DB_t are left *free*, as defined in Definition 2. More generally, we can model the fact that the adversary know the database by considering the constraint set $\mathfrak{C}^{DB_t} = \{C^{DB_t}, DB_t \in \mathcal{DB}_t\}$.

Now, we recall that the non-persistent adversary only captures an interval t, and search only triggers on encrypted entries inserted in EDB_t. Therefore, we consider the scheme $\Sigma_{NP} = (\text{Setup}, \text{Search})$ at time t for the non-persistent adversary. We start adding a padding mechanism presented in Algorithm 1 (i.e., Padding Strategies) to Σ such that, for every keyword in DB_t, there are at least different $(\alpha - 1)$ keywords with the same number of matching documents. Then, with the knowledge of DB_t, the leakage function of Σ_{NP} is formally defined as $\mathcal{L}_{NP} = (\mathcal{L}^{Stp}, \mathcal{L}^{Srch}, \mathcal{L}^{\alpha-pad})$, where \mathcal{L}^{Stp} and \mathcal{L}^{Srch} reveals the leakage in Setup at at t and Search against EDB_t, respectively (see Section A), and the new leakage $\mathcal{L}^{\alpha-pad}$.

By using Proposition 1, we can show that $\mathfrak{C}^{\mathcal{DB}_t}$ is an $(\mathcal{L}_{NP}, \alpha)$ -acceptable set of constraints, where α is the minimum cluster size (over all constructable databases). The reason is that, since constraints in $\mathfrak{C}^{\mathcal{DB}_t}$ leave all queries *free* for every history $H_t = (\mathrm{DB}_t, q_1, \ldots, q_{n-1})$, we can generate a different history H'_t with the same leakage by choosing

another query $q \neq q_1$ that are both matching the same number of documents, and changing all queries $q_i = q_1$ in H_t to q. Also, if there is queries $q_j = q$ in H_t , we can switch queries in q_j to q_1 . This can give us a history $H'_t \neq H_t$ with the same leakage of H_t . We note that there are at least α choices of q to create $\Gamma_{\mathcal{L}_{NP}}(H_t)$ we can derive $\mathfrak{C}^{\mathcal{DB}_t}(\mathcal{L}_{NP}, \alpha)$ -acceptable.

Now, we are ready to define the notion of constrained adaptive indistinguishability for Σ_{NP} given $\mathfrak{C}^{\mathcal{DB}_t}$ and the leakage (\mathcal{L}_{NP}) .

Definition 5. Let $\Sigma_{NP} = ($ **Setup,Search**) be the SSE scheme of ShieldDB, λ be the security parameter, and \mathcal{A} be a non-persistent adversary. Let $\mathfrak{C}^{\mathcal{DB}_t}$ be a set of $(\mathcal{L}_{NP}, \alpha)$ -acceptable constraints. Let $\mathrm{Ind}_{SSE,\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_t},\alpha}$ be the following game:

Ind_{SSE, $\mathcal{A}, \mathcal{L}_{NP}, \mathfrak{C}^{\mathcal{DB}_t}, \alpha(\lambda)$ Game:}

 $\begin{array}{l} b \stackrel{\$}{\leftarrow} \{0, \ldots, \alpha - 1\} \\ (C_0^{\mathrm{DB}_t}, \mathrm{DB}_t^0, \ldots, \mathrm{DB}_t^{\alpha - 1}) \leftarrow \mathcal{A}(1^{\lambda}) \\ (K, \mathrm{EDB}_t^b) \leftarrow \mathrm{Setup}(\mathrm{DB}_t^b) \\ (C_1^{\mathrm{DB}_t}, q_1^0, \ldots, q_1^{\alpha - 1}) \leftarrow \mathcal{A}(\mathrm{EDB}_t^b) \\ \tau_1^b \leftarrow \mathrm{Search}(q_1^b) \\ \textit{for } i = 2 \textit{ to } n \textit{ do} \\ (C_i^{\mathrm{DB}_t}, q_i^0, \ldots, q_i^{\alpha - 1}) \leftarrow \mathcal{A}(q_{i-1}^b) \\ \tau_i^b \leftarrow \mathrm{Search}(q_i^b) \\ \textit{end for} \\ b' \leftarrow \mathcal{A}(\tau_n^b) \\ \textit{if } b = b' \textit{ return } 1, \textit{ otherwise return } 0 \end{array}$

where $\tau_i^b \leftarrow \text{Search}(q_i^b)$ presents the transcript of the query q_i^b , and with the restriction that, for all the $H_t^i = (\text{DB}_t^i, q_i^0, \dots, q_i^{n-1})$,

• $C^{\text{DB}_t} \in \mathfrak{C}^{\mathcal{DB}_t}$, and $\forall 0 \leq i \leq (\alpha - 1), C^{\text{DB}_t}(H_t^i) =$ true

• $\mathcal{L}(H_t^0) = \dots = \mathcal{L}(H_t^{\alpha-1})$

We say that Σ is $(\mathcal{L}_{NP}, \mathfrak{C}^{\mathcal{DB}_t}, \alpha)$ -constrained-adaptivelyindistinguishable if for all probabilistic polynomial time adversary \mathcal{A} ,

$$\begin{aligned} \mathbf{Adv}_{\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}},\alpha}^{\mathrm{Ind}}(\lambda) &= \\ \left| \mathbb{P}[\mathrm{Ind}_{\mathrm{SSE},\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}},\alpha}(\lambda) = 1] - \frac{1}{\alpha} \right| \leq negl(\lambda). \end{aligned}$$
(2)

We can see that Σ_{NP} offers at least $log(\alpha)$ bits of security. Given $\mathfrak{C}^{\mathcal{DB}_t}$ $(\mathcal{L}_{NP}, \alpha)$ -acceptable, we can analysing the transcripts τ_i^b under the choice of α . First, we make an observation on the keyword choice in $(\mathrm{DB}_t^0, \ldots, \mathrm{DB}_t^{\alpha-1})$ as follows. We denote by $\Delta_t^i = \{w_1^i, \ldots, w_{n-1}^i\}$ the keyword space of DB_t^i , where $i \in \{0, \alpha - 1\}$. Then, $C^{\mathrm{DB}_t}(H_t^i) = \operatorname{true}$ and all $\mathcal{L}(H_t^0) = \cdots = \mathcal{L}(H_t^{\alpha-1})$ imply $\Delta_t^0 = \cdots = \Delta_t^{\alpha-1}$. Let f(w) be a function returning the frequency of the keyword w, we can see that, for all $w_j^0 \in \Delta_t^0$, where $j \in |\Delta_t^0|$, there are at least one another w_j^i in Δ_t^i (i.e., $\forall i \neq 0$) such that $f_{w_i^0} = f_{w_i^i}$. This turns out that the Setup needs to groups at least α keywords and pad them to be the same length such that, for a given q_i^b in Search, under the chosen b, the transcript τ_i^b can be hardened by at least $(\alpha - 1)$ choices.

Now, we adapt the Theorem 2 in [29] to prove the extended constrained indistinguishability (i.e., Definition 5) by using regular leakage indistinguishability and extended acceptability of constraint set $\mathfrak{C}^{\mathcal{DB}_t}$ as follows.

Theorem 3. Let $\Sigma_{NP} = ($ Setup, Search) be our SSE scheme, and $\mathfrak{C}^{\mathcal{DB}_t}$ a set of knowledge constraints. If Σ_{NP} is \mathcal{L}_{NP} -constrained-adaptively-indistinguishable secure, and $\mathfrak{C}^{\mathcal{DB}_t}$ is $(\mathcal{L}_{NP}, \alpha)$ -acceptable, then Σ_{NP} is $(\mathcal{L}_{NP}, \mathfrak{C}^{\mathcal{DB}_t}, \alpha)$ -constrained-adaptively-indistinguishability secure.

Proof. Let \mathcal{A} be an adversary in the $\operatorname{Ind}_{\operatorname{SSE},\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_t},\alpha}$ game. We construct an adversary \mathcal{B} against the game. \mathcal{B} first randomly picks two integer $\alpha_0, \alpha_1 \in \{0, \alpha - 1\}$. Then, \mathcal{B} starts \mathcal{A} and receives α databases $(\operatorname{DB}_t^0, \ldots, \operatorname{DB}_t^{\alpha-1})$. Upon giving the pair $(\operatorname{DB}_t^{\alpha_0}, \operatorname{DB}_t^{\alpha_1})$ to the challenger, where the challenger holds a random secret bit b, \mathcal{B} receives the challenge encrypted database EDB_t^* which she forwards to \mathcal{A} . Then, \mathcal{A} repeatedly outputs α queries $(q_i^0, \ldots, q_i^{\alpha-1})$ and gives to \mathcal{B} . To respond, \mathcal{B} outputs $(q_i^{\alpha_0}, q_i^{\alpha_1})$ to the game, and receives back the transcript τ_i^* and forwards it to \mathcal{A} . Then, \mathcal{A} outputs the integer α' . If $\alpha' = \alpha_0$, \mathcal{B} outputs b' = 0, else if $\alpha' = \alpha_1$, \mathcal{B} outputs b' = 1, and otherwise outputs the probability 1/2 for the output 0 and the probability 1/2 for the output 1.

We first make an observation: for the pair $(H_t^{\alpha_0}, H_t^{\alpha_1})$, the views of the adversary \mathcal{B} are indistinguishable due to $\mathcal{L}_{NP}(H_t^{\alpha_0}) = \mathcal{L}_{NP}(H_t^{\alpha_1})$, presenting both satisfying $\mathfrak{C}^{\mathcal{DB}_t}$. Then we can formalise \mathcal{B} as follows:

$$\mathbf{Adv}_{\mathcal{B},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}}}^{\mathrm{Ind}}(\lambda) = \left|\mathbb{P}[b=b'] - \frac{1}{2}\right| \le negl(\lambda) \quad (3)$$

Now, we evaluate $\mathbb{P}[b = b']$ as follows.

$$\mathbb{P}[b = b'] = \mathbb{P}[b = b' | \alpha' \in \{\alpha_0, \alpha_1\}] \cdot \mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] + \mathbb{P}[b = b' | \alpha' \notin \{\alpha_0, \alpha_1\}] \cdot \mathbb{P}[\alpha' \notin \{\alpha_0, \alpha_1\}] = \mathbb{P}[b = b' \cap \alpha' \in \{\alpha_0, \alpha_1\}] + \mathbb{P}[b = b' | \alpha' \notin \{\alpha_0, \alpha_1\}] \cdot \mathbb{P}[\alpha' \notin \{\alpha_0, \alpha_1\}] = \mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\mathrm{SSE}, \mathcal{A}, \mathcal{L}_{NP}, \mathfrak{C}^{\mathcal{DB}_t}, \alpha} \text{ game}] + \frac{1}{2} \left(1 - \mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}]\right)$$

$$(4)$$

Now, we evaluate $\mathbb{P}[\alpha' \in {\alpha_0, \alpha_1}]$ as follows.

$$\mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] = \mathbb{P}[\alpha' = \alpha_0] + \mathbb{P}[\alpha' = \alpha_1]$$

Since we have

$$\mathbb{P}[\alpha' = \alpha_0] + \mathbb{P}[\alpha' = \alpha_1] = \\\mathbb{P}[\alpha' = \alpha_b | b = 0] + \mathbb{P}[\alpha' = \alpha_b | b = 1]$$

then,

$$\mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] = \frac{1}{2} \left(\mathbb{P}[\alpha' = \alpha_b | b = 0] + \mathbb{P}[\alpha' = \alpha_0] \right) \\ + \frac{1}{2} \left(\mathbb{P}[\alpha' = \alpha_b | b = 1] + \mathbb{P}[\alpha' = \alpha_1] \right)$$

We note that $\mathbb{P}[\alpha' = \alpha_b]$ is the probability \mathcal{A} wins the 1-outof- α indistinguishability game, and α_0 and α_1 are uniformly selected from $\{0, \alpha - 1\}$, then we have

$$\mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] = \mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\mathrm{SSE}, \mathcal{A}, \mathcal{L}_{NP}, \mathfrak{C}^{\mathcal{DB}_t}, \alpha} \text{ game}] + \frac{1}{\alpha}$$
(5)

Applying Eq. 5 to Eq. 4, we have

$$\begin{split} \mathbb{P}[b = b'] = \\ & \frac{1}{2} \cdot \mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\mathrm{SSE},\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}},\alpha} \text{ game}] \\ & + \frac{1}{2} - \frac{1}{2\alpha} \end{split}$$

Then, from Equation 3, we can derive

$$\begin{aligned} \mathbf{Adv}_{\mathcal{B},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}}}^{\mathrm{Ind}}(\lambda) &= \\ \frac{1}{2} \left(\mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\mathrm{SSE},\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}},\alpha} \text{ game}] - \frac{1}{\alpha} \right) \end{aligned} \tag{6}$$

Applying Equation 6 to Equation 2, finally, we can have

$$\mathbf{Adv}_{\mathcal{B},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}}}^{\mathrm{Ind}}(\lambda) = \frac{1}{2}\mathbf{Adv}_{\mathcal{A},\mathcal{L}_{NP},\mathfrak{C}^{\mathcal{DB}_{t}},\alpha}^{\mathrm{Ind}}(\lambda)$$
(7)

A.4 Security against Persistent Adversary

Prior knowledge of the databases We start to generalise the knowledge of the non-persistent adversary over the time to be the persistent adversary's knowledge of databases. Namely, we denote by $(DB_{t=0}, \ldots, DB_{t=T})$ such knowledge, where T denotes the streaming period. We also make use of the constraint set $\mathfrak{C}^{\mathcal{DB}_t} = \{C^{\mathrm{DB}_t}, \mathrm{DB}_t \in \mathcal{DB}_t\}$, defined in Section A.3, to formulate $\mathbf{C}^{[1,\ldots,T]} = \{\mathfrak{C}^{\mathcal{DB}_0}, \ldots, \mathfrak{C}^{\mathcal{DB}_T}\}$ the generalisation of constraint sets over the period such that we know every $\mathfrak{C}^{\mathcal{DB}_t}(\mathcal{L}_{NP}, \alpha)$ -acceptable, $\forall t \in [0, T]$.

Let δ be a stateless function that outputs the keyword set difference in a pairwise different inputs. Then, $\delta(\text{DB}_t, \text{DB}_{t'}) = W^{t,t'}$, where $W^{t,t'} = \{w_i | w_i \in \text{DB}_t, w_i \notin \text{DB}_{t'}\}$. We consider the leakage function only depends on the query itself (*i.e.*, q(.)) and on the state of database at the querying time: $\mathcal{L}_{NP}(q)_t$ and $\mathcal{L}_{NP}(q)_{t'}$ be presented as stateless functions of $f_{\mathcal{L}_{NP}}(q, \text{DB}_t)$, and $f_{\mathcal{L}_{NP}}(q, \text{DB}_{t'})$, respectively.

Let $Q = \{q_1, \ldots, q_{n-1}\}$ be a query set, and C^{DB_t} and $C^{\text{DB}_{t'}}$ be constraints applied on the $H_t = (\text{DB}_t, Q)$ and $H_{t'} = (\text{DB}_t, Q)$, respectively. From Proposition 1, we denote by $\Gamma_{\mathcal{L}_{NP}, C^{\text{DB}_t}}(H_t) = \{G_{1,t}, \ldots, G_{m,t}\}$ the clustering $\Gamma_t = \{G_{1,t}, \ldots, G_{m,t}\}$ of queries induced by the leakage \mathcal{L}_{NP} after history H_t is a partition of Q, for which, in every cluster, queries share the same leakage after running the history H_t . Similarly, we also derive the clustering $\Gamma_{t'} = \{G_{1,t'}, \ldots, G_{m',t'}\}$ of queries Q_t induced by the leakage \mathcal{L}_{NP} after history H'_t . We make an observation on EDB_t and $\text{EDB}_{t'}$ that: let q(w) (resp. q(w')) be the query of w (resp. w'), where $w \notin W^{t,t'}, w' \in W^{t,t'}$, and $q(w), q(w') \in G_{v,t'}$ ($\exists v \in [1, m]$), such that:

 $(\widetilde{H}_t^w = H_t || q(w), \widetilde{H}_t^{w'} = H_t || q(w'))$

and

$$(\widetilde{H}_{t'}^{w} = H_{t'} || q(w), \widetilde{H}_{t'}^{w'} = H_{t'} || q(w'))$$

We can see that $f_{\mathcal{L}_{NP}}(q(w), \mathsf{DB}_t) = f_{\mathcal{L}_{NP}}(q(w'), \mathsf{DB}_t)$, but $f_{\mathcal{L}_{NP}}(q(w), \mathsf{DB}_{t'}) \neq f_{\mathcal{L}_{NP}}(q(w'), \mathsf{DB}_{t'})$ due to $w \in \mathsf{DB}_{t'}$ while $w' \notin \mathsf{DB}_{t'}$, causing $\mathsf{EDB}_{t'}(w) \neq \mathsf{EDB}_{t'}(w')$. We can see that: if both $q(w), q(w') \in G_{v,t'}$, then $f_{\mathcal{L}_{NP}}(q(w), \mathsf{DB}_{t'}) = f_{\mathcal{L}_{NP}}(q(w'), \mathsf{DB}_{t'})$. This observation can be iterated for all

other pairwise different queries in G_{v_t} and $G_{v_{t'}}$. More generally, we need to have $|G_{v,t}| = |G_{v,t'}|$, $\forall t, t \in [0,T]$ such that $\forall q(w), q(w') \in G_{v,t}$, they always have the same leakage at different $t' \in [1,T]$. Formally, given m the number of clusters, we define

$$\forall G_{v,t}, G_{v,t'} \neq \emptyset, F_{t,t',v}(G_{v,t}, G_{v,t'}) = (|G_{v,t}| \stackrel{?}{=} |G_{v,t'}|)$$

Now, we also use *constrained* security to formalise that leakage over EDB_t and EDB_{t-1} , $\forall t \ge 1$ as in.

Definition 6. A constraint $\mathbb{F}^t = (F_{t,t-1,1}, \ldots, F_{t,t-1,m})$ over two clusters $\Gamma_t = \{G_{1,t}, \ldots, G_{m,t}\}$ and $\Gamma'_t = \{G_{1,t'}, \ldots, G_{m,t'}\}$ induced by the leakage \mathcal{L}_{NP} after histories H_t (resp. H_{t-1}) over Q_t (resp. Q_{t-1}), is a sequence of algorithms such that $F(t, t-1, i) = flag_i$, where $flag_i$ is true or false. The constraint is consistent if (., false, .) = (false, .), then $\mathbb{F}^t = false$ (the constraint remains false if it once evaluates to false).

Let a constraint set $\mathcal{F} = (\mathbb{F}^1, \dots, \mathbb{F}^T)$ is a sequence of algorithms evaluated at every $t \in [1, T]$. The set is consistent if (., false, .) = (false, .), then $\mathcal{F} = \texttt{false}$ (the constraint remains <code>false</code> if it once evaluates to <code>false</code>). In a short form, we write \mathcal{F}^T to present the condition $\mathcal{F} = \texttt{true}$.

The security of a scheme $\Sigma_P = (\text{Setup}, \text{Stream}, \text{Search})$ against the persistent adversary over a streaming period T. We start adding a padding mechanism against the persistent adversary in Algorithm 1 (i.e., Padding Strategies) to Σ_P such that, $\forall G_{i,t}$ in $\Gamma_t = \{G_{1,t}, \ldots, G_{m,t}\}$ induced by Search_t (i.e., searching at time t) against EDB_t, $G_{i,t}$ always has the same size $|G_{i,t}| = |G_{i,t'}|$, where $G_{i,t'}$ in $\Gamma_{t'} = \{G_{1,t'}, \ldots, G_{m,t'}\}, \forall t' \neq t$. Let $\mathcal{L}_{1^{stream}}^{Stream}$, $L_T^{Stream}\}$, and $\mathcal{L}_{1^{sarch}}^{Search} = \{\mathcal{L}_{NP,i}^{Stream}\}$, for $i \in [1, \ldots, T]$, where $\mathcal{L}_{NP,i}^{Srch} = (\mathcal{L}_i^{Srch}, \mathcal{L}_i^{\alpha-pad})$ is the search leakage at time i, where $\mathcal{L}_i^{\alpha-pad}$. Then, the leakage function of Σ_P can be quantified via the leakage function $\mathcal{L}_P = (\mathcal{L}_{1^{stream}}^{Stream}, \mathcal{L}_{1^{sarch}}^{Search})$.

By using Definition 6, we can show that $\mathbf{C}^{[1,...,T]} = \{\mathfrak{C}^{\mathcal{DB}_0}, \ldots, \mathfrak{C}^{\mathcal{DB}_T}\}$ is an $(\mathcal{L}_P, \alpha, \mathcal{F})$ -acceptable set of constraint sets, where α denotes the minimum cluster size (over all constructable databases) and \mathcal{F}^T denotes the condition $\mathcal{F} = \mathtt{true}$. The reason is that, for every time $t \in [0, T]$, $\mathfrak{C}^{\mathcal{DB}_t}$ is $(\mathcal{L}_{NP}, \alpha)$ -acceptable, and $\forall G_{i,t}$ in $\Gamma_t = \{G_{1,t}, \ldots, G_{m,t}\}$ induced by Search_t (i.e., searching at time t) against EDB_t, $G_{i,t}$ always has the same size $|G_{i,t}| = |G_{i,t'}|$, where $G_{i,t'}$ in $\Gamma_{t'} = \{G_{1,t'}, \ldots, G_{m,t'}\}, \forall t' \neq t$

Now, we are ready to define the notion of constraned adaptive indistinguishability for Σ_P given $\mathbf{C}^{[1,...,T]}$. This security game is formalised in Definition 7.

Definition 7. Let $\Sigma = ($ **Setup,Streaming,Search**) be the DSSE scheme of ShieldDB, λ be the security parameter, and \mathcal{A} be a persistent adversary. Let $\mathbf{C}^{[1,...,T]}$ be a set of $(\mathcal{L}_P, \alpha, \mathcal{F})$ -acceptable constraint sets. Let u_t (**streaming**) (resp. Q_t (**search**)) be an update (resp. query set, i.e., $Q_t = \{q_{t,1}, \ldots, q_{t,n}\}$) at time t, and \mathcal{L}^{Stream} (resp. \mathcal{L}^{Srch}) be the leakage after the query u(resp. q), respectively. Let $\mathrm{Ind}_{DSSE,\mathcal{A},\mathcal{L}_P,\mathbf{C}^{[1,...,T]},\alpha,\mathcal{F}}$ be the following game:

$$\begin{aligned} & \operatorname{Ind}_{DSSE,\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,...,T]},\alpha,\mathcal{F}}(\lambda) \ \ \textit{Game:} \\ & b \stackrel{\$}{\leftarrow} \{0,\ldots,\alpha-1\} \\ & (\mathfrak{C}^{\mathcal{D}\mathcal{B}_{0}},\mathrm{DB}_{t}^{0},\ldots,\mathrm{DB}_{t}^{\alpha-1}) \leftarrow \mathcal{A}(1^{\lambda}) \\ & (K,\mathrm{EDB}_{0}^{b}) \leftarrow \operatorname{Setup}(\mathrm{DB}_{0}^{b}) \\ & \textit{for } t = 1 \ \textit{to } T \ \textit{do} \\ & \operatorname{EDB}_{t}^{b} \leftarrow \operatorname{Streaming}(u_{t}) \\ & (\mathfrak{C}^{\mathcal{D}\mathcal{B}_{t}},Q_{t}) \leftarrow \mathcal{A}(\mathrm{EDB}_{t}^{b}) \\ & \{\tau_{t,1}^{b},\ldots,\tau_{t,n}^{b}\} \leftarrow \operatorname{Search}(Q_{t},\mathrm{EDB}_{t}^{b}) \\ & \textit{end for} \\ & b' \leftarrow \mathcal{A}(\tau_{T,1}^{b},\ldots,\tau_{T,n}^{b}) \\ & \textit{if } b = b' \ \textit{return } 1. \ \textit{otherwise return } 0 \end{aligned}$$

where $\tau_{t,i}^{b}$ presents the transcript of the query $q_{t,i}$, and with the restriction that, given $\mathbf{C}^{[1,...,T]} = \{\mathfrak{C}^{\mathcal{DB}_0}, \ldots, \mathfrak{C}^{\mathcal{DB}_T}\},$ for $\mathfrak{C}^{\mathcal{DB}_t} = \{C^{\mathrm{DB}_t}, \mathrm{DB}_t \in \mathcal{DB}_t\},$ for all the $H^i_t =$ $(\mathsf{DB}_t^i, q_{t,1}, \ldots, q_{t,n}),$

- $C^{\mathrm{DB}_t} \in \mathfrak{C}^{\mathcal{DB}_t}$, and $\forall 0 \leq i \leq (\alpha 1), C^{\mathrm{DB}_t}(H^i_t) =$
- $\mathcal{L}(H_t^0) = \cdots = \mathcal{L}(H_t^{\alpha-1})$ $\mathcal{F} = (\mathbb{F}^1, \dots, \mathbb{F}^T) = \texttt{true}$

We say that Σ is $(\mathcal{L}_P, \mathbf{C}^{[1,...,T]}, \alpha, \mathcal{F})$ -constrained-adaptivelyindistinguishable if for all probabilistic polynomial time adversary $\mathcal{A},$

$$\begin{aligned} \mathbf{Adv}_{\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,...,T]},\alpha,\mathcal{F}}^{\mathrm{Ind}}(\lambda) &= \\ \left| \mathbb{P}[\mathrm{Ind}_{\mathrm{DSSE},\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,...,T]},\alpha,\mathcal{F}}(\lambda) = 1] - \frac{1}{\alpha} \right| \leq negl(\lambda). \end{aligned}$$
(8)

We can see that Σ_P offers at least $log(\alpha)$ bits of security. Given $\mathbf{C}^{[1,...,T]}$ is an $(\mathcal{L}_P, \alpha, \mathcal{F})$ -acceptable set of constraint sets, we can analysing every transcript in the set $\{\tau_{t,1}^b, \ldots, \tau_{t,n}^b\}$ under the choice of α . Let u_t simply contains a pair of (w_i, id) , we can make an observation in ShieldDB as follows.

If $ST[w_i] = 0$, presenting that w_i appears in the first time, then Padding Controller checks the cache cluster that expects to have w_i against the *first batch* condition. We recall that the condition ensures the existence of all keywords in the cluster before padding. If the condition is fail, we see that both EDB_i^0 and EDB_i^1 are indistinguishable under the choice of $b \stackrel{\$}{\leftarrow} \{0, \ldots, \alpha - 1\}$. The reason is because the challenger does not send any batch to the server. In contrast, if the condition is passed, Padding Controller pads all the keywords in the cluster to be the same length and encrypt them before sending a batch to the server. Meanwhile, $ST[w_i].c$ gets updated. Accordingly, EDB_t^b is indistinguishable under the choice of because these databases receive the batch of keywords that have the same length. The first batch condition is crucial when ShieldDB is against the persistent adversary. It ensures there is no new keyword in the cluster appears in subsequent batches. Hence, the adversary cannot distinguish when a new keyword is added in EDB_i^b .

If $ST[w_i].c > 0$ and first batch condition has been met, Padding Controller performs padding similarly with the padding strategy against the non-persistent adversary, presented in Algorithm 1. We can also see that EDB_t^b is indistinguishable because Padding Controller guarantees all the keywords in a cluster have the same length.

Now, we start analysing the query q_t , *i* that queries the keyword w_i , with $ST[w_i].c = 0$ or $ST[w_i].c > 0$.

If $ST[w_i].c = 0$, the adversary cannot guess the picked database because $\tau_{t,i}^b$ return nothing.

If $ST[w_i].c > 0$, $\tau^b_{t,i}$ is indistinguishable to all other query keywords in the same cluster at time *t*.

Theorem 4. Let Σ_P = (Setup,Streaming,Search) be our DSSE scheme, and $\mathbf{C}^{[1,\ldots,T]} = \{\mathfrak{C}^{\mathcal{DB}_0},\ldots,\mathfrak{C}^{\mathcal{DB}_T}\}$ is a set of constraint sets. If Σ is \mathcal{L}_P -constrained-adaptivelyindistinguishable secure, and $\mathbf{C}^{[1,...,T]}$ is $(\mathcal{L}_P, \alpha, \mathcal{F})$ -acceptable, is $(\mathcal{L}_P, \mathbf{C}^{[1,...,T]}, \alpha, \mathcal{F})$ -constrained-adaptivelythen Σ indistinguishability secure.

Proof. Let \mathcal{A} be an adversary in the $\begin{array}{l} \operatorname{Ind}_{\operatorname{DSSE},\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,\ldots,T]},\alpha,\mathcal{F}} \text{ game. We construct an adversary} \\ \mathcal{B} \text{ against the game. } \mathcal{B} \text{ first randomly picks two integer} \end{array}$ $\alpha_0, \alpha_1 \in \{0, \alpha - 1\}$. Then, \mathcal{B} starts \mathcal{A} and receives α databases $(DB_0^0, \dots, DB_0^{\alpha-1})$. Upon giving the pair $(DB_0^{\alpha_0}, DB_0^{\alpha_1})$ to the challenger, where the challenger holds a random secret bit b, \mathcal{B} receives the challenge encrypted database EDB_0^* which she forwards to \mathcal{A} . Then, for every $t \in [1, \ldots, T]$, we have:

- \mathcal{A} sends u_t (stream queries) to challenger and receives EDB_t^* .
- \mathcal{A} outputs $((q_{t,1}^0, \dots, q_{t,1}^{\alpha-1}), \dots, (q_{t,n}^0, \dots, q_{t,n}^{\alpha-1}))$ and gives to \mathcal{B} .
- To respond, \mathcal{B} outputs $((q_{t,1}^{\alpha_0}, q_{t,1}^{\alpha_1}), \dots, (q_{t,n}^{\alpha_0}, q_{t,n}^{\alpha_1}))$ to the game and receives back the transcripts $(\tau_{t,1}^*,\ldots,\tau_{t,n}^*)$, and forwards them to \mathcal{A} .

After executing all $t \in [1, ..., T]$, \mathcal{A} outputs the integer α' . If $\alpha' = \alpha_0$, \mathcal{B} outputs b' = 0, else if $\alpha' = \alpha_1$, \mathcal{B} outputs b' = 1, and otherwise outputs the probability 1/2 for the output 0 and the probability 1/2 for the output 1.

We first make an observation: for the pair $(H_t^{\alpha_0}, H_t^{\alpha_1})$ at $\forall t \in [1,T]$, the views of the adversary \mathcal{B} are indistinguishable due to $\mathcal{L}_P(H_t^{\alpha_0}) = \mathcal{L}_P(H_t^{\alpha_1})$, presenting both satisfying $\mathbf{C}^{[1,...,T]}$. Then we can formalise \mathcal{B} as follows:

$$\mathbf{Adv}^{\mathrm{Ind}}_{\mathcal{B},\mathcal{L}_{P},\mathbf{C}^{[1,\ldots,T]},\mathcal{F}}(\lambda) = \left|\mathbb{P}[b=b'] - \frac{1}{2}\right| \le negl(\lambda) \quad (9)$$

Now, we evaluate $\mathbb{P}[b = b']$ as follows.

$$\mathbb{P}[b = b'] = \mathbb{P}[b = b' | \alpha' \in \{\alpha_0, \alpha_1\}] \cdot \mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] + \mathbb{P}[b = b' | \alpha' \notin \{\alpha_0, \alpha_1\}] \cdot \mathbb{P}[\alpha' \notin \{\alpha_0, \alpha_1\}] = \mathbb{P}[b = b' \cap \alpha' \in \{\alpha_0, \alpha_1\}] + \mathbb{P}[b = b' | \alpha' \notin \{\alpha_0, \alpha_1\}] \cdot \mathbb{P}[\alpha' \notin \{\alpha_0, \alpha_1\}] = \mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\text{DSSE},\mathcal{A},\mathcal{L}_P, \mathbf{C}^{[1,\dots,T]},\alpha,\mathcal{F}} \text{ game}] + \frac{1}{2} \left(1 - \mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}]\right)$$

$$(10)$$

Now, we evaluate $\mathbb{P}[\alpha' \in {\alpha_0, \alpha_1}]$ as follows.

$$\mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] = \mathbb{P}[\alpha' = \alpha_0] + \mathbb{P}[\alpha' = \alpha_1]$$

Since we have

$$\mathbb{P}[\alpha' = \alpha_0] + \mathbb{P}[\alpha' = \alpha_1] = \\\mathbb{P}[\alpha' = \alpha_b|b = 0] + \mathbb{P}[\alpha' = \alpha_b|b = 1]$$

then,

$$\mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] = \frac{1}{2} \left(\mathbb{P}[\alpha' = \alpha_b | b = 0] + \mathbb{P}[\alpha' = \alpha_0] \right) \\ + \frac{1}{2} \left(\mathbb{P}[\alpha' = \alpha_b | b = 1] + \mathbb{P}[\alpha' = \alpha_1] \right)$$

We note that $\mathbb{P}[\alpha' = \alpha_b]$ is the probability \mathcal{A} wins the 1-outof- α indistinguishability game, and α_0 and α_1 are uniformly selected from $\{0, \alpha - 1\}$, then we have

$$\mathbb{P}[\alpha' \in \{\alpha_0, \alpha_1\}] = \mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\text{DSSE}, \mathcal{A}, \mathcal{L}_P, \mathbf{C}^{[1, \dots, T]}, \alpha, \mathcal{F}} \text{ game}] + \frac{1}{\alpha}$$
(11)

Applying Eq. 11 to Eq. 10, we have

$$\begin{split} \mathbb{P}[b = b'] = \\ & \frac{1}{2} \cdot \mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\mathrm{SSE},\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,\dots,T]},\alpha,\mathcal{F}} \text{ game}] \\ & + \frac{1}{2} - \frac{1}{2\alpha} \end{split}$$

Then, from Equation 9, we can derive

$$\mathbf{Adv}_{\mathcal{B},\mathcal{L}_{P},\mathbf{C}^{[1,...,T]},\mathcal{F}}^{\mathrm{Ind}}(\lambda) = \frac{1}{2} \left(\mathbb{P}[\mathcal{A} \text{ wins the } Ind_{\mathrm{SSE},\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,...,T]},\alpha,\mathcal{F}} \text{ game}] - \frac{1}{\alpha} \right)$$
(12)

Applying Equation 12 to Equation 8, finally, we can conclude

$$\mathbf{Adv}_{\mathcal{B},\mathcal{L}_{P},\mathbf{C}^{[1,\ldots,T]},\mathcal{F}}^{\mathrm{Ind}}(\lambda) = \frac{1}{2}\mathbf{Adv}_{\mathcal{A},\mathcal{L}_{P},\mathbf{C}^{[1,\ldots,T]},\alpha,\mathcal{F}}^{\mathrm{Ind}}(\lambda) \quad (13)$$



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