DATASHARE: A Decentralized Privacy-Preserving Search Engine for Investigative Journalists

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Abstract

Investigative journalists collect large numbers of digital documents during their investigations. These documents could greatly benefit other journalists’ work. However, many of these documents contain sensitive information and their possession of such documents can endanger reporters, their stories, and their sources. Thus, many documents are only used only for single, local, investigations. We present DATASHARE, a decentralized and privacy-preserving global search system that enables journalists worldwide to find documents via a dedicated network of peers. DATASHARE combines well-known anonymous authentication mechanisms and anonymous communication primitives, a novel asynchronous messaging system, and a novel multi-set private set intersection protocol (MS-PSI) into a decentralized peer-to-peer private document search engine. We show that DATASHARE is secure and scales to thousands of users and millions of documents using a prototype implementation.

1 Introduction

Investigative journalists research topics such as corruption, crime, and corporate misbehavior. Well-known examples of such practices are the Panama Papers, that resulted in several politicians’ resignations and sovereign states recovering hundreds of millions of dollars hidden in offshore accounts [3]; and the Boston Globe investigation on child abuse, that resulted in a global crisis for the Catholic Church [5]. These investigations are essential for a healthy democracy [15]. They provide the greater public with information kept secret by governments and corporations, effectively holding these institutions accountable to society at large.

In order to obtain significant, fact-checked, and impactful results, journalists require large amounts of documents. These documents often contain sensitive and/or confidential information. In a globalized world, local issues are increasingly connected to global phenomena. Thus, journalists’ collections can be very relevant for other colleagues working on related investigations. However, possessing such documents puts journalists and their sources increasingly at risk of identification, prosecution, and persecution [34, 35]. As a result journalists go to great lengths to protect both their documents and their interactions with other journalists [36]. With these risks in mind, the International Consortium of Investigative Journalists (ICIJ) approached us with the question: can a global community of journalists search each other’s documents while minimizing the risk for them and their sources?

To build a system that addresses this question we must solve five key challenges:

1) Avoid centralizing information. A party with access to all the documents and journalists’ interaction would become a very tempting target for attacks by hackers or national agencies, and for legal cases and subpoenas by governments.
2) Avoid reliance on powerful decentralized infrastructure. While ICIJ has journalists worldwide, it does not have highly-available servers in different jurisdictions.
3) Deal with asynchrony and heterogeneity. Journalists are spread around the world. There is no guarantee that they are online at the same time, nor that they have the same resources.
4) Practical on commodity hardware. For the system to be useful for journalists, they must be able to search documents and communicate with other journalist without hindering their day-to-day work. This requires the system to be computationally and communicationally efficient.
5) Enable data sovereignty. Journalists are willing to share but not unconditionally. Since journalists make their personal collection searchable, they want to have control over the sharing process. Journalists should be able to make informed decisions on revealing documents on a case-by-case basis.

The first four requirements preclude the use of available technologies in search while the fifth requirement precludes the use of automatic and rule-based document retrievals. More concretely, the first requirement eliminates central databases and private information retrieval (PIR) [12, 26, 31] between journalists, as standard PIR requires a central list of all searchable (potentially sensitive) keywords. The second requirement rules out multi-party computation (MPC) between distributed
The third and fourth requirement precludes the use of technologies that require many round trips or high bandwidth between journalists such as custom private set intersection [18, 23, 28, 30, 43], keyword-based PIR [9, 16], and generic MPC protocols [28, 41, 42, 51]; and they preclude the use of privacy-preserving communication systems that require all users to be online [32, 50].

In this paper, we introduce DataShareNetwork, a decentralized document search engine for journalists to be integrated within ICIJ’s open source tool to organize information DataShare: [1]. DataShareNetwork addresses the challenges as follows. One, journalists keep their collections in their computers such that if they are hacked, coerced, or corrupted, only her collection is compromised; even if an adversary gains the ability to search others’ documents, she cannot extract all documents nor all users in the system. Two, we introduce a new multi-set private set intersection (MS-PSI) protocol that enables asynchronous search and multiplexes queries to reduce computation and communication cost. Three, we combine existing privacy-preserving technologies [8, 21] to build a pigeonhole-like communication mechanism that enables journalists to non-irrevocably converse with each other in an unobservable manner. In the rest of the document, for simplicity, we refer to DataShareNetwork as DataShare.

Our contributions are as follows:

✓ We elicit the security and privacy requirements of a document search system for investigative journalists.
✓ We introduce MS-PSI, a private set intersection protocol to efficiently search in multiple databases without incurring extra leakage with respect to traditional PSI with pre-computation.
✓ We propose an asynchronous messaging system that enable journalists to search and converse in a privacy-preserving way.
✓ We design DataShare, a secure and privacy-preserving decentralized document search system that protects the identity of its users, the content of the queries, and to a large extent the collections themselves, from malicious users and third parties. We show that DataShare provides the privacy properties required by journalists. Using a prototype implementation of the core cryptographic primitives we show that the system can easily scale to more than 1000 participants even if their document collections have more than 1000 documents.

2 Towards Building DataShare

We build DataShare at the request of ICIJ. From now on, we may refer to ICIJ as the organization.

2.1 Requirements gathering

In order to understand the needs of investigative journalists, ICIJ ran a survey among 70 of their members and provided us with aggregate statistics, reported below. We refined the requirements in weekly meetings held for more than one year with the members of ICIJ’s Data & Research Unit, who are in charge of the development and deployment of DataShare.

User base. ICIJ consists of roughly 250 permanent journalist members in 84 countries. These members occasionally collaborate with external reporting partners. The maximum number of reporters working simultaneously on an investigation has reached 400. The organization estimates that each member is willing to make around one thousand of their documents available for searching. To accommodate growth we consider that DataShare needs to scale to (at least) 1000 users, and (at least) 1 million documents.

Journalists work and live all over the globe, ranging from Sydney to San Francisco, including Nairobi and Kathmandu, resulting in large timezone differences. Around 38% of the journalists have a computer permanently connected to the Internet, and another 53% of them only have connection during work hours (i.e., eight hours a day, five days a week). The rest are only connected during a few hours per day. Thus, message delivery time can be as high as 24 hours, therefore, the search system needs to enable asynchronous requests and responses. Furthermore, many journalists live in regions with low-quality networks: only half of the journalists report having a fast connection. Thus, DataShare cannot require high bandwidth.

Waiting time. As the system must be asynchronous, the survey asked journalists how much they are willing to wait to obtain a the result of a query. A 21% of the surveyees are willing to wait for hours, while another 56% can wait for one or more days. Thus, DataShare does not need to enable real-time search. Yet, given delivery times of up to 24 hours, to keep search latency within a few days DataShare must use protocols that can operate with just one communication round. Therefore, multi-round techniques such as multi-party computation [28, 41, 42, 51] incur too much delay.

Queries nature. The queries made by journalists are in a vast majority formed by keywords called named entities: names of organizations, people, or locations of interest. Therefore, journalists do not require very expressive querying languages. DataShare only must support queries made of conjunctions of keywords. Journalists have interest in a small set of these entities at a time: only those related to their current project. Thus, queries are not expected to include more than 10 terms at a time and each journalist is not expected to issue a large number of queries in parallel.

During the design phase we also learned that, because most terms of interest are investigation-specific (e.g., XKeyScore in the Snowden leaks, or Mossack Fonseca in the Panama Papers), a pre-defined list of terms can not cover all potentially
relevant keywords for journalists. Therefore, techniques based on fixed lists such as private information retrieval (PIR) [12, 26, 31] are not suitable to build DATASHARE.

Security and privacy. When asked about their security and privacy concerns, journalists identify four types of principals: the journalists themselves, their sources, the people mentioned in the documents, and the organization which runs DATASHARE. They also identify three assets: the named entities in documents, the documents themselves, and the conversation they have during an investigation. Disclosure of named entities could leak information about the investigation, or could harm the cited entities (who could in turn could trigger a lawsuit). They consider whole documents to be the most sensitive as they provide context for the named entities, worsening the situation. Finally, they fear that disclosure of conversations could endanger the journalists involved, their sources, the organization, and the whole investigation.

Regarding the threat model, journalists mostly consider third party adversaries such as corporations, governments (intelligence agencies), and organized crime. Sources and other journalists are in general considered non-adversarial. Similarly, journalists trust the organization as an authority for membership and to run their infrastructure. However, the organization does not want to be trusted for privacy to prevent coercion and external pressures.

The main requirement for DATASHARE is thus to protect the confidentiality of assets from third parties that are not in the system. This naturally implies that DATASHARE cannot require journalists to send their data to third-parties for analysis, storage, indexing, or search. Journalists are concerned about subsets of these adversaries at a time. Therefore, DATASHARE does not need to defend against global adversaries.

Journalists initially did not consider their colleagues as adversaries. However, our threat analysis shows that there is a non-negligible risk that powerful adversaries like governments can bribe or compromise honest journalists, in particular when those journalists live in jurisdictions with less protection for civil rights. Thus, we require that DATASHARE must minimize the amount of information that journalists, or the organization learn about others’ interests (searched keywords), collections, and conversations. This ensures that neither journalists nor the organization becomes a profitable target for adversaries. To achieve this, we require that searches are anonymous and the searched terms are kept confidential with respect to both journalists and the organization.

With respect to conversations, 64% of the surveyees report that they would prefer to stay anonymous in some cases. Furthermore, 60% of the respondents declare that they prefer to have a screening conversation before deciding to share documents. This means that search and sharing features need to be separated to enable screening. Moreover, to provide such protection, DATASHARE must provide anonymous means for journalists to discuss document sharing. Conversations within DATASHARE are expected to be short, as their only goal is to either agree on whether to collaborate. After they agree, they switch to an alternative secure communication channel. In particular, DATASHARE does not provide built-in document retrieval functionality.

2.2 Sketching DATASHARE

DATASHARE is run by ICIJ. Access to the system is exclusive to ICIJ members, and authorized collaborators. Journalists trust ICIJ to act as a token issuer that certifies authorized journalists. To enable journalists to stay anonymous, these tokens are implemented using blind signatures, so that journalists can demonstrate membership without revealing their identities.

DATASHARE assumes infrastructure to facilitate asynchronous communication between journalists. It consists of: a bulletin board that journalists use to broadcast information, and a pigeonhole for 1-to-1 communication. Communication between journalists and the infrastructure (pigeonhole or bulletin board) is anonymous. Moreover, all communication is end-to-end encrypted (i.e., from journalist to journalist). Thus, the infrastructure needs to be trusted for availability, but not to protect the privacy of the journalists and their documents.

Each authorized journalist in DATASHARE owns a corpus of documents which they make available for search. Journalists can take two roles in the system: i) querier, to search for documents of interest, and ii) document owner, to have their corpus searched. Journalists first search for matching documents, and then (anonymously) converse with the corresponding document owners to request the document.

Figure 1 sketches DATASHARE’s architecture. First, journalists upload privacy-preserving representations of their collections and contact information to the bulletin board. Then, to issue a query, journalists construct a privacy-preserving representation of their keywords authorized by a token, and broadcast it using the bulletin board. Owners periodically retrieve new queries from the bulletin board. If the authorization is valid, they send a response back to the querier using the pigeonhole. This response enables the querier to identify
matches with the documents in the owner’s collection.

When journalists find a match in a collection, i.e., a document that contains all the keywords in the query, they can start a conversation with the document owner to ask them to share the document. Document owners append a public contact key to their collection to enable queriers to carry out this conversation in an anonymous way via the pigeonhole.

**Instantiation.** DATASHARE uses four main privacy-preserving building blocks: a multi-collection search mechanism, a messaging system, an anonymous communication channel, and an authorization mechanism.

We implement the privacy-preserving search mechanism using a novel primitive, which we call multi-set private set intersection (MS-PSI) described in Section 3. We design a privacy-preserving messaging system in Section 4 which provides both the bulletin board and pigeonhole functionality. As anonymous communication channel, we rely on the Tor [21] network. Finally, we use blind signatures to implement privacy-preserving authorization, see Section 5.1. Section 5.2 explains how DATASHARE combines these building blocks.

### 3 Multi-Set PSI

Private set intersection (PSI) protocols enable two parties holding sets X and Y to compute the intersection \( X \cap Y \) without revealing information about the individual elements in the sets. We review existing PSI variants in Section 6. In this section we introduce a multi-set private set intersection (MS-PSI) protocol that computes intersections of set X with N sets \( \{Y_1, \ldots, Y_N\} \) at the server simultaneously.

**Notation.** (See Table 1) We use a cyclic group \( \mathbb{G} \) of prime order \( p \) generated by \( g \). We write \( x \leftarrow \mathcal{U} \mathbb{G} \) to denote that \( x \) is drawn uniformly at random from the set \( \mathbb{G} \). Let \( \ell \) be a security parameter. We define two hash functions \( H : \{0,1\}^\ell \rightarrow \{0,1\}^\ell \) and \( \tilde{H} : \{0,1\}^\ell \rightarrow \mathbb{G} \). Finally, we write \( [n] \) to denote the set \( \{1, \ldots, n\} \).

| Client | Server |
|--------|--------|
| \( X = \{x_1, \ldots, x_m \} \subset \mathbb{G} \) | \( Y = \{y_1, \ldots, y_n \} \subset \mathbb{G} \) |
| \( c \leftarrow \mathcal{U} \mathbb{Z}_p \) | \( s \leftarrow \mathcal{U} \mathbb{Z}_p \) |
| \( \tilde{x}_i = x_i^c \) | \( \tilde{y}_i = y_i^s \) |
| \( \mathcal{T}_i = H(x_i^{-1}) \) | \( \tilde{y}_i = H(y_i^s) \) |
| Return \( \{x_i | \mathcal{T}_i \in \mathcal{T}\} \) | TC = \( \{H(y^s) \mid y \in Y\} \) |

**Figure 2:** Vanilla PSI protocol by De Cristofaro et al. [17].

**Related PSI schemes.** We build on the single-set PSI protocol by De Cristofaro et al. [17], see Figure 2. In this protocol, before sending her elements \( x_i \in \mathbb{G} \) to the server, the client blinds them as \( \tilde{x}_i = x_i^c \) using a blinding factor \( c \). The server applies its own secret to the blinded elements, \( \tilde{x}_i = x_i^s \), and sends them back to the client in the same order, together with a tag collection of her own blinded elements: \( \mathcal{T}_i = \{H(y^s) \mid y \in Y\} \). The client unblinds her elements, obtaining a list of \( x_i^s \). She computes a tag \( H(x_i^s) \) for each of them and compares it to the server’s tags TC to find matching elements.

To increase efficiency when the server set is large, client-server PSI (C-PSI) schemes in the literature [23, 30, 48] introduce optimizations to avoid that the server has to compute and send a large fresh set of tags every execution. Instead, the server precomputes the tag collection with a long-term secret key \( s \) and sends it to the client once. In subsequent online phases, the server answers clients’ queries using the long-term key \( s \). This drastically improves the communication and computation cost as the server does not compute nor send the tag collection.

**A new multi-set PSI protocol.** Our multi-set private set intersection protocol (MS-PSI) intersects a client set \( X = \{x_1, \ldots, x_m\} \subset \{0,1\}^\ell \) with \( N \) sets \( Y_1 = \{y_1, \ldots, y_{i,n}\} \subset \{0,1\}^\ell \) at the server to obtain the intersections \( X \cap Y_i \). Our protocol computes all intersections simultaneously, lowering the computation and communication cost with respect to running \( N \) parallel PSI protocols. In DATASHARE, \( X \) contains the query which is a conjunction of search keywords, and \( Y_i \) represents document \( i \)’s keywords. (see Section 5.2). We use \( \tilde{H} \) to map keywords to group elements.

A naive approach is to mimic the client-server protocols and reuse the long-term key \( s \) for all sets \( Y_i \). This approach, however, maps identical elements in sets \( Y_i, Y_j \) to the same tag, thus, revealing intersection cardinalities \( |Y_i \cap Y_j| \).

To remove the link between tags across sets, we add a tag diversifying step to the precomputation phase of client-server PSI (see Figure 3). We first compute pretags \( \tau_i \) for each set \( Y_i \) by raising each element to the power of the long-term secret \( s \). Then, we compute per-set tags by hashing the pretags \( r \) with the set index \( j \) to obtain \( H(y^s \parallel j) \). The hash-function ensures that the tags of each set are independent. The server publishes the tag collection TC and the number of sets \( N \).
During the online phase, the client blinds its set as in the vanilla PSI protocol and sends it to the server. The server re-blinds with its secret $s$ and sends them back to the client in the same order. The client unblinds the result to obtain the pretags for her elements. The client then computes the corresponding tags $T^{(d)}$, for each document $d \in [N]$, and computes the intersection.

In Appendix A we prove the following theorem to show that the server learns nothing about the client’s set, and that the client learns nothing more than the intersections $X \cap Y_i$.

**Theorem 1.** The MS-PSI protocol is private against malicious adversaries in the random oracle model for $H$ and $\hat{H}$, assuming the one-more-gap Diffie-Hellman assumption holds.

The MS-PSI protocol does not provide correctness against a malicious server. A malicious server can respond arbitrarily which leads to the client computing an incorrect intersection. However, Theorem 1 shows that the malicious server cannot gain any information about the client’s set from doing so.

**Performance.** Table 2 compares the performance of our MS-PSI protocol with the vanilla and the client-server PSI protocols in the multi-set setting. We show the computation and communication cost for a server with $N$ sets and a client set with $m$ elements. MS-PSI reduces the server’s online communication and computation by a factor $N$. The client can replace expensive group operations by cheap hash computations, drastically reducing the online cost of the client as well. The example costs for $N = 1000$ (in brackets) bear this out and show an improvement of 3 orders of magnitude.

### Table 2: Performance of PSI variants in a multi-set scenario

|               | Vanilla | C-PSI   | MS-PSI  |
|---------------|---------|---------|---------|
| **Precomputation phase** |         |         |         |
| Server        | $S\tau_{H+e}$ | $S\tau_{H+e}$ | $S\tau_{H+e}$ |
| Comms         | $S$     | $S$     | $S$     |
| **Online phase** | [11 s]  | [1 s]   | [1 ms]  |
| Client        | $2mN\tau_{H+e}$ | $2mN\tau_{H+e}$ | $2m\tau_e + mN\tau_H$ |
|               | [2 s]   | [2 s]   | [12 ms] |
| Server        | $m\tau_e + mN\tau_e$ | $m\tau_e$ | $m\tau_e$ |
|               | [11 s]  | [1 s]   | [1 ms]  |
| Comms         | $S + 2mN$ | $2mN$   | $2m$    |
|               | [3.84 MB]| [640 KB]| [640 B] |

## 4 Privacy-preserving messaging

In this section, we introduce DATASHARE’s communication system (CS). Journalists use the CS to support MS-PSI-based search and to converse anonymously after they find a match. The CS needs to respect the organization’s limitations (see Section 2.1). The communication cost should not hinder the day to day operation of journalists, and the system must support asynchronous communication. As the organization cannot deploy non-colluding nodes, the communication system uses one server. This server is trusted for availability, but not for privacy.

DATASHARE’s communication system is designed to host short conversations for discussing the sharing of documents. We anticipate that journalists will migrate to using encrypted email or secure messengers if they need to communicate over a long period or they need to send documents.

### 4.1 Messaging system construction

The server provides two components: a bulletin board for broadcast messages, and a pigeonhole for point-to-point messages. We use communication server to refer to the entity that operates the bulletin board and the pigeonhole. To hide their network identifiers from the server and network observers, journalists always use Tor [21] when communicating with this server. DATASHARE creates a new circuit for every request to ensure unlinkability.

**Bulletin board.** The bulletin board implements a database that stores broadcast messages. Journalists interact with the bulletin board using two protocols: BB.broadcast$(m)$, which
adds a message $m$ to the database and broadcasts it to all jour-
nalists; and $m \leftarrow \text{BB.read}()$ to retrieve any unseen messages.

**Pigeonhole.** The pigeonhole consists of a large number of
one-time-use mailboxes. Journalists use the pigeonhole to
send and receive replies to search-queries and conversation
messages. Journalist call PH.SendRaw (Protocol 1) to send
query replies, and use the asynchronous process PH.Recv-
Process (Protocol 2) to retrieve incoming query replies and
conversation messages. Journalists use PH.Monitor (Pro-
col 3) to receive notifications of new messages from the pi-
geonhole and to trigger PH.RecvProcess. The pigeonhole
deletes old messages. In agreement with the organization,
it deletes messages older than 7 days, as journalists are ex-
pected to connect to the system several times a week (see
Section 2.1).

Journalists are likely to initiate a conversation after receiv-
ing a successful match. To hide this event we ensure that the
sending of conversation messages is unobservable (see Defini-
tion 1): the server cannot determine whether a user
sends a conversation message or not. This hides whether a
conversation happens, which in turn hides whether the search
revealed a match or not. To ensure unobservability of con-
versation messages, journalists run PH.Cover (Protocol 4)
to send cover messages at a constant Poisson rate to every
other journalist. To send a conversation message, it suffices to
replace one of the cover messages with the real message (see
PH.HiddenSend, Protocol 5).

Journalists use the Diffie-Hellman key exchange to com-
pute mailbox addresses and message encryption keys. They
use different keys for different purposes. Queriers generate
a fresh key for every query and use that key to receive query
replies, and to send conversation messages associated with a
query. Document owners use a medium-term key to send
query replies and to receive conversation messages from queri-
ers (see Section 5.2). Moreover, journalists exchange
cover traffic. They use fresh cover keys to send cover traffic
and their medium-term keys to receive cover traffic. Journal-
ists use an authenticated encryption scheme $AE$ to encrypt
messages.

**Protocol 1** (PH.SendRaw($sk_5, pk_R, m$)). To send message $m$
to recipient $R$ with public key $pk_R$, a sender with private key
$sk_5$ proceeds as follows. Let $n_i$ be the number of times $S$ called
PH.SendRaw to send a message to $R$ before the sender:
1. computes the Diffie-Hellman key $k' = \text{DH}(sk_5, pk_R)$;
2. computes the random rendezvous mailbox $addr =
H(\text{addr}' || k' || pk_R || n_i)$ and a symmetric key
$k = H(\text{key}' || k' || pk_R || n_i)$;
3. pads the message $m$ to obtain $m'$ of length $mlen$, and
computes the ciphertext $c = \text{AE.enc}(k, m')$;
4. opens an anonymous connection to the pigeonhole and
uploads $c$ to mailbox $addr$.

For every upload, the pigeonhole notifies all monitoring re-
cievers (see PH.Monitor below) that a message arrived at $addr$.

**Protocol 2** (PH.RecvProcess($sk_R, pk_R$)). To receive a mes-
sage from sender $S$ with public key $pk_S$, a receiver $R$ with
private key $sk_R$ runs the following asynchronous process. Let
$n_i$ be the number of times $R$ successfully received a message
from $S$. The receiver:
1. computes the Diffie-Hellman key $k' = \text{DH}(sk_R, pk_S)$;
2. uses $k'$ to compute a random rendezvous mailbox
$addr = H(\text{addr}' || k' || pk_S || n_i)$ and a symmetric key
$k = H(\text{key}' || k' || pk_S || n_i)$;
3. waits until PH.Monitor (see below) receives a notification
of a new message on address $addr$. If no message is posted
to $addr$ in 7 days, the process terminates;
4. opens an anonymous connection to the pigeonhole and
downloads the ciphertext $c$ at address $addr$ (if there was
no message due to a false positive, the process continues
at step 3); and
5. decrypts the message $m' = \text{AE.dec}(k, c)$ and returns the
unpadded message $m$ or ⊥ if decryption failed.

When the receiver goes offline, this process is paused, and
resumed when the receiver comes online again.

We note that a sender may send multiple messages with-
out receiving a response. The receiver calls PH.RecvProcess
repeatedly to receive all messages ($n_i$ increases every time).
Participants keep track of the message counters $n_i, n_r$ for
each pair of keys ($sk_5, pk_R$) and ($sk_R, pk_S$) respectively to ensure
they derive the correct addresses and decryption keys.

**Protocol 3** (PH.Monitor). Journalists run the PH.Monitor pro-
cess to monitor for incoming messages. The receiver:
1. opens an anonymous monitoring connection to the pi-
geonhole and requests a list of addresses $addr$ that re-
ceived a message since she was last online
2. via the same anonymous connection receives notifications
of addresses $addr$ with new messages.

Addresses $addr$ received in step 1 or 2 can cause the PH.Recv-
Process processes to continue past step 3. To save bandwidth,
the pigeonhole sends a cuckoo filter [24] containing the ad-
dresses in step 1, and only the first 2 bytes of the address in
step 2 (PH.RecvProcess handles false positives).

The PH.Cover and PH.HiddenSend protocols ensure con-
versation messages are unobservable. Senders store a queue
of outgoing conversation messages for each recipient.

**Protocol 4** (PH.Cover($sk_5$)). Every journalist starts the
PH.Cover process as soon as they come online. Let $sk_5$ be the
medium-term private key, and $pk_1, \ldots, pk_{m-1}$ be the medium-
term public keys of the other journalists. The process runs the
following concurrently:
- **Cover keys.** Draw an exponential delay $t_k \leftarrow \text{Exp}(1/k_k)$,
and wait for time $t_k$. Generate a fresh cover key-pair
$(sk_, pk_)$ and upload $pk_2$ to the bulletin board by calling
BB.broadcast($pk_2$). Repeat.
- **Sending messages.** Wait until the first cover key $pk_2$ has
been uploaded. For each recipient $pk_3$ proceed as follows:
1. Draw \( t_i \leftarrow \text{Exp}(1/\lambda_c) \) and wait for time \( t_i \).
2. Let \( m_i \) be the first message in the send queue for \( \text{pk}_S \) or a dummy message if the queue is empty. Send the message by calling \( \text{PH.SendRaw}(\text{sk}_S, \text{pk}_R, m_i) \).
3. Repeat.

- **Receiving cover messages.** For each non-expired cover key \( \text{pk}'_C \) on the bulletin board call \( m \leftarrow \text{PH.RecvProcess}(\text{sk}_R, \text{pk}'_C) \). If \( m \) is a real message (see Section 5.2) forward the message to DATASHARE, otherwise discard. Repeat.

This process stops when the user goes offline, and \( \text{PH.RecvProcess} \) processes started by \( \text{PH.Cover} \) are canceled.

**Protocol 5** (\( \text{PH.HiddenSend}(\text{sk}_S, \text{pk}_R, m) \)). To send a message \( m \) to recipient \( R \) with public key \( \text{pk}_R \), sender \( S \) with private key \( \text{sk}_S \) places \( m \) in the send queue for \( \text{pk}_R \).

### 4.2 Messaging service privacy

We first define what we mean by unobservable messages and then prove that conversation messages sent using \( \text{PH.HiddenSend} \) are unobservable.

**Definition 1** (Unobservability). A conversation message is unobservable if all PPT adversaries have a negligible advantage in distinguishing a scenario in which the sender \( S \) sends a conversation message to the receiver \( R \), from a scenario where \( S \) does not send a conversation message to \( R \).

**Theorem 2.** Messages sent using \( \text{PH.HiddenSend} \) are unobservable towards any adversary who controls the communication server but does not control the sender or the receiver, assuming the receiver awaits both conversation and cover messages. This statement is also true when the adversary can break the network anonymity Tor provides.

**Proof.** To show conversation messages are unobservable, we must prove that the following two scenarios are indistinguishable: the scenario in which the sender sends a conversation message (sent by \( \text{PH.Cover} \) after a conversation message has been queued using \( \text{PH.HiddenSend} \)), and the scenario in which the sender sends a cover message (sent by \( \text{PH.Cover} \) when no conversation message has been queued). The intuition behind this proof is that conversation and cover messages are indistinguishable: (1) both are encrypted so that the adversary cannot distinguish them based on content; and (2) conversation messages replace cover messages, so they are sent using the same schedule.

All messages go through the pigeonhole. For each message, the adversary observes: 1) the pigeonhole address, 2) the content, 3) the length, 4) the timestamps at which the message was posted and retrieved, and 5) the sender and the receiver (in a worst case scenario in which the adversary can break the anonymity Tor provides). We show that the adversary’s views in both scenarios are indistinguishable.

The content and pigeonhole address of messages are graphically indistinguishable. Senders and receivers compute rendezvous mailbox addresses using a Diffie-Hellman key exchange based on either the query public key and the owner’s public key (when the message is a conversation messages) or the sender and receiver’s cover keys (when the message is a cover message). Since the adversary does not control the sender or the receiver, it does not know the corresponding private keys in either scenario. Under the decisional Diffie-Hellman assumption, the adversary cannot distinguish between mailbox addresses for conversation messages and mailbox addresses for cover messages.

Under the same DH assumption, the adversary cannot learn the symmetric key \( k \) which is used to encrypt the message either. Moreover, all messages are padded to a fixed length of \( mlen \). Thus, the adversary cannot distinguish between the two situations based on message content or length.

As a result, all messages sent between sender \( S \) and receiver \( R \) are indistinguishable to the adversary on the cryptographic layer. We now show that the post and retrieve times of the messages are also independent of whether the message is a cover message or a conversation message.

**Sender.** The “cover keys” and “sending messages” processes of \( \text{PH.Cover} \) are by design independent of whether a conversation message should be sent or not. In the “sending messages” process, the sender sends real or cover messages to the recipient at a constant rate \( \lambda_c \). The send times are independent of whether the sender’s queue for the receiver is empty or not.

**Receiver.** The receiver is listening to both conversation and cover messages from the sender. Therefore, as soon as it is notified of a new message, \( \text{PH.RecvProcess} \) will retrieve this message. The retrieval time therefore does not depend on the type of message.

As a corollary of the unobservability proof, we have the following theorem.

**Theorem 3.** The pigeonhole protects the secrecy of messages from non-participants including the communication server.

Users of DATASHARE communicate with the communication server via Tor to hide their (network) identities from the communication server. In particular, we require sender anonymity to hide a querier’s identity from document owners, and receiver anonymity to hide a document owner’s identity from queriers. Using Tor ensures these properties even when journalists collude with the communication server. Formally, we define sender and receiver anonymity as follows:

**Definition 2** (Sender anonymity). A communication system provides sender anonymous if any PPT adversary has a negligible advantage in guessing the sender of a message.

**Definition 3** (Receiver anonymity). A communication system provides receiver anonymous if any PPT adversary has a negligible advantage in guessing the receiver of a message.
We shaped the traffic based on the Poisson distribution to provide unobservability. However, such strong protection comes at a cost [20]: Regardless of whether they have zero, one, or many conversations, every journalist sends messages at a rate \( \lambda_c \) to the other \( N \) journalists, \( \lambda_cN \) per day. Consequently, every journalist also receives \( \lambda_cN \) messages a day.

Figure 4, left, illustrates the trade-off between bandwidth overhead and latency for a given cover traffic rate. When journalists send few messages a day, the bandwidth requirements are very low. For instance, setting \( \lambda_c \) to be 4 messages per day requires every journalist to use 16.5 MB per day, including the sending of notifications and the updating of cover keys. For these messages to be unobservable, however, journalists can only exchange a few messages per day. Journalists have to wait on average 6 hours between messages (less than 18 hours in 95% of the cases). If journalists require better throughput they must consume more bandwidth. For example, setting \( \lambda_c = 48 \) messages a day ensures that messages are sent within half an hour on average (and within 90 minutes with probability 95%). Storing messages from the last 7 days on the pigeonhole for 1000 journalists and send rate of \( \lambda_c = 48 \) requires 390 GB which is manageable for a server.

The latency we report in Figure 4 assumes that journalists are online. If they disconnect from the system before a message is sent, they must, after coming online again, first upload a new cover key, and then draw a new sample from \( \text{Exp}(\lambda_c) \) to decide when to send their message. We propose to set the update latency \( \lambda_k \) to \( \lambda_c/4 \), so that the initial latency is at most 25% more than the latency under normal circumstances.

For the current size of the population that will use DATASHARE, 250 journalists (see Section 2.1), the bandwidth can be kept reasonable at the cost of latency. However, as journalists send cover traffic to everyone, the bandwidth cost increases quadratically with the size of the population, see Figure 4, center, and becomes pretty heavy after reaching 2000 journalists.

**An alternative construction.** If the traffic requirements become too heavy for the organization members, bandwidth can be reduced by increasing the computation cost at the pigeonhole server. Instead of using cover traffic to all journalists to
hide the mailboxes that contain real messages, journalists can retrieve messages using computational private information retrieval (PIR) \cite{8,31}.

In this approach, senders send cover messages at a rate $\lambda_{PIR}$, independent of the number of journalists, to random mailboxes. When they have a real message, they send it instead of a cover message. They use the same rate to retrieve messages using PIR. The PIR hides the messages which are getting retrieved from the pigeonhole and breaks the link between the send and receive time. As a result, the server’s observation of the system is independent of whether journalists send a real message or not.

We illustrate the trade-off of this approach in Figure 4, right, using SealPIR \cite{8} to retrieve cover and conversation messages. Responding to a PIR request in a scenario of 1000 journalists and send rate of 6 message per hour takes 12 seconds. Therefore, we assume a server with 24 cores (approx 1300 USD/month in AWS) can handle this scenario. We see that this approach enables the system to send conversation messages at a higher rate and a lower cost. For example, sending 6 messages per hour (144 messages a day) requires around 59 MB. However, as opposed to the Poisson cover approach described in the previous section, this rate limits the total number of messages per day regardless of recipient. Thus, depending on the number of receivers journalists want to communicate on average, one or the other method could be more advantageous.

5 The DATASHARE System

In this section, we present DATASHARE. DATASHARE’s design combines the multi-set private set intersection protocol (Section 3), the privacy-preserving communication system (Section 4), and an anonymous authentication mechanism to enable asynchronous decentralized peer-to-peer document searching.

5.1 Preliminaries

Processing documents. The primary interests of investigative journalists are named entities, such as people, locations, and organizations (see Section 2.1). ICIJ has already developed a tool \cite{1} which uses natural language processing to extract named entities from documents. After the extraction, the tool transforms named entities into a canonical form to reduce the impact of spelling variation in names. We employ this tool to canonicalize queries too. An advantage of using this tool over simply listing all words in a document is that it reduces the number of keywords per document: the majority of documents have less than 100 named entities.

Search. DATASHARE uses the MS-PSI protocol as a pairwise search primitive between journalists. The querier acts as MS-PSI client, and the client’s set represents the querier’s search keywords. The document owners act as MS-PSI servers, where the server’s $N$ sets represent the keywords in each of the owner’s $N$ documents. Therefore, each document owner has a different corpus and secret key. Matching documents correspond to documents that contain all query keywords (i.e., the conjunction of the query keywords, see Section 2.1). MS-PSI speeds up the computation and reduces the communication cost by a factor of $N$ compared to the naive approach of running one PSI per document.

Authenticating journalists. Only authorized journalists such as members of the organization or collaborators are allowed to make queries and send conversation messages. DATASHARE’s authentication mechanism operates in epochs for which journalists obtain a limited number of anonymous tokens. Tokens can only be used once, rate-limiting the number of queries that journalists can make per epoch. This ensures that compromised journalists can extract limited information from the system by making search queries. We considered using identity-escrow mechanisms to mitigate damage by misbehaving journalists. However, in agreement with the organization, we decided against this approach since such mechanisms could too easily be abused to identify honest journalists.

Recall from Section 2.1 that journalists trust the organization as an authority for membership, and already have means to authenticate themselves to the organization. Therefore, the organization is the natural choice to issue anonymous tokens. We note that, even if the organization is compromised, it can do limited damage as it cannot link queries nor conversations to journalists (because of token anonymity). However, it can ignore the rate-limit, enabling malicious queriers to extract more information than allowed. To mitigate this risk, DATASHARE could also work with several token issuers and require a threshold of valid tokens.

For the epoch duration, the organization proposes one month to provide a good balance between protection and ease of key management. Rate-limits are flexible. The organization can decide to provide additional one-time-use tokens to journalists that can motivate their need. While this reveals to the organization which journalists are more active, it does not reveal what they use the tokens for.

Instantiation. Tokens take the form of a blind signature on an ephemeral signing key. We use Abe’s blind signature (BS) scheme \cite{6}. The organization runs BS.Setup$(1^n)$ to generate a signing key $\text{msk}$ and a public verification key $\text{mpk}$. To sign an ephemeral key $\text{pk}_T$, the journalist and the organization jointly run the BS.Sign$(\cdot)$ protocol. The user takes as private input the key $\text{pk}_T$, and the organization takes as private input its signing key $\text{msk}$. The user obtains a signature $C$ on $\text{pk}_T$. The verification algorithm BS.Verify$(\text{mpk}, C, \text{pk}_T)$ returns $\top$ if $C$ is a valid for $\text{pk}_T$ and $\bot$ otherwise. These blind signatures are anonymous: the blindness property of BS ensures that the signer cannot link the signature $C$ or the key $\text{pk}_T$ to the journalist that ran the corresponding signing protocol.

Let $sk_f$ be the private key corresponding to $\text{pk}_f$. We call
T = (s_{kr}, C) an authentication token. The organization requires journalists to authenticate themselves before issuing a query or sending a message. To authenticate, journalists create a signature σ on the message using s_{kr}, and append the signature σ and blind signature C on pk_{r}.

Anonymous authentication with rate-limiting could alternatively have been instantiated with n-times anonymous credentials [14]; single show anonymous credentials [11, 13]; or regular anonymous credentials [10, 46] made single-show. We opted for the simplest approach.

Cuckoo filter. DATASHARE uses cuckoo filters [24] to represent tag collections in a space-efficient manner. The space efficiency comes at the price of having false positives when answering membership queries. The false negative ratio is always zero. The false positive ratio is a parameter chosen when instantiating the filter. Depending on the configuration, a cuckoo filter can compress a set to less than 2 bytes per element regardless of the elements’ original size.

Users call CF.compress(S, params) to compute a cuckoo filter CF of the input set S using the parameters specified in params. Then, CF.membership(CF, x) returns true if x was added to the cuckoo filter, and false otherwise. For convenience, we write CF.intersection(CF, S′) to compute the intersection S′ ∩ S with the elements S contained in the cuckoo filter. The function CF.intersection can be implemented by running CF.membership on each element of S′.

5.2 DATASHARE protocols and design

The journalists’ organization sets up the DATASHARE system by running SystemSetup (Protocol 6). Thereafter, journalists join DATASHARE by running JournalistSetup (Protocol 7). Journalists periodically call GetToken (Protocol 8) to get new authentication tokens, and Publish (Protocol 9) to make their documents searchable. DATASHARE does not support multi-devices and the software running on journalists’ machines automatically handles key management without requiring human interaction. If a journalist’s key is compromised, she contacts the organization to revoke it. Figure 5 shows how these protocols are integrated into DATASHARE.

Protocol 7 (JournalistSetup). The journalist organization runs SystemSetup to set up the DATASHARE system:

1. The organization generates a cyclic group G of prime order p with generator g, hash functions $H : \{0, 1\}^* \rightarrow \{0, 1\}^t$ and $\hat{H} : \{0, 1\}^* \rightarrow G$ for use in the MS-PSI protocols. It selects parameters params for the cuckoo filter and sets the maximum number of query keywords $\text{lim}$ (we use $\text{lim} = 10$). The organization publishes these.
2. The organization sets up a token issuer by running $(\text{msk}, \text{mpk}) = \text{BS.Setup}(1^t)$ and publishes mpk.
3. The organization sets up a communication server, which provides a bulletin board and a pigeonhole.

Protocol 8 (GetToken). Journalists run GetToken to obtain one-time-use authentication tokens from the organization.

1. The journalist J connects to the organization and authenticates herself. The organization verifies that J is allowed to obtain an extra token, and aborts if not.
2. The journalist generates an ephemeral signing key $(s_{kr}, pk_{r})$; runs the BS.Sign() protocol with the organization to obtain the organization’s signature C on the message pk_{r} (without the organization learning s_{kr}); and stores the token T = (s_{kr}, C).

At the beginning of each epoch, journalists repeatedly run the GetToken protocol to obtain tokens for the new epoch.

Protocol 9 (Publish). Journalists run Publish to make their documents searchable. It takes as input a token $T = (s_{kr}, C)$ and a set Docs = {d_1, ..., d_N} of N documents such that each document $d_i$ is a set of keywords in $\{0, 1\}^*$. This protocol includes the pre-computation phase of MS-PSI.

1. The journalist chooses a secret key $s \leftarrow \mathbb{Z}_p$ and computes her tag collection for the MS-PSI protocol as $TC = \{H(i \| \hat{H}(y)^i) \mid i \in [N], y \in d_i\}$, and compresses it into a cuckoo filter $CF = CF.compress(TC, \text{params})$.
2. The journalist generates a long-term pseudonym nym, and a medium-term contact key pair $(\text{sk}, \text{pk})$.
3. The journalist encodes her pseudonym nym, public key pk, compressed tag collection CF, and the number of documents N as her public record

$$\text{Rec} = (\text{nym}, \text{pk}, CF, N).$$

4. The journalist signs her record $\sigma = \text{Sign}(s_{kr}, \text{Rec})$ and runs $\text{BB.broadcast}(\text{Rec} \parallel \sigma \parallel \text{pk}_{r} \parallel C)$ to publish it.

DATASHARE automatically rotates (e.g., every week) the medium-term contact key of journalists $(\text{sk}, \text{pk})$ to ensure forward secrecy. This prevents that an attacker that obtains a journalist’s medium-term private key can recompute the mailbox addresses and encryption key of messages sent and received by the compromised journalist.

Journalists retrieve all public records from the bulletin board. They run $\text{Verify}(pk_{r}, \sigma, \text{Rec})$ to verify the records against the ephemeral signing key, run BS.Verify(pk_{r}, C, mpk) to validate the blind signature, and check that they have not seen pk_{r} before. Journalists discard invalid records.

DATASHARE incorporates MS-PSI into its protocols to enable the search. Querying works as follows (Fig. 5): (1) The querier posts a query together with a fresh key pk_{q} to the bulletin board (Protocol 10); (2) Document owners retrieve these
queries from the bulletin board (2a), they compute the reply address, and they send the reply to a pigeonhole mailbox (2b, see Protocol 11); (3) The querier monitors the reply addresses for all document owners, retrieves the replies, and computes the intersection to determine matches (Protocol 12).

**Protocol 10 (Query).** Queriers run Query to search for keywords $X$. The protocol takes as input a token $T = (sk_F, C)$.

1. The querier generates a key pair $(sk_q, pk_q)$ for the query and pads $X$ to 160 keywords by adding random elements.

2. As in the MS-PSI protocol, the querier picks a fresh blinding factor $c \leftarrow \mathbb{Z}_p$, and computes:

\[
Q = \{\tilde{H}(x)^c \mid x \in X\}.
\]

3. The journalist signs the query $Q$ and its public key $pk_q$ as

\[
\sigma = \text{Sign}(sk_F, Q || pk_q),
\]

and broadcasts the query $Q$, public key $pk_q$, signature $\sigma$, ephemeral token key $pk_F$, and token $C$ by running $BB$.broadcast($Q || pk_q || \sigma || pk_F || C$).

Recall that MS-PSI perfectly hides the keywords inside queries, so they can be safely broadcasted.

**Protocol 11 (Reply).** Document owners run Reply to answer a query ($Q, pk_q, \sigma, pk_F, C$) retrieved from the bulletin board.

1. The owner verifies the query by checking $\text{Verify}(pk_F, \sigma, Q || pk_q)$, $BS$.Verify($mpk, C, pk_q$), and that she did not see $pk_F$ before. If any verification fails, she aborts.

2. The owner uses her secret key $x$ to compute the MS-PSI response $R = \{x^c \mid x \in Q\}$ to the query.

3. Let $sk$ be the owner’s medium-term private key. She runs $PH$.SendRaw($sk, pk_q, R$) to post the result to the pigeonhole, and starts the process $PH$.RecvProcess($sk, pk_q$) to await conversation messages from the querier (see Converse below).

**Protocol 12 (Process).** Queriers run the Process protocol for every journalist $J$ with record $Rec = (nym, pk, CF, N)$ to retrieve and process responses to their query ($Q, sk_q, c$).

1. The querier runs the asynchronous protocol $R \leftarrow PH$.RecvProcess($sk_q, pk$) to get the new response.

2. Similar to MS-PSI, the querier computes the size of the intersection $I_i$ for each document $d_i, 1 \leq i \leq N$, as

\[
I_i = \left|\text{CF}.\text{intersection}\left(\text{CF}, \{H(i || x^{e^{-1}}) \mid x \in R\}\right)\right|,
\]

3. Let $q = |Q|$. The querier learns that the owner’s key has $t = \{|I_i = q|\}$ matching documents.

After finding a match the querier and owner can converse via the pigeonhole to discuss the sharing of documents using the Converse protocol.

**Protocol 13 (Converse).** Let $(sk_q, pk_q)$ be the query’s key-pair, and $(sk_o, pk_o)$ the owner’s medium-term key-pair at the time of sending the query.

- The querier sends messages $m$ to the owner by calling $PH$.HiddenSend($sk_q, pk_o, m$), and awaits replies by calling $PH$.RecvProcess($sk_q, pk_o$).
- The owner sends messages $m$ to the querier by calling $PH$.HiddenSend($sk_o, pk_q, m$), and awaits replies by calling $PH$.RecvProcess($sk_o, pk_q$).
- After receiving a message, the receiving party calls $PH$.RecvProcess again, to await further messages.

Querier and owner know they communicate with legitimate journalists: Both the query’s key $pk_q$ and the owner’s key $pk_o$ are signed using a one-time-use token.

### 5.3 DATASHARE security analysis

**DATASHARE** provides the following guarantees:

**Protecting queries.** The requirements state (see Section 2.1) that **DATASHARE** must protect the searched keywords and identity of the querier from adversaries that control the communication server and a subset of document owners. The Query protocol, which handles sending queries, is based on MS-PSI. **DATASHARE** represents searched keywords as the client’s set in MS-PSI. Theorem 1 states that MS-PSI perfectly hides the client’s set from malicious servers. Therefore, **DATASHARE** protects the content of queries from document owners.

**DATASHARE** does not reveal any information about the identity of queriers at the network and application layer. Theorem 4 shows that the communication system provides sender and receiver anonymity and protects the querier’s identity at the network layer. At the application layer, the querier sends $(Q || pk_q || \sigma || pk_F || C)$ as part of the Query protocol to the bulletin board. The values $\sigma, pk_F$, and $C$ form an anonymous authentication token based on Abe’s blind signature [6]. Anonymous tokens are independent of the querier’s identity. The value $pk_q$ is an ephemeral public key, and $Q$ is a MS-PSI query which uses an ephemeral secret for the client. Hence, both $pk_o$, and $Q$ are independent of the querier’s identity too. Therefore, the content of the query does not leak querier’s identity at the application layer.
Protecting conversations. The requirements state (see Section 2.1) that DATASHARE must protect 1) the content and 2) the identity of participants of a conversation from non-participants. Moreover, DATASHARE must protect 3) the identity of journalists in a conversation from each other.

First, Theorem 3 proves the secrecy of the communication system and enforces that only the sender and receiver can read their messages. Therefore, adversaries who do not control a participant cannot read the conversation message \( m \) in the Converse protocol.

Second, Theorem 2 proves that communication is unobservable as long as participants are awaiting both conversation and cover messages. DATASHARE enforces this requirement by construction. Immediately after answering a query (see Reply, Protocol 11), the owner starts a PH.RecvProcess to listen for messages from the querier. Similarly, the querier starts to listen for conversation messages from the owner right after sending him a conversation message (see Converse, Protocol 13). Moreover, “cover keys” and “receiving cover messages” in the PH.Cover protocol ensures that all journalists broadcast their cover keys and start PH.RecvProcess after receiving a new cover key. Therefore, DATASHARE satisfies the requirements on the communication systems in Theorem 2 and thus provides unobservability.

Finally, DATASHARE aims to hide the identity of journalists from their counterparts in a conversation. Theorem 4 shows that the communication system does not reveal the identity of journalists at the network layer. DATASHARE also ensures protection at the cryptographic layer. Queries are unlinkable because queriers use an ephemeral public key \( pk_q \), and document owners are pseudonymous (identified by their public key \( pk_D \)). However, DATASHARE cannot provide unconditional protection for conversations. Queries or document owner could identify themselves as part of the conversation. Moreover, by their very nature, messages in a conversation are linkable. Finally, as we discuss below, insiders can use extra information to identify communication partners.

Protecting document collections. Any functional search system inherently reveals information about the documents that it makes available for search. To be useful it must return at least one bit of information. An attacker can learn more information by making additional queries. We show that DATASHARE provides comparable document owner’s privacy to that of ideal theoretical search systems. We use as a security metric the number of queries an attacker has to make to achieve each of the following goals:

Document recovery. Given a target set of keywords of arbitrary length (e.g. “XKeyscore” and “Snowden”), an adversary aims to learn which keywords from the target set are contained in a document for which some keywords are already known.

Corpus extraction. Given a set of target keywords, an adversary aims at knowing which documents in a corpus contain which target keywords. If the target set contains all possible keywords, the adversary effectively recovers the full corpus.

Table 3: Privacy and scalability of the hypothetical and DATASHARE’s MS-PSI based search protocols. Number of necessary queries to achieve document recovery and corpus extraction when interacting with a corpus of \( d \) documents over a set \( n \) keywords. The document extraction bound for the 1-bit system extracts up to uniqueness bound \( u \).

|          | Doc Extract | Scale |
|----------|-------------|-------|
| 1-bit    | \( n \)     | \( n^u + nd \) | -- |
| #doc     | \( n \)     | \( nd \) | - |
| DATASHARE | \( n/\text{lim} \) | \( n/\text{lim} \) | + |

Any functional search system is also susceptible to confirmation attacks. An adversary interested in knowing whether a document in a collection contains a keyword (e.g., “XKeyscore” to learn whether the collection contains the Snowden documents) can always directly query for the keyword of interest.

We compare the number of queries an adversary needs to extract the corpus or recover a document in DATASHARE to the number of queries required in two hypothetical systems. First, an ideal search system in which given a query the querier learns only one bit of information: whether the owner has a matching document. Second, a search system where the querier learns how many matching documents the owner has.

Table 3 compares these hypothetical systems with DATASHARE’s use of MS-PSI, where \( d \) is the number of documents and \( n \) the number of relevant keywords. In Appendices B.1 and B.2 we show that extracting all the keywords from a document requires at most \( n \) queries in the 1-bit and #docs search systems.

Extracting the full corpus using the one-bit search system is not always possible. Define the uniqueness number \( u_D \) to be the smallest number of keywords that uniquely identify a document \( D \). If \( D \) is a strict subset of another document \( D' \), the document cannot be uniquely identified and we set \( u_D = \infty \). However, since corpora are small, we expect that most documents can be identified by a few well-chosen keywords, resulting in small uniqueness numbers.

In Appendix B.1 we show that extracting all documents with uniqueness number less or equal to \( u \) takes \( O(n^u + nd) \) queries in the 1-bit search system. In Appendix B.2 we show that extracting all documents (regardless of uniqueness number) takes \( O(nd) \) queries in the #doc search system.

In DATASHARE, we limit MS-PSI queries to \( \text{lim} \) keywords per query. Therefore, any document extraction attack must make at least \( n/\text{lim} \) queries to ensure all keywords are queried at least once. In fact, this bound is tight for both document recovery and corpus extraction in MS-PSI as one can simply compute the intersection with all keywords.

In summary, DATASHARE offers similar protection against corpus extraction as the #doc ideal system. For document
recovery, not even the ideal one-bit-search system offers much better protection. At the same time, MS-PSI is much more efficient than their ideal counterparts.

**Internal Adversaries.** An adversary may use auxiliary information about a journalist’s behavior or corpus to gain an advantage in identifying the journalist. Some of these attacks are inherent to all systems which provide search or messaging capability. These attacks, however, do not allow the adversary to extract additional information from journalists’ corpora. **Intersection attacks.** A malicious sender (respectively, receiver) who has access to the online/offline status of journalists can use this information to reduce the anonymity set of the receiver (respectively, sender) to only those users that are online. As more messages are exchanged, this anonymity set becomes unavoidably smaller [29]. This attack is inherent to all low-delay asynchronous messaging systems, including the one provided by the communication server. In the context of DATASHARE we note that once document owners and queriers are having a conversation, it is likely that they reveal their identity to each other. Yet, we stress that preserving anonymity and, in general, minimizing the digital traces left by the journalists in the system is very important to reduce the risk that journalists become profitable targets for subpoenas or hacking attempts.

**Stylometry.** A malicious receiver can use stylometry, i.e., linguistic style, to guess the identity of the sender of a message. The effectiveness of this attack depends on the volume of conversation [33, 38]. This attack is inherent to all messaging systems, as revealing the content of the messages is required to provide utility.

**Partial knowledge of corpus.** Adversaries who have prior knowledge about a journalist’s corpus can use this knowledge to identify this journalist in the system. However, due to MS-PSI’s privacy property (see Theorem 1), learning more about the documents in that journalist’s corpus requires making search queries.

If an adversary convinces a journalist to add a document with a unique keyword pattern to his corpus, then the adversary can detect this journalist’s corpus by searching for the pattern. DATASHARE cannot prevent such out of band watermarking. However, the adversary still needs to make further queries to learn anything about non-watermarked documents.

**Non-goals.** Finally, we discuss security properties that are not required in DATASHARE.

**Query unlinkability.** DATASHARE does not necessarily hide which queries are made by the same querier. Even though anonymity is ensured at the network and application layers, queries that have made multiple queries may retrieve responses for all these queries in quick succession after coming online. Document owners know the corresponding query of their messages, and if they collude with the communication server, then they can infer that the same person made these queries. As no adversary can learn any information about the queries themselves, we consider this leakage to be irrelevant.

**Owner unlinkability.** DATASHARE also reveals which pseudonymous document owner created a MS-PSI response, making responses linkable. DATASHARE cannot provide unlinkability for document owners when using MS-PSI. While MS-PSI itself could be modified to work without knowing the document owner’s pseudonym, an adversary could simply repeat a specific rare keyword (for example, “one-word-to-link-them-all”), and identify document owners based on the corresponding pretag they produce. We believe that revealing the document owner’s pseudonym is an acceptable leakage for the performance gain it provides.

### 5.4 Cost Evaluation

At the time of writing, the journalist’s organization has implemented the local search and indexing component of DATASHARE [1]. We have also implemented a Python prototype of the cryptographic building blocks underlying search (Section 3) and authentication (Section 5.1). The messaging service (Section 4) relies on standard cryptographic operations so we have not implemented any prototype.

We are currently running a user study among the organization members to agree on the final configuration of the system. The goal is to familiarize journalists with a kind of search and messaging that is different than those they typically use in their daily activities (Google and email or instant messaging, respectively); as well as with the threat model within which DATASHARE provides protection. We recall that DATASHARE hides all key management and cryptography from the users, thus we do not study those aspects.

In this section, we evaluate the performance of the cryptographic operations involved in search and authentication. Our prototype uses the petibb [19] binding to OpenSSL on the fast NIST P-256 curve for the elliptic curve cryptography in MS-PSI. We implement the Cuckoo filter using cuckoo.py [7]. We ran all experiments on an Intel i3-8100 processor running at 3.60GHz using a single core. We note that operations could be easily parallelized to improve performance.

We focus our evaluation on the computational cost and bandwidth cost of the authentication and search primitives to ensure that DATASHARE fulfills the requirements in Section 2.1 without journalists needing fast hardware or fast connections. When reporting bandwidth cost we omit the overhead of the meta-protocol that carries messages between system parties. We do not consider any one-time setup cost, nor the standard cryptography used for messaging. We also do not measure network delay as the latency the Tor network introduces – around 1 second [4] – is negligible compared to the waiting time imposed by connection asynchrony; and it is orders of magnitude less than the journalists waiting limits (see Section 2.1).

We provide performance measurements for different system work loads. We consider the base scenario to be 1000
journalists, each of whom makes 1000 documents available for search. There is no requirement for the number of keywords per document or keywords per query. As a conservative estimate, we assume that each document contains 100 keywords, and that each query contains 10 keywords.

**Authenticating journalists.** We implement the BS scheme using anonymous credentials light (ACL) [11]. Running BS:Sign requires transferring 367 bytes and takes 1.44 ms and 2.1 ms respectively for the organization and the journalist. Each blind signature is 335 bytes and verifying it using BS:Verify takes 0.87 ms. We include these costs in the respective protocols.

**Publishing documents.** Data owners run Publish to make their documents available. For the base scenario, this one-time operation takes 14 seconds, and results in a cuckoo filter of size 400 KB for a FPR of 0.004%. As a conservative estimation we assume all keywords are different. When documents contain duplicate elements the precomputation can be amortized: the pretag \( y^t \) has to be computed only once.

**Querying a single journalist.** Figure 6, left, shows the time and bandwidth required to issue one query on one collection depending on the collection size. The querier constructs the query using Query and sends it to the document owner (the querier’s computation cost includes the cost of obtaining the one-time-use token using GetToken). The document owner responds using Reply. These operations are independent of the number of documents. The querier runs Process to retrieve the responses, and to compute the intersection of query and collection. This takes 27 ms in the base scenario. Bandwidth cost reflects the raw content size, they are then padded to 1 KB.

**Querying all journalists.** As expected, the processing time and bandwidth of Query are independent of the population size, while the cost of processing the responses grows linearly with the number of queried journalists (Figure 6, center). For the baseline scenario, processing all 999 responses takes about 27 seconds in total and requires retrieving 1 MB of padded responses. We note that this cost is only paid by the querier, and does not impact the document owners (see below). Moreover, since replies are unlikely to arrive all at once, processing can be spread out over time reducing the burden on the querier’s machine.

This computation assumes that each journalist has the same number of documents. In practice, this may not hold. However, as we see in Figure 6, left, as soon as collections have more than 50 documents the computation time grows linearly with the collection size. Thus, as long as journalists have collections with at least 50 documents, the measurements in Figure 6, center, are largely independent of how these documents are distributed among journalists.

**The cost for document owners.** Document owners also spend time and bandwidth to answer queries by other journalists. Figure 6, right, shows how these costs depend on the total number of queries an owner receives per day. Even when all journalists make 10 queries of 10 keywords each day (unlikely in practice) the total computation time for document owners is less than 20 seconds, and they send and receive less than 7 megabytes (10 MB when padded).

**Overall cost of DATASHARE.** Finally, we plot in Figure 7 the
total bandwidth a journalist needs per day to run DATASHARE depending on the number of journalists in the system and the strategy implemented by the communication system. Regardless of the size of the system, the cost associated to hide communications dominates the cost stemming from searches. Regarding the communication cost, as explained in Section 4.3, for small organizations Poisson-rate cover traffic provides a better trade-off with respect to throughput, but as more journalists join the system, the PIR-based system starts performing better.

6 Related work

Many PSI protocols [18,27,30,39] differ from De Christofaro et al.’s [17] only in how they instantiate the oblivious pseudorandom functions (OPRFs). Our MS-PSI protocols can easily be adjusted to use alternative OPRFs to compute the pretags. However, since, bandwidth is at a premium in our scenario, we base our MS-PSI protocols on De Christofaro et al. [17], as their scheme has the lowest communication cost.

The restrictions on computational power and bandwidth rule out many other PSI schemes. Protocols based on oblivious polynomial evaluation [25] have very high computational cost. Hash-based PSI protocols [42–44] have low computational cost, but instead require a lot of communication. Finally, PSI protocols can be build from generic secure multi-party computation directly [28,41,42]. However, this approach also suffers from a high communication cost and requires more than one communication round.

Secure multi-party computation based PSI protocols can be extended to provide better privacy than MS-PSI: The underlying circuits can be extended to implement either the ideal 1-bit search or the #doc search system. However, their high communication and round complexity rules out their use in our document search system. Recently, Zhao and Chow proposed a threshold PSI protocol based on polynomial evaluation [52] that can implement the #doc search system (by setting the threshold equal to the number of keywords). But its communication and computation complexity rule it out.

Document search could also be implemented using private information retrieval (PIR): Queriers use PIR to private query keywords in the document owner’s database. Computational PIR protocols [8,31,37] (IT-PIR protocols [12,26] do not apply) place a high computational burden on the database owner. Moreover, PIR requires a fixed set of keywords, which we cannot assume exists. Keyword-based PIR approaches [9,16] sidestep this issue, but instead require multiple communication rounds. Therefore, PIR does not apply.

Encrypted databases hide the queries of data owners from an untrusted database server [22,40,47,49]. While DATASHARE could operate such a central encrypted database, any collusion between a journalist and the database server would leak the entire database. Document owners also cannot operate an encrypted database themselves, as these systems are not designed to provide query privacy against a database server that colludes with the data owner (i.e., the document owner).

7 Future steps: better protection for DATASHARE

We have introduced DATASHARE, a decentralized privacy-preserving search engine that enables journalists to find and request information held by their peers. DATASHARE has great potential to help journalists collaborate to uncover cross-border crimes, corruption, or abuse of power.

Our collaboration with a large organization of investigative journalists provided us with a novel set of requirements that, despite being deeply grounded in practicality, are rarely considered in academic publications. These requirements forced us to design new building blocks that we optimized for different security trade-offs than previous work. We combined these building blocks into an efficient and low-risk decentralized search system.

Yet, DATASHARE’s protections are not perfect. Both the search primitive, and the availability of timestamps of actions in the system, leak information. At the time of writing, the high cost in bandwidth and/or computation of state-of-the-art techniques that could prevent this leakage – e.g., PIR to hide access patterns and efficient garbled circuits to implement one-bit search – precludes their deployment.

We hope that this paper fosters new research that addresses these problems. We believe that the new set of requirements opens an interesting new design space with lots of potential to produce results that have high impact, not only by helping investigative journalism to support democratic societies, but also in other domains.

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**A Security of MS-PSI**

In this section, we prove MS-PSI’s privacy. The client’s interaction with the server is identical to PSI [17] and C-PSI [30] protocols. Hence, we argue that they have the same privacy. We use the ideal/real world paradigm in the random oracle model to show that the MS-PSI client does not learn anything beyond the intended output of the protocol.

In the MS-PSI protocol, the number of queried keywords determines how much information is revealed, rather than the number of queries in which the client asks the server. We measure the client’s interaction by keywords queried. We assume a non-uniform adversary since the protocol reveals the size of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. 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The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set. The protocol is interactive; the client asks keywords in multiple queries and receives the response of each party’s set.
We define ideal\(_{f,q}\) as ideal incorporation of PSI in which a trusted third party receives the server’s input and responds to the client’s PSI\(_{haw}\) queries at most \(q\) times. If required, ideal\(_{f,q}\) can answer non-adaptive queries with \(t\) keywords by calling PSI\(_{haw}\) process \(t\) times and concatenating their responses. It’s important to note that this operation costs \(t\) adaptive queries. We define the real world Real\(_{mspsi,q}\) as running the MS-PSI protocol and allowing the client to ask up to \(q\) queries.

The MS-PSI protocol consists of 2 parts: 1) publish: which corresponds to the pre-process phase (Protocol 9) and 2) exponentiation: which corresponds to the online interaction (Protocols 10 and 12). MS-PSI uses two hash-functions \(H\) and \(\hat{H}\), which are modeled in the random oracle model (ROM). We define following oracles to represent the MS-PSI scheme.

\[
x \leftarrow O^{\text{Ideal}}_{\text{mspsi,q}}(w)\text{ hashes the keyword }w\text{ into a uniformly random group element }x \in_R G.
\]

\[
TC \leftarrow O^{\text{Pub}}(w)\text{ performs the publish protocol 9, i.e. choses the server’s secret key }\alpha,\text{ and publishes server’s tag collection }TC\text{ which consists of }N = \sum_{i=1}^n n_i\text{ tags with uniformly random distribution.}
\]

\[
\alpha^x \leftarrow O^{\exp}(x)\text{ takes a group element }x\text{ and exponentiates it with }\alpha\text{ and returns }\alpha^x.\text{ The adversary is limited to asking up to }q\text{ queries.}
\]

\[
tg \leftarrow O^{\text{Ideal}}_{\text{haw}}(s)\text{ hashes input }s\text{ to a random }l\text{-bit tag }tg.
\]

We assume a PPT adversary \(A\) which interacts with Real\(_{mspsi,q}\). We design a simulator \(S\) which extract the same information from the ideal world given black-box access to \(A\). Since MS-PSI’s output is deterministic and we have proven it correct, we only need to show that the view of \(A\) in real and ideal worlds are indistinguishable.

\[
\text{Real}^{\text{mspsi,q}}(\{(w,[i] \in [q]), \forall i, N\}) \equiv \text{Ideal}_{f,q}^{S(A)}(\{(w,[i] \in [q]), \forall i, N\})
\]

We start with a high-level overview of the proof. The simulator \(S\) uses MS-PSI’s publish and exponentiation with a random secret key, which is identical to the real world. However, \(S\) has to extract the adversary’s effective input to query the ideal oracle and respond. The key idea is that the adversary needs to query every keyword from the oracle \(O_{haw}\) to compute its tag and the intersection. The simulator uses \(\bar{O}_{haw}\) and the server’s secret \(\alpha\) to decrypt client’s query \(x^\alpha\) and extract the input \(x\). After extracting \(A\)‘s input, \(S\) can query the ideal oracle and respond accordingly. We show that \(S\) is indistinguishable from the real world.

If the simulator \(S\) ask more than \(q\) ideal queries \(\text{Ideal}\), the simulation fails. We show that the probability of failure is negligible. The failure happens when an adversary asks \(q + 1\)‘th valid \(O_{haw}\) query without querying \(O_{exp}\) more than \(q\) times. Informally, this means that the adversary can compute the exponentiation \(r^\alpha\) of \(q + 1\) random values \(r_i\) with only \(q\) queries to the exponentiation oracle, which translates into the One-more-Gap-DH problem.

**Proof.** We build the simulator \(S\) as follow:

\[
x \leftarrow O^{\text{Ideal}}_{\text{haw}}(w)\text{ responds the same way as }O^{\text{Real}}_{\text{haw}}\text{ and stores the mapping between each keyword and its matching group element }\{(w,x) \in \{0,1\}^*,\hat{G}\}.
\]

\[
TC \leftarrow O^{\text{Pub}}(\alpha)\text{ chooses a random key }\alpha\text{ and publishes }N\text{ uniformly random }l\text{-bit tags }TC\text{ to represent the tag collection. The adversary is non-uniform, so the simulator receives }N,\text{ which is }TC\text{'s size, as part of its input.}
\]

\[
x^\alpha \leftarrow O^{\exp}(x)\text{ same as }O^{\exp}_{\text{Real}}.\text{ The adversary is limited to asking up to }q\text{ queries.}
\]

\[
tg \leftarrow O^{\text{Ideal}}_{\text{haw}}(s)\text{ the oracle remembers every query to respond to repeated queries consistently. The protocol expects to receives inputs in the form of }s = “id||z” = “id||x^\alpha”\text{ and proceeds as follows.}
\]

1. If the input does not have a “id||z” form, respond with a random \(l\)-bit tag \(tg\).
2. Use the secret key to compute \(A\)’s input element \(x = \alpha^{-1}z\text{ from }s\).
3. If element \(x\) is not queried from \(O^{\exp}_{\text{haw}}\) respond with a random \(l\)-bit tag \(tg\).
4. Retrieve \(x\)’s keyword \(w\) from \(O^{\exp}_{\text{haw}}\)’s mapping \((w,x)\).
5. If \(S\) has not asked \(w\) from the ideal oracle and already asked \(q\) queries from \(\text{Ideal}\), then fail.
6. If \(S\) has not asked \(w\) from the ideal oracle, ask and store the response as \(f[w] = \text{Ideal}(w,y)\).
7. If \(id \in f[w]\), respond with an unused tag \(tg \in TC\).
   Otherwise, respond with a random \(l\)-bit tag \(tg\).

Oracles \(O^{\exp}_{\text{haw}}\) and \(O^{\exp}_{\text{pub}}\) are identical, and it is easy to see that \(O^{\exp}_{\text{haw}}\) and \(O^{\exp}_{\text{pub}}\) are indistinguishable from their Ideal counterpart.

Now we show that as long as \(S\) does not fail, \(O^{\text{Ideal}}_{\text{haw}}\) and \(O^{\text{Ideal}}_{\text{haw}}\) are indistinguishable. Both oracles claim to respond to a query representing \((w,id)\) with a tag \(tg \in TC\) for \(w \in Y_{id}\) and with a uniformly random \(l\)-bit tag for \(w \notin Y_{id}\). Therefore, these two oracles are indistinguishable if they are correct. We have already proved that MS-PSI is correct, so we only need to show that \(S\) is correct. The oracle \(O^{\text{Ideal}}_{\text{haw}}\) responds positively to the query \((w,id)\) if and only if the input is in form of \(s = “id||O^{\exp}_{\text{haw}}(w)\alpha”\) and the document identifier is in the ideal response \(id \in \text{Ideal}(w,y) \Rightarrow w \in Y_{id}\). We show that probability of false-positive and true-negative in \(O^{\text{Ideal}}_{\text{haw}}\) is negligible to prove the correctness. We name the number of queries to oracles \(O^{\exp}_{\text{haw}}\) and \(O^{\exp}_{\text{pub}}\) as \(Q_G\) and \(Q_{kw}\) respectively. A false-positive happens when there is collision between adversary’s input \(z\) to the oracle \(O^{\exp}_{\text{haw}}\) and one of keyword queried from \(y \leftarrow O^{\exp}_{\text{haw}}(w), z = y^\alpha\). This event has a probability of \(Q_GQ_{kw}/\text{Ord}(\hat{G})\) which is negligible. A false-negative
can only happen if \( O_{H_G}^S (w) \) is not known at the time of the query. The probability of \( O_{H_G}^S (w) \) matching to one of previous \( O_{H_w}^S (s) \) queries is \( Q_G \cdot Q_w / \text{Ord}(\mathbb{G}) \) which is negligible. \( \square \)

The simulator \( S \) fails when the adversary asks \( q + 1 \) queries representing \( q + 1 \) different keywords from \( O_{H_w}^S \) while respecting \( O_{exp}^S \)'s at most \( q \) queries restriction. We assume that \( A \) triggers a failure with probability \( \varepsilon \). Now we define One-more-Gap-DH assumption and relate it to the failure probability \( \varepsilon \).

**One-more-Gap-DH assumption** informally states that computing CDH is hard even if the adversary has access to a CDH oracle and DDH problem is easy.

The adversary \( A \) gets access to a CDH oracle \( \alpha \leftarrow O_{CDH} (x) \) and an \( DL_a \) oracle 1/0 \( \leftarrow O_{DL_a} (x, z) \) which determines whether a pair of elements \( x, z \in \mathbb{G} \) are a DH pair with oracle’s secret \( z = x^\alpha \). The \( DL_a \) oracle is a weaker form of DDH assumption since \( O_{DL_a} (x, z) = DDH (h, h^\alpha, x, z) \).

The One-more-Gap-DH assumption states that the adversary has negligible chance in producing \( q + 1 \) DH pairs \( (x_i, x_i^\alpha) \) from \( M \) random challenge elements \( Ch = (c_1, \ldots , c_M) \) while asking at most \( q \) queries from the CDH oracle \( O_{CDH} \).

\[
Pr\{ \{(x_i, x_i^\alpha) \mid x_i \in Ch\}_{i \in [q+1]} \leftarrow A^{O_{CDH}(),O_{DL_a}()} (Ch) \} < \mu
\]

If \( A \) has a non-negligible chance of creating failures in simulator \( S \), an adversary \( B \) exists which has non-negligible advantage in solving One-more-Gap-DH problem.

The simulator \( S \) has two main functionality: computing exponentiation with a secret key in \( O_{exp}^S \) and finding the matching input element \( x = z^{\varepsilon^{-1}} \) in the \( O_{H_G}^S \). We build adversary \( B \) by replacing the secret key \( \alpha \) in the simulator \( S \) with a One-more-Gap-DH challenge and interacting with \( A \) in a black-box manner. The adversary \( B \) uses \( O_{H_G}^S \) to fix input elements to challenge points and uses the CDH oracle \( O_{CDH} \) for responding to \( O_{exp}^S \) queries. Finally, \( B \) uses \( O_{H_w} \) to detect which challenge point matches \( z \) in \( O_{H_w}^S \)’s query. Receiving \( q + 1 \) queries from \( O_{H_w}^S \) with different keywords corresponds to having \( q + 1 \) DH pair from the challenge set without asking more than \( q \) queries from \( O_{CDH} \).

**Proof.** We build the adversary \( B \) as follows:

\[
x \leftarrow O_{H_G}^S (w) \quad \text{responds with a new challenge element } x \in Ch \quad \text{and stores the mapping between each keyword and its matching group element } (w, x) \in \{0, 1\}^* \cap Ch \subset R \mathbb{G}.
\]

\[
TC \leftarrow O_{Pub}^B () \quad \text{since } O_{CDH} \text{ has its own secret } \alpha \text{ the } O_{Pub}^B \text{ does not need to chose another secret, but it publishes } TC \text{ in the same manner as } O_{Pub}^S.
\]

\[
x^\alpha \leftarrow O_{exp}^B (x) \quad \text{uses } O_{CDH} (x) \text{ to response to up to } q \text{ queries.}
\]

\( tg \leftarrow O_{H_w}^S (s) \) is similar to \( O_{H_G}^S \). the oracle remembers every query to respond to repeated queries consistently. The protocol expects to receives inputs in the form of \( s = "id||z" = "id||x^a" \). Unlike, \( O_{H_w}^S \) this oracle does not know the secret \( \varepsilon \) to decrypt the input element. Instead, it uses \( O_{DL_a} \) to check against all challenge points \( x_i \in Ch \) and find the corresponding element \( 1 = O_{DL_a} (x_i, z) \implies z = x_i^a \).

1. If the input does not have a “id||z” form, respond with a random \( l \)-bit tag \( tg \).
2. Find challenge point \( x \in Ch \) where \( 1 = O_{DL_a} (x, z) \).
3. Since \( Range(O_{H_w}^S) \subset Ch \), if there is no such point in \( Ch \) then \( x = z^{\alpha^{-1}} \) does not have a corresponding query in \( O_{H_w}^S \), and the oracle responds with a random \( l \)-bit tag \( tg \).
4. Retrieve \( x \)'s keyword \( w \) from \( O_{H_w}^S \)’s mapping \( (w, x) \).
5. If \( S \) has not asked \( w \) from the ideal oracle and already asked \( q \) queries from \( Ideal \), then fail.
6. If \( S \) has not asked \( w \) from the ideal oracle, ask and store the response as \( f[w] = Ideal(w; y') \).
7. If \( id \in f[w] \), respond with an unused tag \( tg \in TC \). Otherwise, respond with a random \( l \)-bit tag \( tg \).

The adversary \( A \) cannot distinguish \( B \) from the simulator \( S \). Oracles \( O_{exp}^S \) and \( O_{Pub}^B \) are identical to their \( S \) counterpart. The oracle \( O_{H_w}^B \) responds with challenge points which are indistinguishable from uniformly random elements used in \( O_{H_G}^S \). Oracles \( O_{H_w}^S \) and \( O_{H_w}^B \) only differ in how they compute \( x = z^{\alpha^{-1}} \) in steps 2 and 3. For each input \( z, x \) is unique and if \( x \in Ch \) then \( z = x^a \iff 1 = O_{DL_a} (x, z) \). On the other hand, if \( x \notin Ch \), then \( x \) is not a response from \( O_{H_w}^B \) and it responds with challenge points. Knowing the exact value of \( x \notin Ch \) is not important since both oracles respond with a random tag. Hence, \( O_{H_w}^B \) and \( O_{H_w}^B \) are indistinguishable.

A simulation failure means that \( A \) has asked \( q + 1 \) queries corresponding to \( q + 1 \) keywords \( \{(z_i, w_i)\}_{i \in [q+1]} \) without asking more than \( q \) queries from \( O_{exp}^S \). The oracle \( O_{H_w}^S \) ensures that each \( w_i \) maps to a unique element \( x_i \) from the challenge points, and \( B \) asks one \( O_{CDH} \) query per \( O_{exp}^S \) query. Therefore, \( B \) produces \( q + 1 \) DH pair \( \{(x_i, z_i = x_i^a)\}_{i \in [q+1]} \), with at most \( q \) queries from \( O_{CDH} \) with probability equal to \( A \)'s advantage \( \varepsilon \). This shows that \( \varepsilon \leq \mu \). If \( \varepsilon \) is non-negligible, then \( B \) breaks the One-more-Gap-DH assumption. \( \square \)

**B The limits of document search**

We show that even with ideal adversary an adversary can recover documents or even extract the whole corpus. We formalize the extraction problem as follows: an adversary receives
a list of \( n \) keywords \( U = \{a_1, \ldots, a_n\} \) and a search oracle \( O \)
which responds to queries using the server’s set of \( N \) documents
\( \text{Docs} = \{d_1, \ldots, d_N\} \). The adversary’s goal is recovering
the document set \( \text{Docs} \). Since the adversary is only interested
in the set \( U \) of keywords, we ignore any keyword outside of
this set in our analysis.

### 2.1 One-bit search extraction

In this section, we consider a 1-bit search oracle \( O \) which
returns a boolean answer for each query which determine
whether at least one matching document exists. The oracle
support one operation, query, which takes a set of keywords
\( P \) as input and returns boolean answer 0/1 \( \leftarrow O\text{.query}(P) \). If
there are two documents \( D_x \) and \( D_y \) in the document set \( \text{Docs} \)
such that \( D_x \subset D_y \), then the smaller document \( D_x \) is not visible
to the adversary. Therefore, we assume that \( \text{Docs} \) does not
contain any pair of document where one entirely covers the
second one. Furthermore, we only recover documents with
a document uniqueness number \( u_D \) less than the uniqueness
limit \( u_l \).

A set of keywords \( P \) corresponds to a document if and only
if this set returns a positive search result \( O\text{.query}(P) = 1 \) and
adding any other keyword to this set \( P \) results in a negative
response \( \forall x, x \notin P : O\text{.query}(P \cup \{x\}) = 0 \).

**Document recovery.** If an adversary has partial knowledge
about a document \( D \) that contains \( m \) keywords in total and the
adversary wants to recover the rest of the document, then the
adversary needs to ask at least \( t = n - m \) and at most \( n \) queries
from the oracle which leads to a \( \Theta(n) \) query complexity. We
claim that the adversary needs to ask at least one query for
each keyword which is not inside the document, i.e., that
it must make at least \( t = n - m \) queries. We assume to the
contrary that the adversary recovers the document with less
than \( t \) queries and show that there are two possibilities for
\( D \) that it cannot distinguish. Since the number of queries is
smaller than \( t \), there exists a keyword \( x \notin D \) which either is
not queried or it has been queried, but in each of these queries
\( x \) was queried together with at least one other keyword \( y \)
such that \( y \notin D \) (leading to the oracle returning 0). In both
cases, the adversary cannot distinguish the document \( D \) from
the document \( D \cup x \) since they both conform to all queries.
Therefore, the adversary needs to make at least \( t \) queries.
Clearly, \( n \) queries suffice. Showing the result.

Algorithm 1 recovers a document with \( n \) queries. The doc-
ument starts with a known set of keywords \( P \) and then keeps
extending this set with keywords from the remaining set
\( \{a_1, \ldots, a_n\} \) as long as the oracle keeps returning 1. Eventually,
the algorithm returns a maximal extension of the initial set \( P \).

**Corpus extraction.** Knowing a partial document \( P \), it is simple
to extend it to one document, but extracting all possible
documents from this set is hard. The reason behind this is
that when the adversary adds another keyword \( a_i \) to the set \( P \)
and receives a positive query response, he cannot determine
whether all documents that match \( a_i \) also match \( P \cup a_i \); or
there exists a document which only contains \( P \), but not \( P \cup a_i \).

We designed a corpus extraction algorithm that takes care
of this uncertainty, see Algorithm 2. This recursive algo-
rimth is called with the current set of documents \( D \), the set
of keywords \( P \) that it is currently considering, and the
index \( k \) into the list of keywords (the keywords with index
less than \( k \) have already been considered). To find all
documents with respect to the set of keywords \( S = \{a_1, \ldots, a_n\} \),
call \( \text{EXTRACT}(\emptyset, 0, 1) \).

The algorithm is recursive. It considers the current set of
keywords \( P \) and tries to extend it with a keyword \( a_i \) \( (k \leq i < n) \).
If the oracle returns 0, clearly there is no document matching
\( P \cup \{a_i\} \). If the oracle returns 1, we cannot distinguish the
two cases above, so we recurse along both paths, one for
documents that contain \( a_i \), and the other for documents
that do not contain \( a_i \). If we reach the uniqueness limit \( u_l \), we
check if \( D \) already contains a document containing the current
set \( P \) (by calling \( \text{ISINDOC} \) to check), if so we stop because
we extracted this document already. Otherwise we continue
extending \( P \), but no longer branch (as \( |P| \geq u_l \)), to find all
keywords as in the \( \text{RECOVER DOCUMENT} \) function in Algorithm 1.
If we exhausted all possible keywords, we add \( P \) to the current
set of documents \( D \) and return.

We argue that this algorithm finds all documents with
uniqueness number \( u_D < u_l \). Clearly, the algorithm explores
all sets \( P \) of size less than \( u_l \) for which there exist match-

---

**Algorithm 1** Recover the rest of the document given a keyword set
\( \{a_1, \ldots, a_n\} \).

Start : \( \text{RECOVER DOCUMENT}(P, 1) \)

function \( \text{RECOVER DOCUMENT}(P, k) \)

for \( i \leftarrow k \ldots n \) do

if \( O\text{.query}(P \cup \{a_i\}) = 1 \) then

\( P \leftarrow P \cup \{a_i\} \)

return \( P \)

---

**Algorithm 2** Extract non-contained documents with an uniqueness number
\( u_D \) smaller than \( u_l \) with a one-bit search oracle based on the keyword set
\( S = \{a_1, \ldots, a_n\} \).

Start: \( \text{EXTRACT}(\emptyset, 0, 1) \)

function \( \text{EXTRACT}(D, P, k) \)

if \( |P| = u_l \) then

if \( \text{ISINDOC}(P, D) = 1 \) then

return \( D \)

for \( i \leftarrow k \ldots n \) do

if \( O\text{.query}(P \cup \{a_i\}) = 1 \) then

\( D \leftarrow \text{EXTRACT}(D, P \cup \{a_i\}, i+1) \)

if \( |P| < u_l \) then

\( D \leftarrow \text{EXTRACT}(D, P, i+1) \)

if \( \text{ISINDOC}(P, D) = 0 \) then

\( D \leftarrow D \cup \{P\} \)

return \( D \)

---

function \( \text{ISINDOC}(P, k) \)

for all \( d \in D \) do

if \( P \subseteq d \) then

return 1

return 0
ing documents. So, eventually, the algorithm will find the unique set for each document, which it will then extend to the corresponding full document.

It is easy to see that the brute-force part, while \(|P| < \text{ulim}\) requires at most \(O(n^{\text{ulim}})\) queries. However, the algorithm does not expand keyword sets with negative responses, and on average, document sparsity leads to a significantly lower number of queries. Once \(|P| \geq \text{ulim}\) the algorithm enters a linear exploration, as it stops branching. It runs through this linear phase for every document. Resulting in a total complexity of \(O(n^{\text{ulim}} + nd)\).

### B.2 #doc search extraction

In this section, we consider a #doc search oracle \(O\) which returns the number of matching documents for each query. The oracle only supports one operation, \(\text{query}\), which takes a set of keywords \(P\) as input and returns the number of matching documents \(t \leftarrow O.\text{query}(P)\).

**Document recover.** Since the 1-bit search oracle’s output can be computed from the #doc oracle, the algorithms from the previous section also work against the #doc search oracle. As a matter of fact, when only considering a single document, the behavior of the #doc oracle is equivalent to that of the 1-bit search oracle. Given an existing set of keywords \(P\), the attacker can query \(P \cup a_i\) and see if the number of matching documents changes, or not. If the number of matching documents changes, there were documents that match \(P\) but not \(P \cup a_i\). If the number of matching documents stays the same, all documents that match \(P\) also match \(P \cup a_i\).

Algorithm 3 exploits this principle. It keeps track of the current set of documents \(D\), the set of keywords \(P\) that it is currently considering, the index \(k\) into the list of keywords (the keywords with index less than \(k\) have already been considered), and the number \(\text{matches}\) of documents that contain the current set of keywords \(P\). To find all documents with respect to the set of keywords \(S = \{a_1, \ldots, a_n\}\), call \(\text{EXTRACT}(\emptyset, 0, 1, \infty)\).

Given the current set \(P\) with \(\text{matches}\) matching documents it proceeds as follows. It asks the next keyword \(a_i\), if there are still matching documents (i.e., \(\text{next} > 0\)) it adds \(a_i\) to \(P\) and continues exploring. If some documents matched \(P\) but did not match \(P \cup a_i\) (i.e., \(\text{matches} > \text{next}\)), the algorithm also continues exploring by skipping the keyword \(a_i\).

In the beginning, the algorithm starts with an empty set and checks every keyword which requires \(n\) queries, and it continues with a deterministic document recovery for \(d\) documents. Therefore, this algorithm requires a total of \(O(nd)\) queries for extracting the corpus.

**Algorithm 3: Extract all matches documents which include the partial document \(P\), with a #doc search oracle based on the keyword set \(S = \{a_1, \ldots, a_n\}\). \(\text{Start : EXTRACT}(\emptyset, 0, 1, \infty)\)**

```
function EXTRACT(D, P, k, matches)
    for i ← k, n do
        next = O.\text{query}(P \cup \{a_i\})
        if next > 0 then
            D ← EXTRACT(D, P \cup \{a_i\}, i + 1, next)
            if matches > next then
                D ← EXTRACT(D, P, i + 1, matches – next)
        end
    end
    return D \cup \{P\}
```
