MUSES: Efficient Multi-User Searchable Encrypted Database

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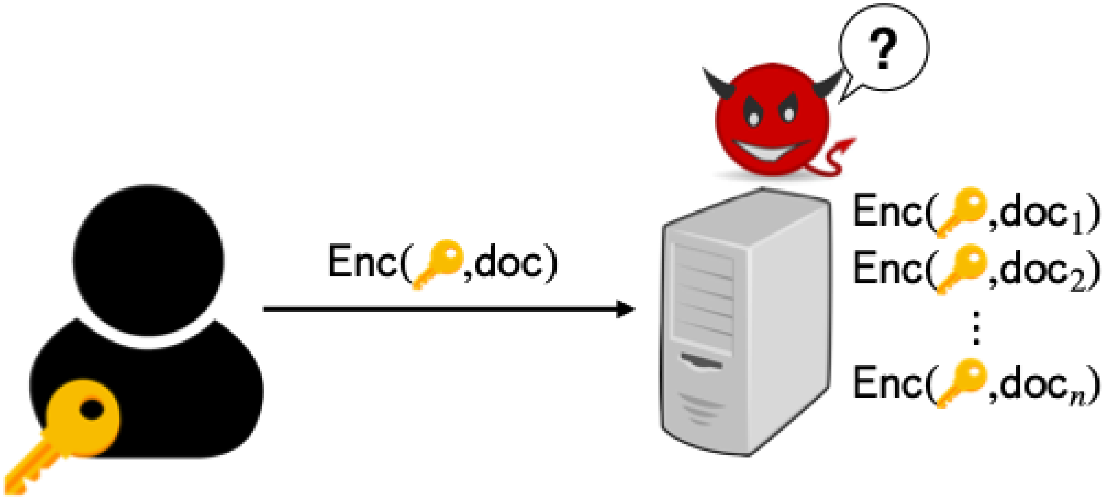
Overview

End-to-end encrypted systems are increasingly popular

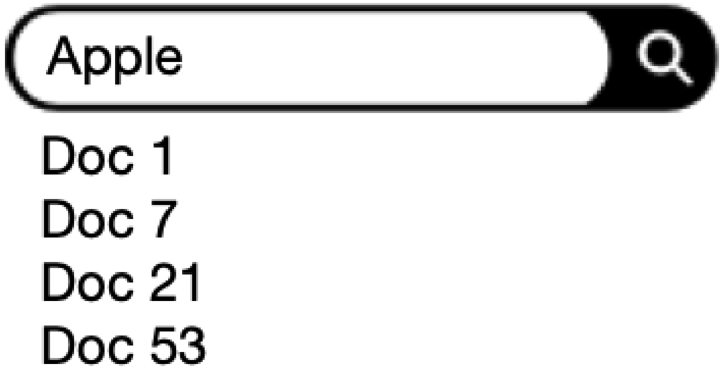
Keybase PREVEIL SpiderOak sync.com tresorit

Provide strong security guarantees if attacker compromises server

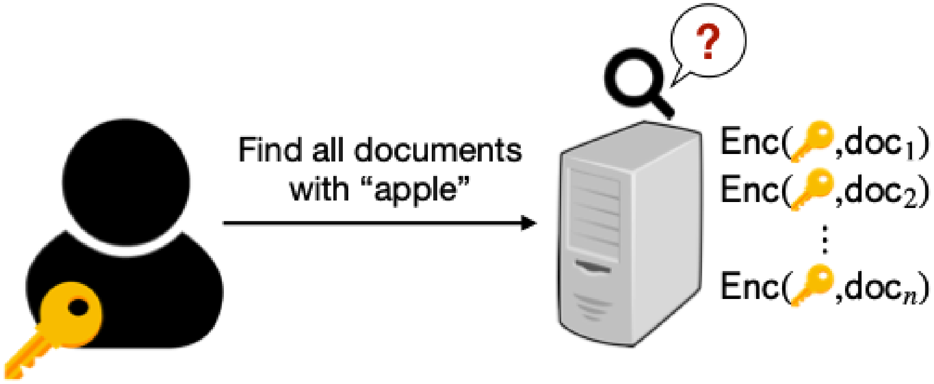


Overview

Users expect the ability to execute search



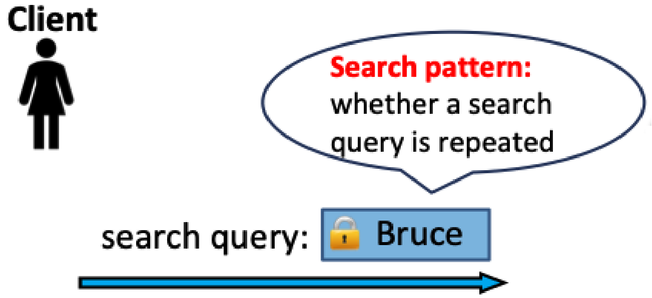
Challenge: server cannot decrypt data to search

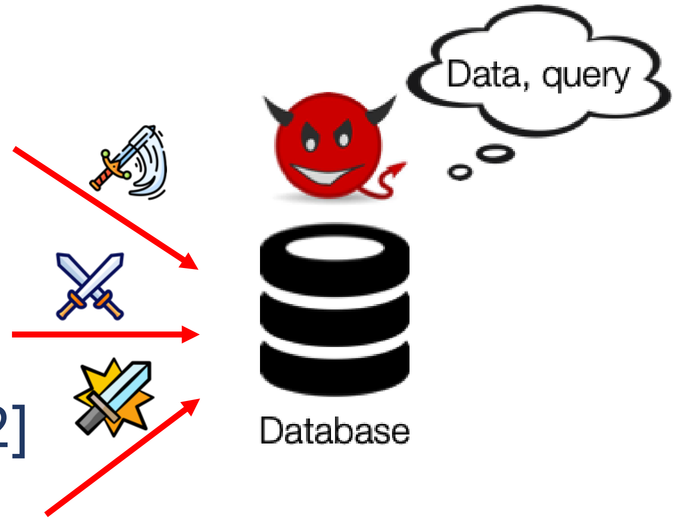


Overview

Leakage-abuse Attacks in Searchable Encryption:

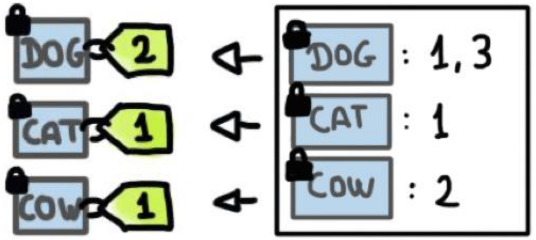
- **Search Pattern:** [IKK’12, LZWT’14, OK’21]





- **Result Pattern:** [IKK’12, CGPR’14, ZKP’16, LCNL’22, OK’22]

Result pattern: Repetition of returned matching documents



Volume pattern: The number of matching documents

- **Volume Pattern:** [BKM’19, LCNL’22, OK’22, ZWXYL’23]

MUSES: Efficient Multi-Writer Encrypted Search

Practical examples of searchable encrypted platforms:

- ✓ Cosmian
- ✓ Amazon AWS Database Encryption SDK
- ✓ MongoDB

We propose **MUSES**, which features by:

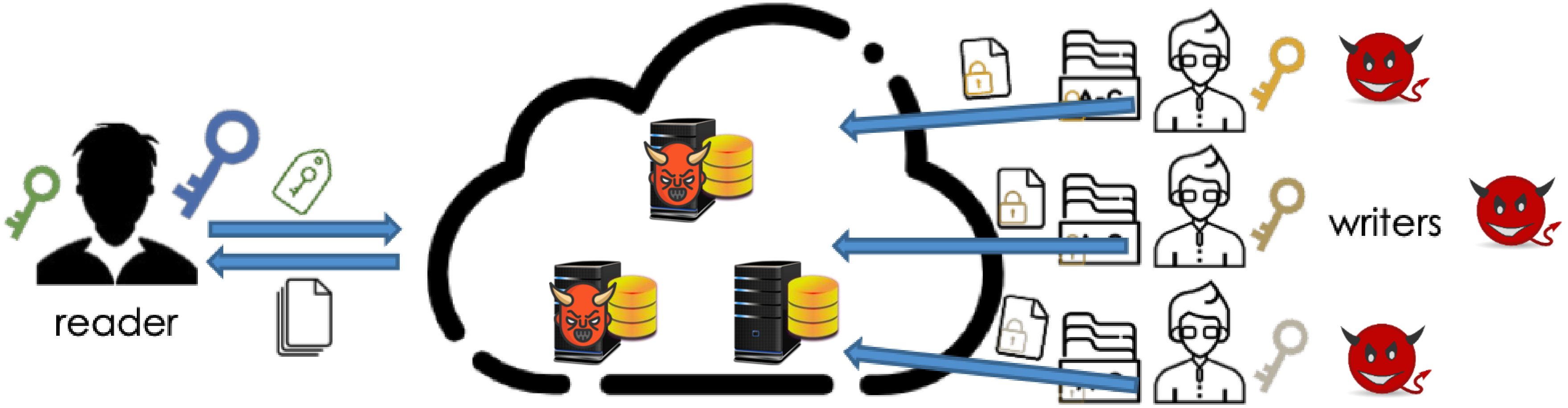
- ✓ Multi-writer support
- ✓ Hide all statistical information, including search, result, and volume patterns
- ✓ Minimal user overhead (regarding computation and communication costs)

System and Threat Model

An honest reader who holds a public/private key pair

Multiple writers, where each owns its independent database

L servers, in which up to $L-1$ servers can be corrupt



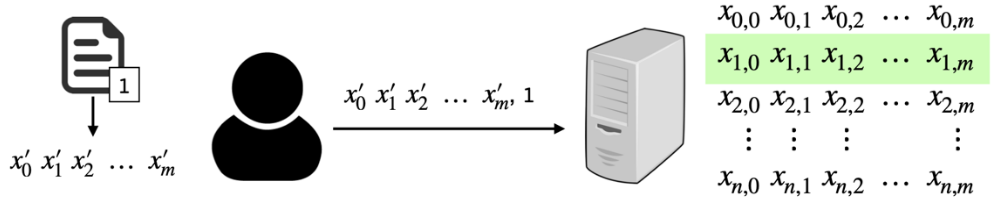
Security against *semi-honest servers* and potentially *corrupt writers*

Search Index

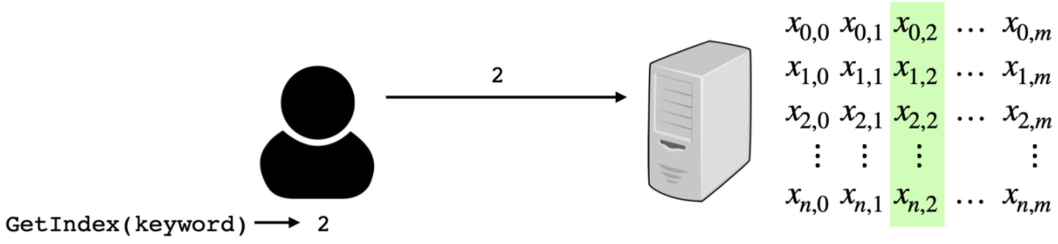
	"amazon"	"google"	"netflix"	...	"apple"
doc 1	1	0	1	0	1
doc 2	0	1	1	0	0
doc 3	1	1	0	0	0
...	0	1	0	1	1
doc N	1	0	0	1	1

Bitmap for keywords in doc 2

Update:

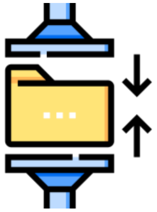


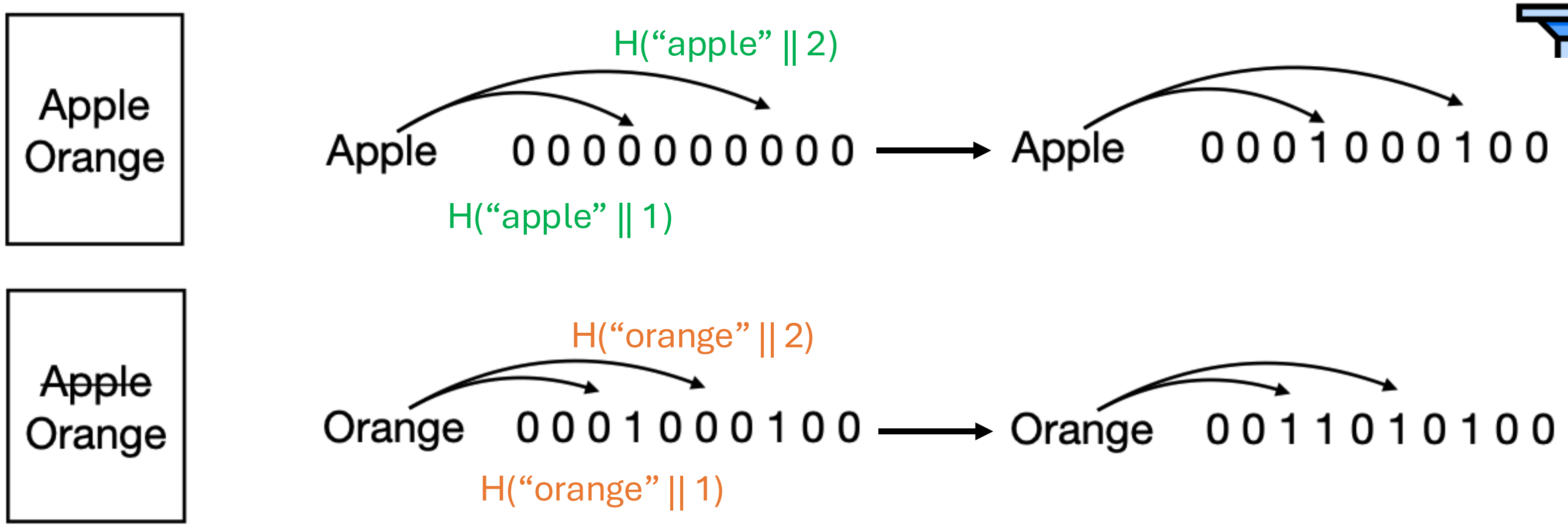
Search:



Compressing Search Index

Using Bloom filter to compress the search index

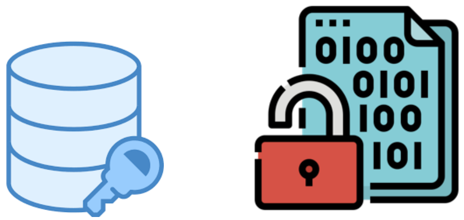




$$
\begin{matrix}
x_{0,0} & x_{0,1} & x_{0,2} & \cdots & x_{0,m} \\
x_{1,0} & x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\
x_{2,0} & x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\
\vdots & \vdots & \vdots & & \vdots \\
x_{n,0} & x_{n,1} & x_{n,2} & \cdots & x_{n,m}
\end{matrix}
$$

Search index with Bloom filters

Encrypted Search Index



Key-Homomorphic Pseudorandom Function (KH-PRF): [BLMR'13]

Learning with Rounding (LWR):

$$F: \mathbb{Z}_q^n \times \{0,1\}^* \rightarrow \mathbb{Z}_p$$

$$F\big(\underbrace{\boldsymbol{k}^{(1)} + \boldsymbol{k}^{(2)}}_{\boldsymbol{k} = \boldsymbol{k}^{(1)} + \boldsymbol{k}^{(2)}}, s\big) = F\big(\boldsymbol{k}^{(1)}, s\big) + F\big(\boldsymbol{k}^{(2)}, s\big) + e,\ \ e \in \{0,1\} \text{ is a small error}$$

$$\begin{matrix} x_{0,0} & x_{0,1} & x_{0,2} & \cdots & x_{0,m} \\ x_{1,0} & x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,0} & x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \vdots & & \vdots \\ x_{n,0} & x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{matrix} \longrightarrow \begin{matrix} \mathsf{Enc}_k(x_{0,0}) & \mathsf{Enc}_k(x_{0,1}) & \mathsf{Enc}_k(x_{0,2}) & \ldots & \mathsf{Enc}_k(x_{0,m}) \\ \mathsf{Enc}_k(x_{1,0}) & \mathsf{Enc}_k(x_{1,1}) & \mathsf{Enc}_k(x_{1,2}) & \ldots & \mathsf{Enc}_k(x_{1,m}) \\ \mathsf{Enc}_k(x_{2,0}) & \mathsf{Enc}_k(x_{2,1}) & \mathsf{Enc}_k(x_{2,2}) & \ldots & \mathsf{Enc}_k(x_{2,m}) \\ \vdots & \vdots & \vdots & & \vdots \\ \mathsf{Enc}_k(x_{n,0}) & \mathsf{Enc}_k(x_{n,1}) & \mathsf{Enc}_k(x_{n,2}) & \ldots & \mathsf{Enc}_k(x_{n,m}) \end{matrix}$$

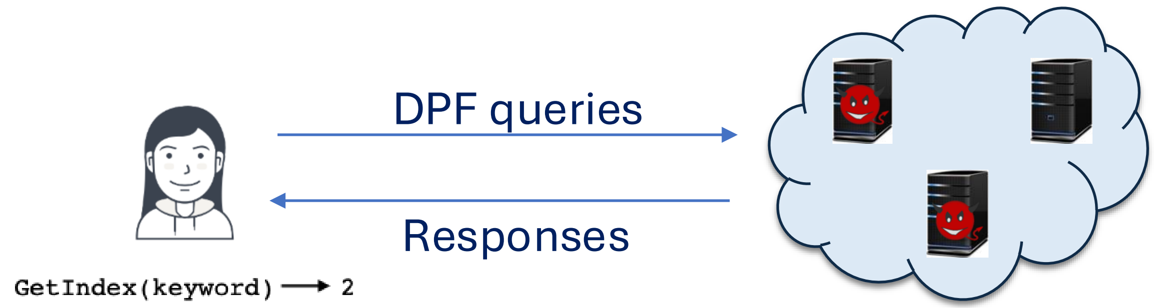
$$\mathrm{Enc}_k(x_{i,j}) = x_{i,j} + F\big(\boldsymbol{k}_j, s_i\big) \pmod p$$

Distributed Point Functions (DPFs)

- Uses multiple servers to hide which element the user is retrieving
- If at least one server is honest, an attacker cannot learn the index requested
- Requires a linear scan over the entire array

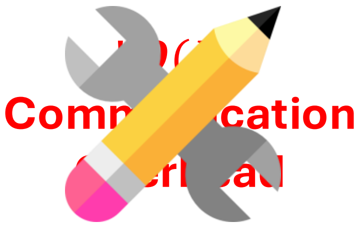
Leveraging DPFs to search

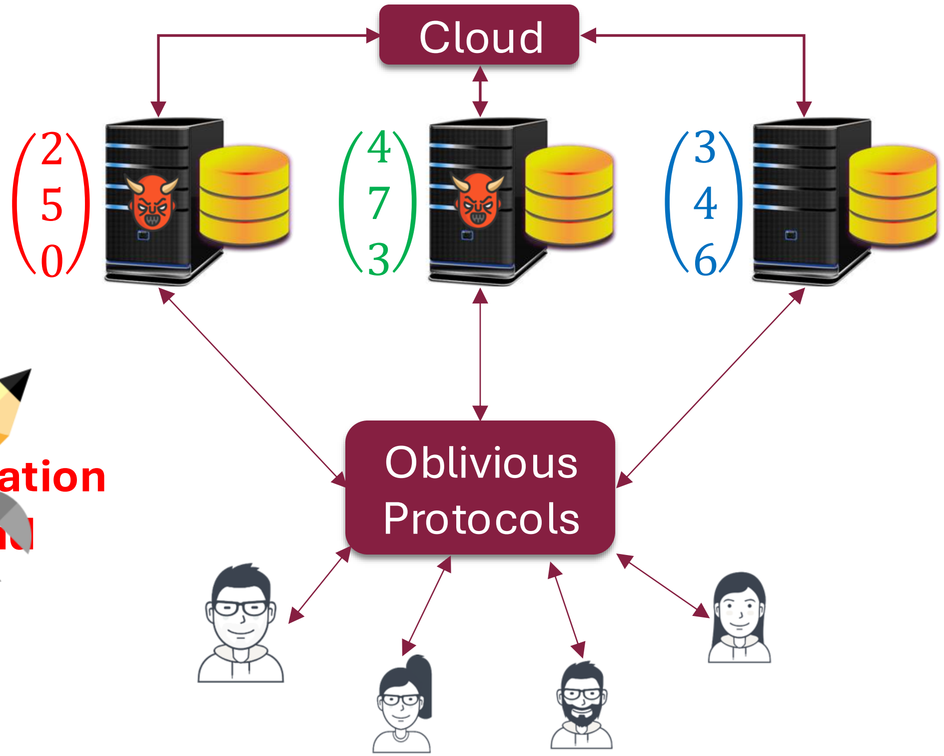
If at least one trust server is honest, MUSES hides search patterns



$$\begin{pmatrix} x_{0,2} \\ x_{1,2} \\ x_{2,2} \\ \vdots \\ x_{n,2} \end{pmatrix}$$

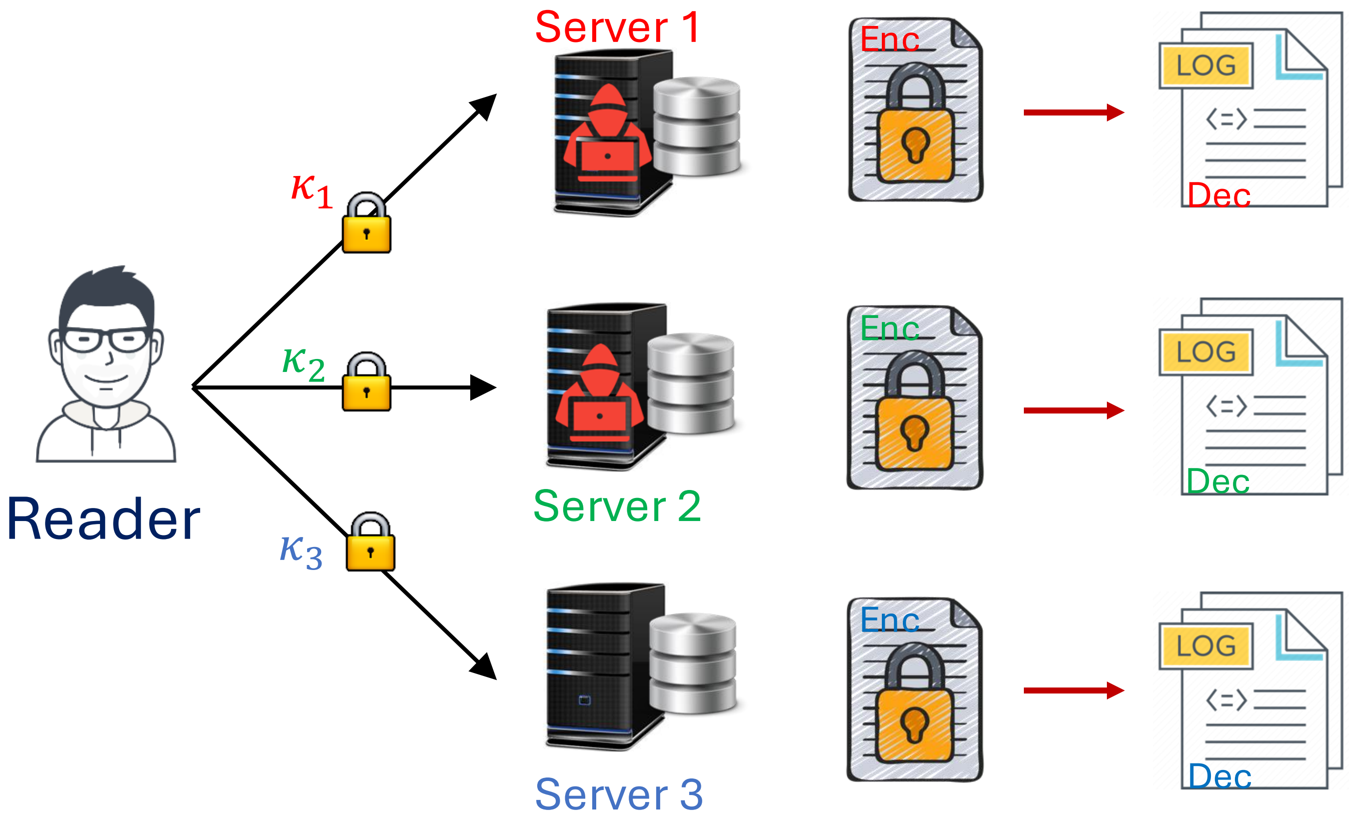
$$\begin{matrix} x_{0,0} & x_{0,1} & x_{0,2} & \cdots & x_{0,m} \\ x_{1,0} & x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,0} & x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \vdots & & \vdots \\ x_{n,0} & x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{matrix}$$





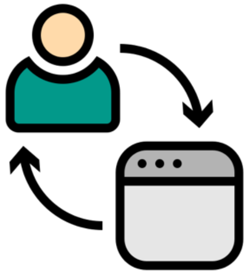
$$\begin{pmatrix} 2 \\ 5 \\ 0 \end{pmatrix} + \begin{pmatrix} 4 \\ 7 \\ 3 \end{pmatrix} + \begin{pmatrix} 3 \\ 4 \\ 6 \end{pmatrix} \bmod 2^3 \underset{\text{Dec}}{=} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

Delegating Decryption



Can the servers open secret shares and output documents?

→ No, it reveals result and volume patterns



Key-homomorphic PRFs:

- Keys are secret shared

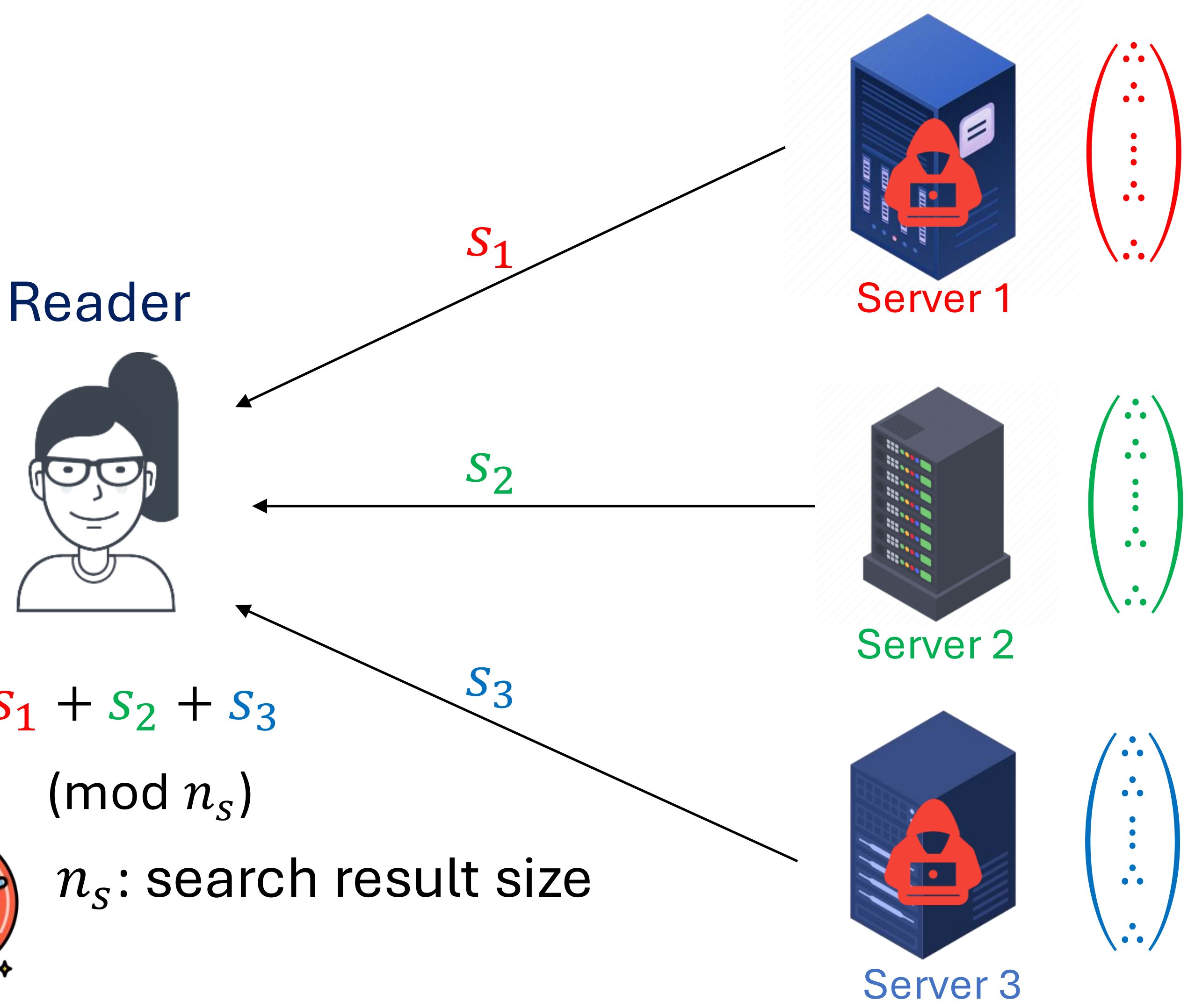
→ No server can learn private data

- Key secret-shares are random

→ Hide search patterns

Our ideas: Oblivious Padding & Shuffling

Multiparty Oblivious Counting

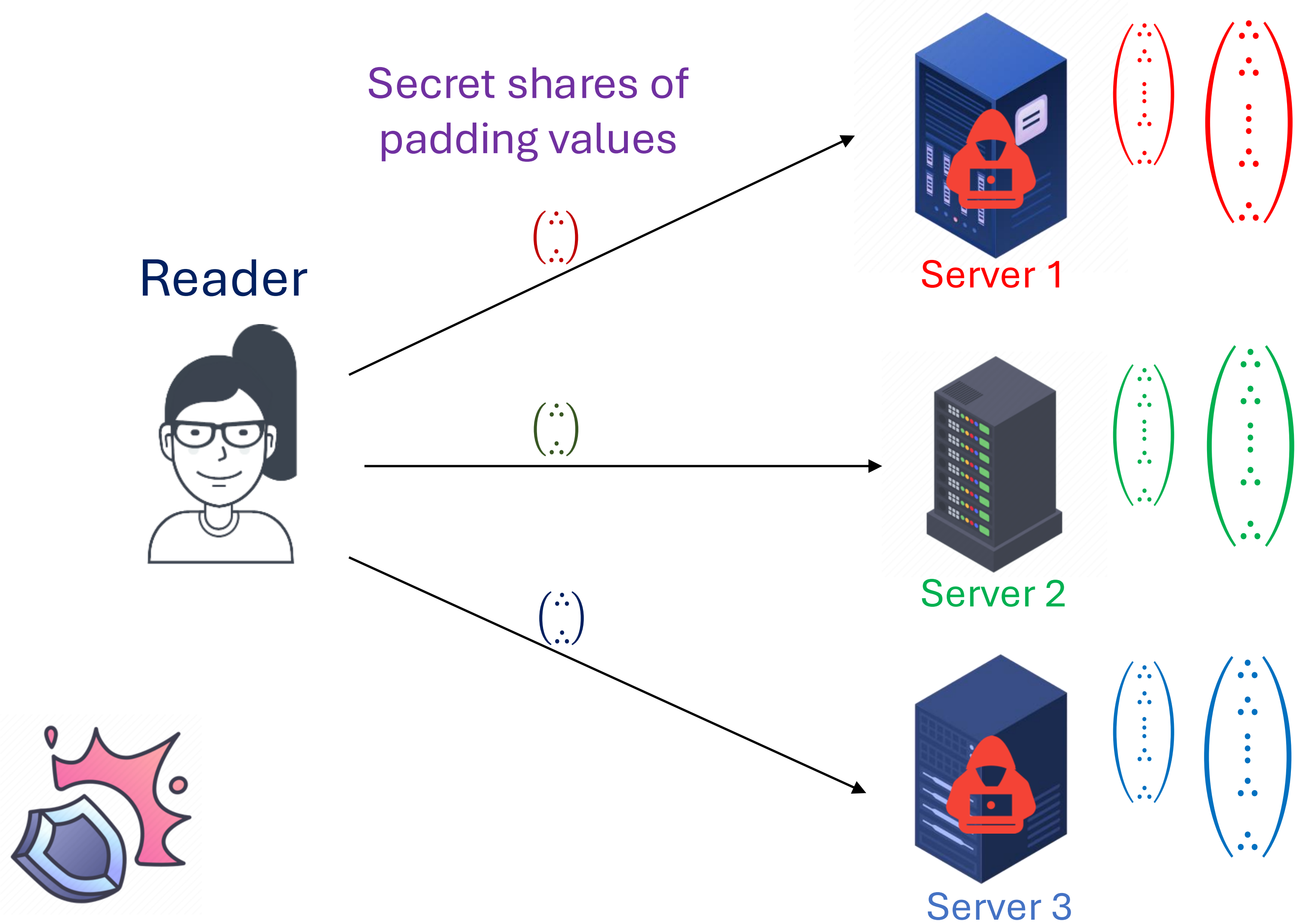


$s = s_1 + s_2 + s_3 \pmod{n_s}$

n_s: search result size

- **Efficiency:**
  - ✓ 1 communication round
  - ✓ Local lightweight operations: circular shifts, additions over small integer numbers
- Most overhead is done in the preprocessing phase
- More efficient than generic MPCs (e.g., Garbled Circuit) when counting values are small (e.g., < 10)

Multiparty Oblivious Padding



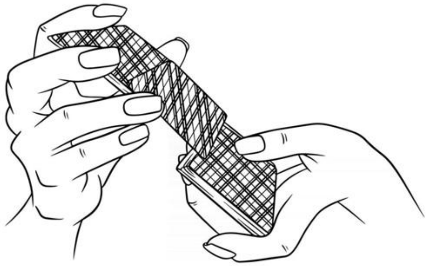
Search result size: n_s

Padding vector size: n_s

Total (padded) size: $N + n_s$

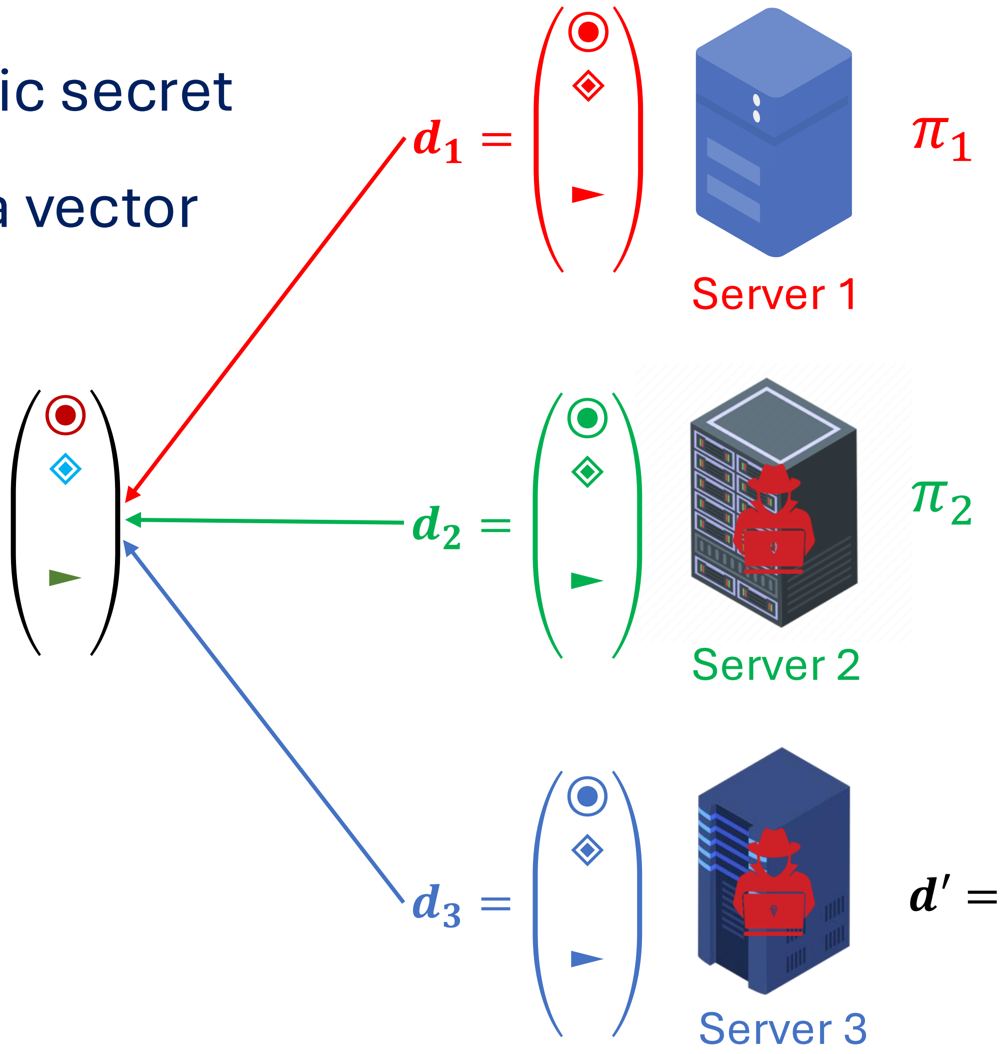
Always the same number of matches is returned for all queries

Multiparty Oblivious Shuffling



Input: Arithmetic secret shares of a data vector

$\boldsymbol{d} = \boldsymbol{d_1} + \boldsymbol{d_2} + \boldsymbol{d_3} =$

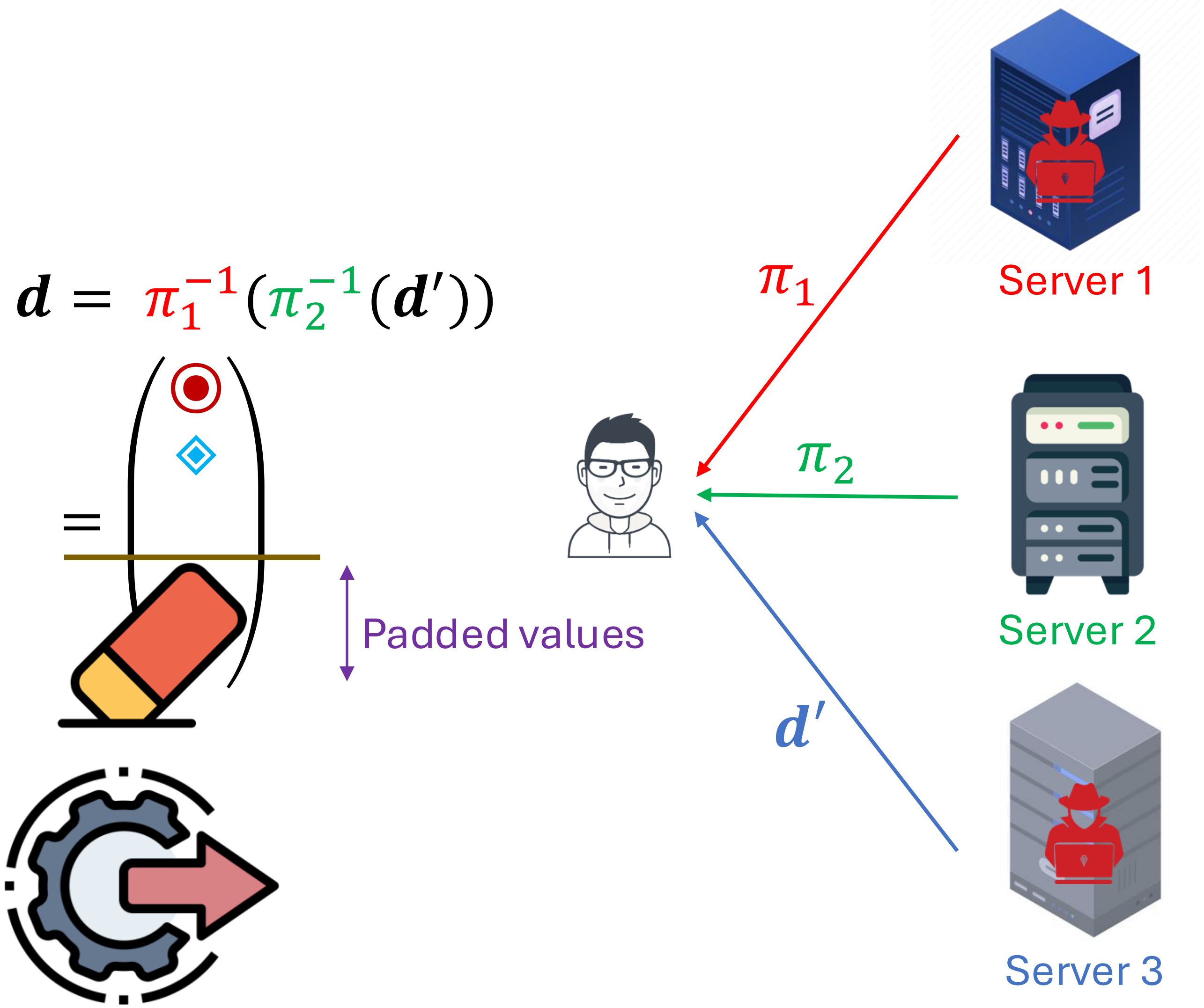


$\boldsymbol{d}' = \pi_2(\pi_1(\boldsymbol{d})) =$

Output:

- A permutation π_i for each server $P_i \in \{P_1, \dots, P_{L-1}\}$
- Opened *shuffled* data vector for server P_L

Final Step – Reverse Shuffling/Output



Search Complexity:

- Reader communication: $O(n_s)$
- Reader computation: $O(N)$
- Server computation: $O(N.m)$, including additions and multiplications over small integer numbers

Parameters:

- n_s: search result size
- m: Bloom filter size
- N: #documents

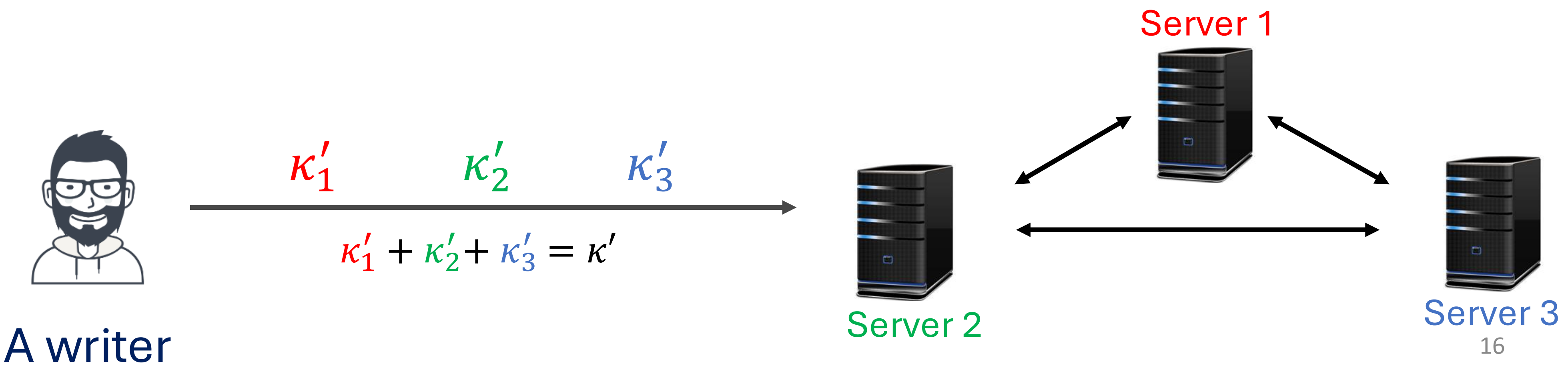
Permission Revocation

A writer needs to revoke the reader's search permission

⟶ Re-encrypt its search index

Key rotation:

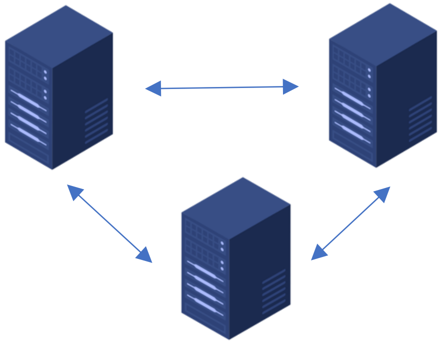
- A good practice recommended by Google, Microsoft, or Amazon
- Mandated by regulations: *NIST.SP.800-57pt1r4*, *PCI-DSS-v4-0*



Evaluation - Configuration

Servers:

- Amazon EC2 r5n.4xlarge instances
- 8-core Intel Xeon Platinum 8375C CPU @ 2.9 GHz, 128 GB RAM



Client:

- Intel i7-6820HQ CPU @ 2.7 GHz, 16 GB RAM

Implementation:

- C++ with ~2,500 LOCs
- Libraries: Secp256k1, OpenSSL, EMP-Toolkit, ZeroMQ

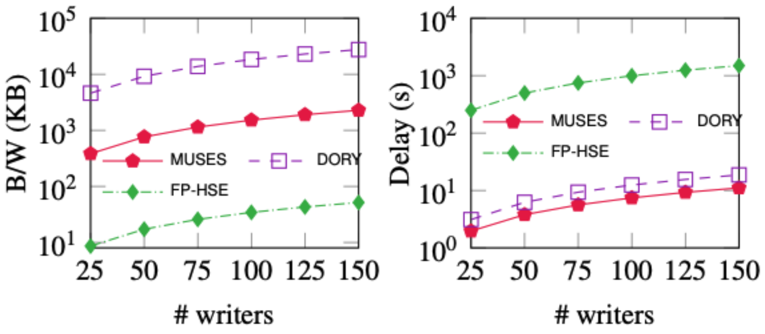
Evaluation – Search

Reader's bandwidth:

$12\times - 97\times$ smaller than DORY (hide patterns), $6\times$ larger than FP-HSE (leak patterns)

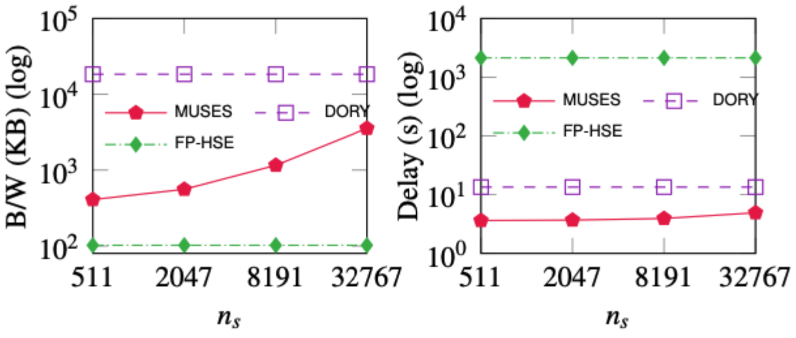
End-to-end latency:

$2\times - 4\times$ faster than DORY, $127\times - 632\times$ faster than FP-HSE



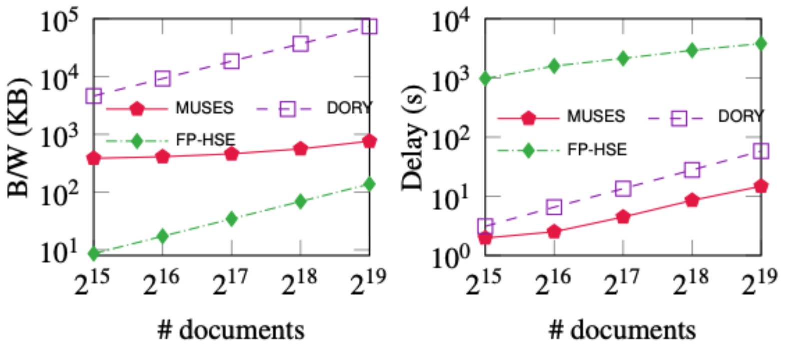
(a) Reader's bandwidth (b) E2E delay

Figure 6: Keyword search performance (log scale on y-axis).



(a) Reader's bandwidth (b) E2E delay

Figure 10: Keyword search performance with varying n_s.



(a) Reader's bandwidth (b) E2E delay

Figure 11: Keyword search performance w/ varying database sizes.

Evaluation – Permission Revocation

Writer's bandwidth:

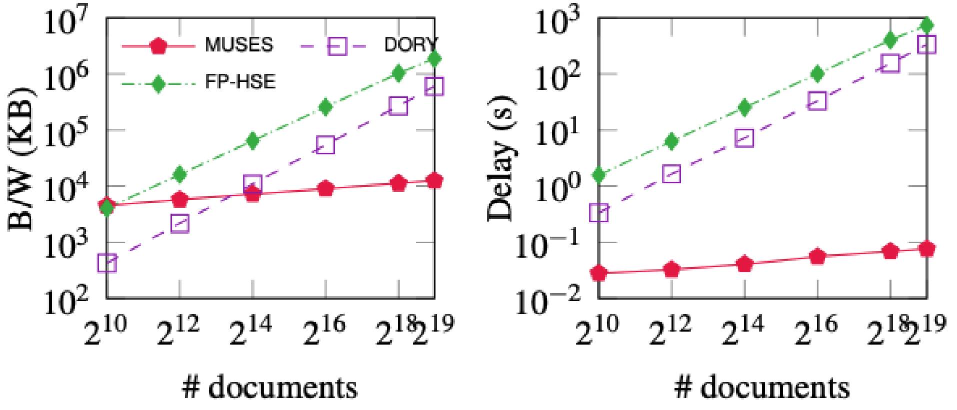
$2\times - 150\times$ smaller than DORY/FP-HSE

Writer's latency:

$12\times - 9600\times$ faster than DORY/FP-HSE

End-to-end latency:

$2\times - 6\times$ faster than DORY/FP-HSE



(a) Writer's bandwidth (b) Writer's latency

Figure 7: Permission revocation performance (log scale on y-axis).

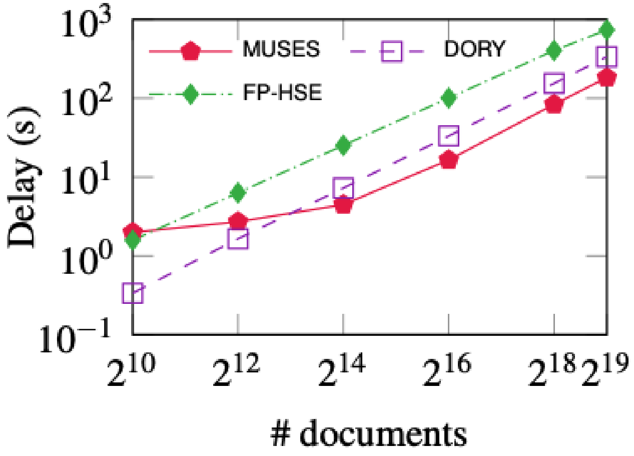
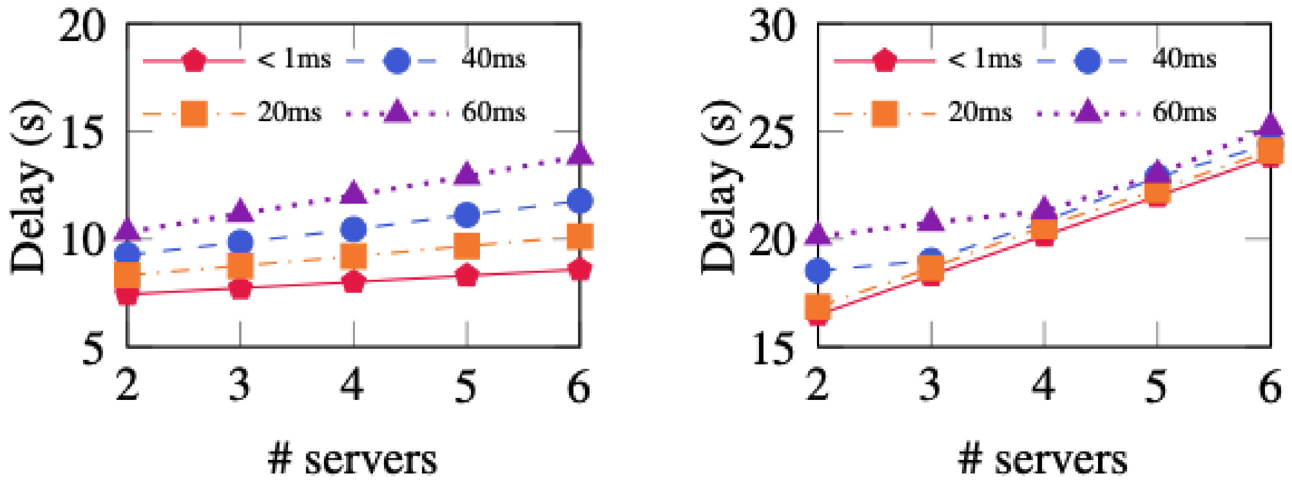


Figure 8: E2E permission revocation delay (log scale on y-axis).

Evaluation – Multiple Servers

Keyword search: 7.4s-8.6s (1ms network latency), 10.3s-13.8s (60ms latency)

Permission revocation: 16.5s-23.8s (1ms latency), 20.1s-25.2s (60ms latency)



(a) Keyword search (b) Permission revocation

Figure 12: MUSES latency with varying numbers of servers.

Conclusion

Our MUSES:

- Hide *all* statistical information: search, result, and volume patterns
- Minimal user overhead for search and permission revocation

Our artifact is available at: github.com/vt-asaplab/MUSES

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THANK FOR YOUR ATTENTION

Q&A