Yggdrasil: Privacy-aware Dual Deduplication in Multi Client Settings

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Abstract—This paper proposes Yggdrasil, a protocol for privacy-aware dual data deduplication in multi client settings. Yggdrasil is designed to reduce the cloud storage space while safeguarding the privacy of the client’s outsourced data. Yggdrasil combines three innovative tools to achieve this goal. First, generalized deduplication, an emerging technique to reduce data footprint. Second, non-deterministic transformations that are described compactly and improve the degree of data compression in the Cloud (across users). Third, delay preprocessing in the clients in the form of lightweight, privacy-driven transformations prior to upload. This guarantees that an honest-but-curious Cloud service trying to retrieve the client’s actual data will face a high degree of uncertainty as to what the original data is. We provide a mathematical analysis of the measure of uncertainty as well as the compression potential of our protocol. Our experiments with a HDFS log data set shows that 49% overall compression can be achieved, with clients storing only 12% for privacy and the Cloud storing the rest. This is achieved while ensuring that each fragment uploaded to the Cloud would have 10²⁰ possible original strings from the client. Higher uncertainty is possible, with some reduction of compression potential.

Index Terms—Compression, privacy, deduplication

I. INTRODUCTION

The massive migration of data from storage facilities on ‘the Premise’ to ‘the Cloud’ has led to a boom in the offer of Cloud Storage Providers (CSPs). Nowadays, people can turn to a vast spectrum of CSPs that offer a virtually unlimited storage accessible from anywhere in the world. To deliver the promised features to multiple clients at a competitive price, CSPs resort to compression techniques that reduce the footprint of data, so as to fit more in less space. A popular approach to reach this goal is to adopt data deduplication techniques. In brief, these solutions work by recognizing whether a freshly uploaded file is the same as one already stored on the server. If so, there is no need to store the new file: a pointer to the already existing copy would suffice. Obviously the chance that clients upload the exact same data is quite low, but applying this technique on chunks of files leads to a non-trivial compression capability. This relevant when a client stores different versions of the same file (thus, files have several common chunks), or different clients use the same kind of files, e.g., virtual machine disk images of different Linux distributions [1], [2].

Vestergaard et al. recently proposed generalized deduplication (GD) [3], [4], a technique to further reduce the footprint of the storage systems. The intuition behind GD is to perform data compression on chunks that are nearly identical rather than exactly the same. This is possible by using a transformation function that maps each chunk to a basis and a deviation, where different chunks may have the same basis but different and unique deviations to differentiate them. The system assigns a fingerprint, e.g., a hash function to each basis and carries out deduplication on the bases. Using GD, similar chunks, i.e., chunks that are mapped to the same basis are deduplicated together. The system then stores a pointer to the basis and the deviation in form of a small textual deviation with the information on how the new chunk differs from the pointed basis. It has been shown that generalized deduplication achieves a higher level of compression than classic deduplication techniques [4].

Trivially, deduplication techniques perform better on highly correlated data. However, similarities appear only if the files are uploaded in plaintext, which is not desirable in many applications. Privacy-conscious clients may upload encrypted data to the Cloud. The semantic security of the encryption implies that ciphertexts look random. In particular, files that could be deduplicated become uncorrelated when encrypted, undermining the whole purpose of deduplication.

Up to now, the bulk of work performs deduplication for storage on plaintext data at one location, usually on the Cloud side, since it is assumed to have more computational power a client. In contrast, we consider the following unorthodox setting: secure deduplication is carried out, in a subsequent manner, by two parties. That is, the client (e.g., user end device, local storage system, private Cloud) and the server (e.g., CSP). We call this method dual deduplication. We present a solution that allows clients to outsource their data in a privacy-preserving manner, while the server is guaranteed a high compression rate.

We achieve this solution by letting the clients preprocess their data prior to upload. The outcome of this process is a pair where the first item is an outsourced generalized deduplication friendly ‘basis’ that the client sends to the cloud. In practice, this could be achieved by the client uploading a single file containing a number of unique bases of the same size or by uploading each basis separately. The second item is a deviation, a short string that simultaneously serves two

¹Alternatively, the files could be encrypted using a deterministic encryption scheme, and then uploaded. However deterministic encryption cannot be semantically secure. Moreover to guarantee meaningful deduplication of ciphertexts generated by different clients there needs to be some coordination on the encryption key.
purposes: (1) enabling the correct recovery of the original data from the outsourced file (e.g., indicating which basis was used and how was it modified to generate the $i$-th data chunk); and (2) providing some level of privacy on the outsourced data.

Having received a set of deduplication-friendly bases, the CSP can use GD to successfully deduplicate bases received from numerous clients, reducing the total storage space to a fraction of what could be achieved from raw, unprocessed data. Although the overall storage space needed by the server and the clients may be higher than if deduplication was carried out only on the server side, the storage space required by each party, i.e., client and server separately, is considerably smaller compared to plain storage on the client side or generalized deduplication on unprocessed data on the server side.

We name our solution Yggdrasil, as the Cosmic Tree of Life in the Norse mythology. Yggdrasil is an enormous ash tree that connects the different worlds with the heavens. We use this as a metaphor for our system (see Fig. 1). The clients preprocess the data and keep a fraction of it for privacy reasons. The Cloud collects the deduplication-friendly bases output by the clients and organizes them into a (compressed) foliage.

The contributions of this paper are organized as follows. Section II introduces the framework of Yggdrasil; the kind of adversary we deal with (an honest-but-curious CSP) and its goal (to reconstruct clients' original data); and the mathematical expressions we use to measure the performance of the system including compression ratios, and the uncertainty metric measuring the privacy retained by clients against our adversary. Section III explains our solution, Yggdrasil, in detail (its algorithms and how they interact). Section IV presents our upper bounds on the different compression ratios and privacy analysis of our solution. Section V collects and discusses the numerical results obtained when testing Yggdrasil on a real dataset of HDFS log files. Our main focus is the compression potential of our proposal Yggdrasil, while Section VI analyzes the trade off between level of uncertainty and storage size on the client end.

II. SYSTEM MODEL AND PERFORMANCE METRICS

In this section, we define our system model, the attacker model and then present the metrics we use to analyze the performance and privacy of our proposal Yggdrasil.

A. System Model

Figure 1 depicts our system model. Clients’ desiderata is to retain some level of privacy on their files while minimizing the amount of local storage. The CSP desiderata is to optimize its storage space. In order to meet all desiderata simultaneously, we let clients apply some transformations on their data, prior to upload. Such transformations aim to prevent the CSP (or any third party) from easily guessing the clients’ original (raw) data while requiring required minimal storage on the clients’ side. To minimize the storage requirements on the Cloud side, we let the CSP perform Generalized Deduplication. To further decrease storage, our model envisions a CSP that processes outsourced data before running GD.

We consider that the system operates on data strings with $k$-bit symbols, i.e., any symbol can take $N = 2^k$ possible values. A file is broken up into a number of original strings of size $n_o$ symbols, i.e., $F \in (\{0, 1\}^k)^{n_o}$. After a client applies its transformation, the resulting base (called $F’$) of size $n_b$ symbols and there is an associated local deviation $D$ that captures the changes performed on the original string. At a given point, there are $f$ strings in the Client and $b$ bases stored in the Cloud.

An instructive example of Client side transformations is the (randomized) $1$-deletion depicted in Figure 2. This transformation takes in input a string $F$ of $n$ elements, selects a component of $F$ at random, say the $i$-th, and outputs the base $F’$ of $n-1$ elements obtained from $F$ by removing (deleting) the $i$-th element, and the $2$-element deviation $D$ consisting of the deleted value and its original position $i$ (in $F$).

To build up intuition, the more deletions a client performs before uploading its data the harder it is for a CSP to reconstruct the original data. This increases the privacy of the outsourced data, however, the storage footprint on the client’s side also increases. Section III-A elaborates on the transformations deployed in Yggdrasil while Section IV analyzes the trade off between level of uncertainty and storage size on the client end.

B. Attacker Model

We consider privacy against a computationally unbounded, honest-but-curious CSP. In detail, we assume this CSP knows the distribution of clients’ raw files $D$, reads all data outsourced by clients, and has unlimited computational power. The attacker’s goal is to correctly reconstruct the clients’ original files. We discuss how to measure the success probability of such attacks in the next section II-C through the ‘uncertainty metric’. Investigating how to reach security against a malicious attacker, either CSP or client is left as future work.

C. Performance Metrics

In what follows, $DB$ denotes a database (collection of arbitrary files $F$), $S$ denotes the dual deduplication system described in Section II-A size is a function that takes as input a system $S$, a party, e.g., Client or Cloud and a database $DB$, and returns the size of the storage space required by the given party to store $DB$ according to the system $S$.  

![Fig. 1. Yggdrasil system model: several independent clients upload data to the same cloud storage provider.](image)
Since our model describes systems where both Client and Cloud store some piece of information, it is natural to define three quantities to measure the system compression capability.

**Client Compression Ratio:**
\[
\mathcal{C}_{\text{Client}} = \frac{\text{size}(S, \text{Client}, DB)}{|DB|}.
\]

**Cloud Compression Ratio:**
\[
\mathcal{C}_{\text{Cloud}} = \frac{\text{size}(S, \text{Cloud}, DB)}{|DB|}.
\]

**Global Compression Ratio:**
\[
\mathcal{C} = \frac{\text{size}(S, \text{Client}, DB) + \text{size}(S, \text{Cloud}, DB)}{|DB|}.
\]

Concretely, \( \mathcal{C} \) measures the compression capability of our system. The lower the value of \( \mathcal{C} \) the better the compression level and the smaller the overall storage space required. An ideal solution would have \( \mathcal{C} < 1 \).

Now we define a metric for evaluating the privacy of a system \( S \). The uncertainty metric \( \mathcal{U} \) measures the degree of uncertainty a honest-but-curious CSP faces when trying to retrieve clients’ original files from the data they outsource. To formally define \( \mathcal{U} \) we need a distribution \( \mathcal{D} \) defined on the database \( DB \). This essentially simulates the fact that CSP may know what are the most common files. Thus we define

**Uncertainty Metric:**
\[
\mathcal{U}(F) = \text{Prob}_{F^* \sim D}[F^* \leftarrow A(\mathcal{D}, F') | F^* = F]
\]

where \( F' \) is the outsourced data uploaded by the clients to the Cloud in correspondence to the original \( F \).

### III. Yggdrasil

We begin by describing the set of allowed transformations in Yggdrasil. Then we explain the protocol in detail.

#### A. Allowed Transformations in Yggdrasil

- From information theory, we know four functions to transform a string. Namely, (i) insert an element to a position, (ii) delete an element from a position, (iii) swap two elements, and (iv) change the value of a given position. Note that swap and change value do not change the length of the string, while insert and delete do.

Yggdrasil allows Client and Cloud to determine policies on how to transform the data to obtain deduplication friendly strings. The aim is to minimize the number of operations to perform while achieving efficient deduplication rate on the Cloud and some level of privacy at the Client side. These policies typically require a metric to determine similarities among strings. A natural metric is the **Hamming distance**, indicating the number of positions with different values in two strings of the same length. This essentially tells us how many **change value** operations we need to transform a string into another. **Swap Distance** indicates the number of operations to change a string into another using only the **swap** and **change value**. **DamerauLevenshtein Distance** is the most complete metric, essentially indicating the number of operations to transform one string into another if we use all 4 transformations (i)-(iv) \(^5\).

Previous work on GD focused primarily on changing values operations using Hamming or Reed-Solomon codes \(^4\), \(^6\). Here we instead consider the three operations (i) insert (Ins), swap (Swap) and change value (ChngV). We discard the **insert** function as it increases the size of a string, which is counterproductive for compressing the data.

In Yggdrasil, Client applies Del transformations on \( DB \) prior to sending data to Cloud to achieve the desired level of privacy.\(^2\) Cloud applies Swap and ChngV to reduce the distance between the strings uploaded by Client, generating strings that are suitable for generalized deduplication.

#### B. Proposed Protocol

We describe Yggdrasil, our protocol for privacy-aware dual deduplication in multi client settings. The protocol is run between Client and Cloud, components of \( S \) and is parameterized by (a) a distance metric dist; (b) a threshold value \( \tau > 0 \) that indicates the maximum number of operations allowed in the Cloud per string; At initialization Cloud holds an initial set \( n_b \)-size called bases \( S = \{\text{base}_1, \ldots, \text{base}_n\} \). \(^3\) \( S \) can be updated over time, but the full potential of updating \( S \) will be studied in future work.

At its core, the protocol performs a number of operations in the Client with a focus on privacy protection prior to uploading to the Cloud. Cloud uses the information from each Client and the \( S \) to attempt deduplication of similar bases that are \( \tau \) operations away given a dist metric. If the data is similar to one basis in the \( S \), it will be deduplicated, otherwise, it will be stored as it is. In the following, we provide a description of the various operations of Yggdrasil and where they take place.

**SetUp(\( S \)):** This algorithm is run by the Cloud periodically.

It takes as input a set of bases \( S \) and outputs a policy \( Policy \) that concisely describes \( S \).

**Upload(Policy, \( F \)):** This algorithm is run by Client using a given Policy On input of a file \( F \), Del are applied to \( F \).
Fig. 3. Yggdrasil System Model for Secure, Multi-client Dual Deduplication

In the following, we analyze the compression rate and the privacy (uncertainty measure) achieved by Yggdrasil. In this section, unless stated otherwise, we use log(x) as the logarithm in base 2 of x.

A. Client Compression Ratio

We begin our analysis with studying the compression ratio on the client side, i.e., \( C_{\text{Client}} \). To compute \( C_{\text{Client}} \) for one string \( F \), we need to accurately measure the size of \( D \). Assuming Client performed \( x = n_o - n_b \) subsequent Del on \( F \), then \( D \) contains the \( x \) deleted values (each value has \( k \) bits) and a pointer to their original locations in \( F \) (each pointer has \( \lceil \log(n_o) \rceil \)). Therefore, the required storage needed in Client is equal to:

\[
\text{size}(S, \text{Client}, F) = x(\lceil \log(n_o) \rceil + k) + s_{\text{fid}},
\]

where \( s_{\text{fid}} \) is the size in bits of a file identifier (\( s_{\text{fid}} = \text{size}(\text{fid}) \)). If our \( DB \) has \( f \) files, the required storage on the Client side for the whole \( DB \) is

\[
\text{size}(S, \text{Client}, DB) = f(x(\lceil \log(n_o) \rceil + k) + s_{\text{fid}}).
\]

B. Cloud Compression Ratio

The data stored in Cloud The size of data stored in the Cloud consists of \( b \) basis, where each basis has \( n_b \) symbols of size \( k \); one file identifier \( \text{fid} \) per string \( F \) and the dev generated in Comp procedure for deduplicated strings. Each Swap in Cloud adds \( 2\lceil \log(n_o) \rceil \) and each ChngV adds \( k + \lceil \log(n_o) \rceil \) to dev. As there are \( f - b \) deduplicated strings and the number of operations in Cloud for each \( F \) is bounded by \( \tau \), we have

\[
\text{size}(S, \text{Cloud}, DB) \leq b \cdot k \cdot n_b + f \cdot s_{\text{fid}} + (f - b) \cdot \tau(2\lceil \log(n_o) \rceil).
\]

Therefore, for the compression ratio in Cloud, we have:

\[
C_{\text{Cloud}} = \frac{s_{\text{fid}} + 2\tau\lceil \log(n_o) \rceil + r(k \cdot n_b - 2\tau\lceil \log(n_o) \rceil)}{k \cdot n_o}.
\]

where \( r \) is the fraction of number of bases to the number of original strings, i.e., \( r = \frac{b}{f} \). The condition for achieving a compression ratio of less than one is:

\[
r \leq 1 - \frac{s_{\text{fid}} - k \cdot x}{k \cdot (n_o - x) - 2\tau\lceil \log(n_o) \rceil} \Leftrightarrow C_{\text{Cloud}} \leq 1.
\]

C. Global Compression Ratio

The global compression ratio of the system is given by the sum of the Client compression ratio and the Cloud one. Thus,

\[
C = \frac{2s_{\text{fid}} + k \cdot x + (2\tau + x)\lceil \log(n_o) \rceil + r(k \cdot n_b - 2\tau\lceil \log(n_o) \rceil)}{k \cdot n_o}.
\]

D. Uncertainty of Multiple 1-Deletions

We now calculate the uncertainty of a data item after Client performs \( x \) 1-deletions. We consider the probability distribution \( D \) over the set of \( k \)-bit symbols to be uniformly random, i.e., every symbol has the same probability \( 1/2^k \) to be selected. In this setting, our definition of uncertainty (Eq. (4)) states that the uncertainty of a string \( U(F') \) is equal to 1 over the number of original strings \( F \) that can be generated by the base \( F' \) output to the Cloud. Let \( m \) denote this value, then [8]:

\[
\]
TABLE I
NUMERICAL COMPUTATION OF \( m \) AND \( U \) FOR VARYING \( k, n_o \) AND \( n_b \).

| \( k \) | \( n_o \) | \( n_b \) | \( m \) | \( U \) |
|------|--------|--------|------|------|
| 2    | 10     | 15     | 8.53 \times 10^6 | 1.17 \times 10^{-7} |
| 4    | 10     | 15     | 2.35 \times 10^9  | 4.26 \times 10^{-10} |
| 8    | 10     | 15     | 3.24 \times 10^{15} | 3.08 \times 10^{-16} |
| 2    | 100    | 150    | 1.72 \times 10^{74} | 5.81 \times 10^{-65} |
| 4    | 100    | 150    | 1.32 \times 10^{99} | 7.58 \times 10^{-100} |
| 8    | 100    | 150    | 4.28 \times 10^{150} | 2.34 \times 10^{-161} |
| 2    | 500    | 1000   | 1.47 \times 10^{538} | 6.80 \times 10^{-539} |
| 4    | 500    | 1000   | 3.21 \times 10^{888} | 3.12 \times 10^{-888} |
| 8    | 500    | 1000   | 5.05 \times 10^{1502} | 1.98 \times 10^{-1503} |

Intuitively, \( m \) counts the number of ‘preimagines of Upload’, i.e., how many \( n_o \)-element strings \( F \) can generate the same base \( F' \) for a combination of \( x \) Del. For large enough \( n_o \) and \( n_b \geq n_b \), a good lower bound is to consider the first term in the summation, i.e., \( m \geq (\binom{n_o}{n_b}(2^k - 1)^{n_o - n_b} - 1) \). Using Eq. (7) the uncertainty metric for a record \( F \leftarrow D \) is

\[
U(F) = \frac{1}{m} \left( \frac{(2^k - 1)^{n_o - n_b}}{\sum_{j=0}^{n_o - n_b} \binom{n_o}{n_b}(2^k - 1)^{n_o - n_b} - j} \right).
\]

Table I shows this number for various symbol sizes \( k \), original string sizes \( n_o \), and basis size \( n_b \). Even for small sequences of \( n_o = 15 \) with \( k = 2 \), the uncertainty is in the order of \( 10^{-7} \). For more realistic cases, e.g., \( n_o = 1000 \), \( n_b = 500 \) and \( k = 8 \), the uncertainty metric is \( 10^{-1503} \), creating a high degree of potential uncertainty on Cloud.

E. Most Probable String

Let \( P(F = o|F', D) \) denote the probability of an original string \( o \) of length \( n_o \), given a basis \( F' \) and a probability distribution of \( D \) for the symbols in the original strings. From an attacker’s perspective, the key is to identify the most probable string, i.e., the string \( o \) in the set of all strings of size \( n_o \), that has \( \max P(F = o|F', D) \). From a system designer’s perspective, a similar question is interesting to achieve a higher privacy in the system. Namely, the system wants to minimize this probability.

In order to generate the original data, the attacker needs to add \( n_o - n_b \) symbols to the basis in arbitrary positions. In this setup, the most probable strings is the string with the most number of duplicates in the reconstruction. The duplicates occur when we insert a value \( i \) between consecutive elements in basis that already has value \( i \). Suppose the longest consecutive elements of value \( i \) in \( F' \) has length \( l_i \), hence, the number of possible duplicates is equal to:

\[
\max_i \sum_{j=0}^{n_o - n_b} (l_i + j) = \max_i \frac{1}{2}(n_o - n_b + 1)(2 \cdot l_i + n_o - n_b).
\]

Therefore, the most probable string has a probability of:

\[
\max_o P(F = o|F', D) = \max_i \frac{1}{2}p_i^{n_o - n_b} \cdot (n_o - n_b + 1)(2 \cdot l_i + n_o - n_b).
\]

Clearly, there is a strong dependence on the probability distribution of the original strings. To reduce this probability for a set of data, we can define several policies:

**Policy 1:** Set the probability distribution of the elements in the basis to be as close as possible to uniformly random distribution, e.g., a ciphertext. This may be counterproductive for the compression process. However, approaching a uniform distribution provides clear privacy advantages. A system designer can try to select the level of protection desired.

**Policy 2:** A basis does not include consecutive identical symbols, especially the symbols with higher probability.

V. SIMULATION RESULTS AND DISCUSSION

In this section, we first show our simulation results and then discuss the results and the performance of Yggdrasil. In order to validate our system, we use the data of 18 GB of HDFS logs as our dataset. We developed a C++ implementation of a Yggdrasil client applying random 1-deletions and a server performing swap and change value operations. The client and server both carry out deduplication steps separately. For the sake of storage friendly implementation, we defined the fid of bases to be a global variable auto-incremented by the Cloud. This means that each fid has a storage size of \( \log(N_b) \) where \( N_b \) is the number of bases after deduplication. This can be later changed to standard fingerprint functions, e.g., SHA-1, SHA-256, in the Cloud. The impact of these slightly larger fid is minor for bases of 1 KB of more in size, which is the case we focus on in the following.

Fig. 4 shows that a judicious selection of the number of transformations results in a total compression ratio \( C = 0.5527 \) for \( n_b = 950 \) and \( C = 0.6583 \) for \( n_b = 900 \). For a fixed value of \( n_b \), the compression ratio in the Client is constant as the client always performs \( n_o - n_b \) deletions. However, the compression ratio of the Cloud differs depending on the maximum number of allowed swap and change value operations (\( \tau \)). A small \( \tau \) results in high compression rates. In fact, overall stored data may be higher than the original size because the number of bases that are deduplicated is low. Thus, the extra storage required to store the operations is larger than the gains from deduplication. A higher \( \tau \) allows for more bases to be deduplicated. We show that there exists a minimum point for both Cloud and overall compression ratio. This is the best compression ratio achievable for a given pair \( (k, n_b) \) for \( n_o = 1024 \). Our analysis shows that this minimum is close to the median of the swap distance between all bases, which can be used in future work as a heuristic for the optimal value of \( \tau \). Larger \( \tau \) values result in an increase in the compression ratio, because there are diminishing returns on the deduplication potential and the cost of recording additional operations results in much higher storage costs.
TABLE II

| $n_b$ | $k$ | $\tau$ | $C$ | $C_{\text{Client}}$ | $C_{\text{Cloud}}$ |
|-------|-----|--------|-----|----------------------|-------------------|
| 900   | 2   | 85     | 0.5527 | 0.2482 | 0.3158 |
| 900   | 4   | 44     | 0.5341 | 0.2119 | 0.3012 |
| 900   | 8   | 25     | 0.5419 | 0.1773 | 0.3645 |
| 900   | 16  | 16     | 0.8493 | 0.1468 | 0.7025 |
| 900   | 32  | 6      | 0.9329 | 0.1159 | 0.8166 |
| 950   | 2   | 115    | 0.6583 | 0.4423 | 0.2159 |
| 950   | 4   | 59     | 0.5927 | 0.4038 | 0.1889 |
| 950   | 8   | 31     | 0.4912 | 0.3645 | 0.1266 |
| 950   | 16  | 15     | 0.8922 | 0.3218 | 0.7025 |
| 950   | 32  | 7      | 1.0657 | 0.2894 | 0.7352 |

Fig. 4(c) shows the best compression ratio achieved for various values of $n_b$ and $k$ and a fixed $n_o$ and shows an optimal selection of $n_b$ and $k$ to achieve the highest overall compression. Fig. 4(c) shows that this minimum point is reached for a lower $n_b$ when $k$ is smaller, e.g., the best compression ratio for $k = 2$ is achieved at $n_b = 900$, while the best compression ratio for $k = 8$ is achieved at $n_b = 950$. We also observe that $k = 8$ provides the best potential for compression overall (49% of original data) with only small degradations of the compression rate around the optimal point. This is important in practice as the Client’s may aim to achieve different uncertainty - storage trade-offs and $k = 8$ corresponds to byte representations that are good to achieve efficient software implementations. Note that for $(k, n_b, n_o) = (8, 950, 1024)$ the number of possible original strings that could generate each basis uploaded to the Cloud is around $10^{293}$. For $k = 16, 32$ the cost of storing the deviation for each elimination in the Client is high, which limits the overall potential for compression in the Client and, thus, in the overall system. Table II provides details for the Cloud and Client compression ratios for different $k$ and $n_b$.

VI. CONCLUSION

We presented Yggdrasil, a protocol that allows Cloud Storage Providers to carry out deduplication across data uploaded by multiple clients, while introducing a level of uncertainty which provides privacy for the data sent by the individual clients. This injection of uncertainty is carried out by each client individually by transforming the data prior to upload and storing a compact description of such transformations locally. We propose an improvement on the concept of generalized deduplication to increase its compression potential, that consists of allowing the CSP to swap and change values of the records it receives from clients. Our numerical results show that Yggdrasil reduces the amount of data stored in the Cloud, in the local device and even in the system as a whole, while providing a high degree of uncertainty regarding the data uploaded by each client. A side advantage of Yggdrasil is that it can protect from side channel attacks from malicious clients trying to gain knowledge about the data stored by other clients in the Cloud. Future work will consider malicious adversaries and clients that do not reveal the original size of the chunk and only comply with the expected basis size of the Cloud. This added uncertainty requires further analysis as the attacker would not have the information about the chunk’s original size as prior knowledge.

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