Cloud Storage Integrity at Scale: A Case for Dynamic Hash Trees

Quinn Burke, Ryan Sheatsley, Rachel King, Michael Swift, and Patrick McDaniel University of Wisconsin-Madison

Abstract

Merkle hash trees are the state-of-the-art method to protect the integrity of storage systems. However, using a hash tree can severely degrade performance, and prior works optimizing them have yet to yield a concrete understanding of the scalability of certain designs in the context of large-scale cloud storage systems. In this paper, we take a first-principles approach to analyzing hash tree performance for storage by introducing a definition of an optimal hash tree and a principled methodology for evaluating hash tree designs. We show that state-of-the-art designs are not scalable; they incur up to 40.1× slowdowns over an insecure baseline and deliver <50% of optimal performance across various experiments. We then exploit the characteristics of optimal hash trees to design Dynamic Hash Trees (DHTs), hash trees that can adapt to workload patterns on-the-fly, delivering >95% of optimal read and write performance and up to $4.2 \times$ speedups over the state-of-the art. Our novel methodology and DHT design provides a new foundation in the search for integrity mechanisms that can operate efficiently at scale.

ACM Reference Format:

Quinn Burke, Ryan Sheatsley, Rachel King, Michael Swift, and Patrick McDaniel. 2024. Cloud Storage Integrity at Scale: A Case for Dynamic Hash Trees. In *Proceedings of ACM Conference (Conference'17)*. ACM, New York, NY, USA, 14 pages. https://doi.org/10. 1145/nnnnnnnnn

1 Introduction

An increasing number of attacks against cloud services has raised significant concerns about how to practically secure data when outsourcing storage resources. This has fueled significant investment and research into trusted cloud storage systems: storage systems that provide high assurance of the confidentiality and integrity of data in-memory and on-disk through hardware-based enforcement mechanisms [4, 13, 32]. To this end, Merkle hash trees have become the stateof-the-art method to protect the integrity of trusted cloud storage systems [1, 3, 13, 32, 34, 40].

However, it is widely known that introducing hash trees on the storage critical path can severely degrade performance [21, 23, 45, 48]. Costs stem largely from the significant number of hashes that need to be computed from leaf to root on every read and write to storage. For example, consider that a 1TB disk contains approx. 268M 4KB blocks. A typical balanced, binary hash tree over the disk blocks would have a height of 28, requiring (at least) 28 hashes to be computed on every read or write request. Considering the total cost of fetching and verifying hashes, the latency of completing a single read or write request may far exceed the baseline latency of reading or writing a single block from a high-performance storage device (which can be $<20\mu$ s).

Several works have examined various hash tree optimizations, mostly in the context of secure memory systems [21, 23], but also recently for storage [1, 3, 13, 32, 34, 40]. We focus specifically on storage, which is subject to vastly different workload characteristics, capacities, and assumptions about cache memory size. While state-of-the-art works optimizing hash trees have claimed to be scalable, we observe that they are not—incurring up to $40.1 \times$ slowdowns under realistic workloads. We attribute this inconsistency to the fact that prior works have yet to yield a principled framework within which to evaluate hash tree performance.

In this paper, we take a first-principles approach to analyzing hash tree performance in the context of cloud block storage. First, we observe that prior works lack a well-defined performance target: it remains unclear how to evaluate whether a hash tree design is performing optimally [27], or even what performance is practically achievable, in a given system. Understanding optimal performance is important to understanding scalability limits. We ask the fundamental question: *How can we model an optimal hash tree for cloud block storage?* We show that the problem of finding an optimal hash tree can be reduced to the problem of finding an optimal prefix tree in the context of lossless data compression [25]. More specifically, by constructing a hash tree as an optimal prefix code, we can produce a hash tree that achieves optimal throughput under a given workload profile.

Next, we observe the lack of a principled methodology to qualitatively evaluate how well a design performs across the various parameters that characterize cloud block storage deployments, including capacity, read/write ratio, cache size, and workload type [3, 42]. For example, a hash tree may appear to have high overheads, but actually be performing optimally, which suggests that complimentary optimizations (e.g., parallelization) may be the only way to break the performance ceiling. Towards this, we introduce a new method to instantiate an optimal hash tree in an *offline* setting (i.e., with a priori knowledge of a workload trace) and evaluate how well a design performs with respect to the optimal.

Building on our observations of optimal trees, we then explore the design of an *online* solution that does not assume a priori knowledge of workload characteristics, but can learn and adapt to workload patterns on-the-fly. It is know that real-world workloads are characterized by skewed access patterns (i.e., with high reference locality, where a small number of blocks are accessed much more frequently than others) across all layers of the memory hierarchy [3, 16, 30, 47, 50]. In an offline setting, this manifests as optimal hash trees often being far from balanced. Thus, frequently accessed blocks have shorter verification/update paths in the tree than infrequently accessed blocks. Towards this, we introduce a novel dynamic, unbalanced hash tree design called Dynamic Hash Trees (DHTs). DHTs are based on the splay trees commonly used in garbage collection and IP routing lookup [43], and they self-adjust to remain adaptive to workload characteristics observed at runtime.

We implemented DHTs and the state-of-the-art designs and evaluated them in a real cloud setting with AWS EC2 instances and EBS block devices. Our experiments under realistic workload patterns and across various system configurations show that: (1) state-of-the-art static, balanced trees [13, 21–23, 34] are not scalable, incurring up to 40.1× slowdowns over an insecure baseline and delivering less than <50% of optimal throughput on average; and (2) DHTs can capitalize on skewed access patterns, delivering >95% of optimal throughput and up to 4.2× speedups on read and write performance over the state-of-the-art.

We conclude that for cloud block storage, balanced trees are ill-suited as the base construction of a hash tree, and DHTs are a preferable alternative. DHTs are an existence proof that online approaches are feasible to implement and even simple heuristics can significantly improve performance over the state-of-the-art. Our methodology and DHT design provides a new foundation in the search for integrity mechanisms that can operate efficiently at scale. Our code is plugand-play into standard Linux systems and is open-sourced at [Anonymized link].

2 Background

Cloud Block Storage. Block storage systems are a backbone of modern cloud infrastructure. As shown in Figure 1, they sit at the lowest level in the software stack and serve as the primary storage interface for various higher-level software. They are composed of three key components: *clients, block layer*, and *cloud storage devices*. Clients are any software requiring persistent storage, such as remote user clients of personal cloud drives, virtual machines, cloud-hosted applications, etc. The client's block layer implements protocols to communicate with local or remote cloud storage devices (also called disks or volumes) and exposes a simple block read/write interface to clients. Widely used cloud block storage services include AWS Elastic Block Store [6], Google

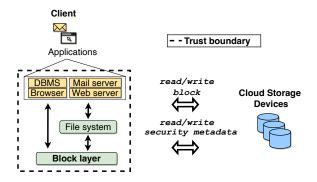


Figure 1. Our system model captures common deployment scenarios for cloud block storage. The block layer (and client code) runs inside a trusted environment, while cloud storage devices managed by the public cloud provider are untrusted.

Cloud Persistent Disks [15], and Microsoft Azure Managed Disks [7]—none of which provides cryptographic integrity protection to customers by default.

Merkle Hash Trees. Merkle hash trees have become the state-of-the-art method to protect the integrity of arbitrary datasets [13, 23, 32, 34, 40]. As shown in Figure 2, a Merkle hash tree (or more simply, a hash tree) is typically a balanced binary tree, with each node in the tree containing a hash value. We note that higher-degree trees (e.g., 64-ary) have been considered in other contexts such as secure memory systems [45]; we defer discussion of these designs to Section 7. A leaf node contains the hash (MAC) of a data block (and a cipher IV when encrypting data), and an internal node contains the hash of the concatenation of the hashes of its two children. Internal node hashes are iteratively computed from leaf to root, and the root hash authenticates the current contents of the storage device and is typically stored in a secure location (e.g., in a TPM on the client machine [39]). All other nodes in the tree are stored on disk alongside the data. The number of leaf nodes in the tree n is equal to the number of blocks on the storage device, and the total number of tree nodes is 2n - 1.

There are two primitive operations on a hash tree: *verification* and *update*. When a block is read, it must be verified against the root hash. The client's block layer first fetches the (encrypted) block data, MAC, and cipher IV from disk. It checks that the retrieved MAC is consistent with the retrieved block data by rehashing the data and comparing. It then fetches the *proof* of authenticity, a set of auxiliary hashes along the path from the accessed leaf to the root (see nodes highlighted in blue). The retrieved MAC is inserted into the tree at the appropriate leaf position, and parent hashes are iteratively computed along the *authentication path* using the auxiliary hashes (see red arrows). The computed root hash is then compared against the known root hash. If the two hashes match, verification succeeds. Block

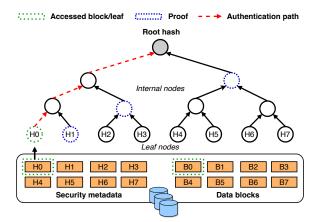


Figure 2. A Merkle hash tree protects against data corruption, relocation, and replay attacks with a tree of hashes. The client's block layer uses a Merkle hash tree to authenticate data when it is read from or written to storage.

updates are handled similarly, with the update committed by saving the new root hash to the secure location.

Caching hashes in a fast memory is also a standard hash tree optimization [3, 23]. Caching provides two advantages: (1) it reduces I/O costs associated with fetching hashes during a verification or update, and (2) it enables early returns when fetching and verifying nodes (during either a verification or update), because cached nodes are already authenticated.

3 Security Model

Trust Model. We assume the clients and block layer are trusted, while cloud storage devices managed by the public cloud provider are untrusted. This trust model broadly captures practical deployment scenarios of trusted storage [4, 9, 26, 44]. For example, for trusted cloud drives, the block layer and all other client code would run in a trusted environment, the remote user's machine, and send read/write requests to storage over a network. For trusted VMs or cloud-hosted applications, the block layer and all other client code would run inside of a trusted execution environment [32] on a cloud server, similarly sending read/write requests to local or remote storage [13, 40]. In either case, the block layer runs underneath the application code, within the trust boundary, and bridges the application to untrusted block storage.

Threat Model. Attacks on cloud block storage may come from either a malicious cloud provider, co-tenant, or another authorized client of the block storage service [13, 21]. We focus specifically on attacks causing integrity violations: any block written to or read from disk may be tampered with. For example, an attacker may corrupt data blocks before they are delivered up to the block layer. They may perform relocation attacks, where blocks are deliberately read from or written to incorrect block addresses. Finally, they may replay an old version of a block to the block layer.

Security Requirements. Three integrity properties are required of *trusted* cloud block storage: correctness (protects against corruptions), spatial uniqueness (protects against relocations), and temporal uniqueness (protects against replays) [5]. Merkle hash trees are the standard method to ensure all three properties, and in particular, replay protection (which per-block hashes cannot ensure). Their use is becoming increasingly important in practice for both storage and memory [2, 3, 23, 31]. For example, hash trees can prevent an adversary from reverting (i.e., replaying) system/application software to a known vulnerable state: the root hash reflects the current version of the storage device, so a replay attack would require changing the root hash, which is stored in a secure location and is out of control of the attacker.

We note that to achieve better performance, some prior works have loosened security requirements by permitting lazy verification or splitting the hash tree into multiple independent trees [3, 22]. However, lazy verification introduces a window of vulnerability, during which an attacker can violate one or more integrity properties. Splitting the hash tree also precludes having global correctness for any data within a single security domain. We therefore do not consider lazy verification or splitting in our analysis.

4 Optimal Hash Trees

Prior works have explored various hash tree optimizations [3, 21, 23, 42], but have yet to concretely characterize what techniques perform *well* (or best) and *when* [27]. We address this problem by introducing a novel definition of an optimal hash tree. Having an optimal tree serves two purposes: it establishes an upper bound on performance (Section 5), and it helps to understand what characteristics of the tree structure are correlated with high-performance, which will help inform new designs (Section 6).

4.1 Optimal Definition

Overheads from storage-level mechanisms are largely attributable to two things: compute costs and I/O costs. For hash trees, this means that if cache performance is poor, then I/O costs may be the bottleneck. In contrast, if cache hit rates are high, then performance is directly related to how quickly hashes can be computed to complete a verification or update—that is, how efficient the base structure of the hash tree is. Prior works have identified that even small caches are very efficient, but as we will show in Section 7, state-of-the-art static, balanced hash trees still cannot scale to large capacities; this is largely due to an increased tree size and thus increased hashing costs. This motivates our search for a more efficient tree structure.

We observe that the problem of finding an optimal hash tree can be reduced to the problem of finding an optimal Quinn Burke, Ryan Sheatsley, Rachel King, Michael Swift, and Patrick McDaniel

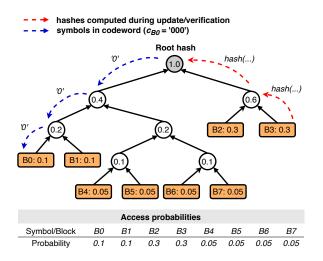


Figure 3. A Huffman tree is an optimal prefix tree. A hash tree constructed as a Huffman tree with a given access probability distribution is an optimal hash tree.

prefix tree (or *prefix code*) in the context of lossless data compression [36]. Prefix codes map a set of symbols onto a set of codewords, with the goal of compression being that codewords are as short as possible to produce a maximally compressed representation of the original data. An example is shown in Figure 3. More formally:

Theorem 1. A hash tree constructed as an optimal prefix code is optimal for a fixed access probability distribution.

Proof. Let $A = \{a_1, a_2, ..., a_n\}$ be a symbol alphabet and $W = \{w_1, w_2, ..., w_n\}$ be a set of associated symbol weights. Let $C = \{c_1, c_2, ..., c_n\}$ be a prefix code that represents the set of codewords for symbols in *A*. A prefix code *C* is said to be optimal if it minimizes the *expected* codeword length: arg min $C \sum_{i=1}^{n} w_i |c_i|, c_i \in C$. The length of a codeword is the number of bits in a codeword, or equivalently, the *number of edges* in the path from the root to the symbol leaf in the prefix tree representation of *C*. Huffman coding is a widely-used algorithm to produce optimal prefix codes [25].

Now let $B = \{b_1, b_2, ..., b_n\}$ be a set of disk blocks and $F = \{f_1, f_2, ..., f_n\}$ be a set of access frequencies to blocks determined by some known workload profile. Suppose we map each block b_i to a symbol a_i and each access frequency f_i to a symbol weight w_i . Running Huffman's algorithm on A and W produces a prefix code with expected codeword length $\sum_{i=1}^{n} w_i |c_i| = \sum_{i=1}^{n} f_i |b_i|$.

In the compression domain, the number of edges represents the number of bits needed to parse a symbol's codeword, while in the hash tree domain it represents the *number of hashes* that must be computed from leaf to root for a block. A hash tree constructed as a Huffman code minimizes the expected number of hashes computed during an update or verification and is therefore an optimal hash tree. \Box

4.2 Extended Optimal Definition

Now we extend our optimal definition to consider the effects of cache performance. Note that both data blocks and hashes can be cached in main memory. In the compression domain, codeword paths in an (optimal) prefix tree can be parsed in a constant amount of work per edge, giving a total amount of work: $\sum_{i=1}^{n} w_i (|c_i| \cdot O(1)) = O(1) \cdot \sum_{i=1}^{n} w_i |c_i|$. However computing a hash requires (at least) two hash fetches in a binary hash tree: the node's two children. If both hashes are present in memory, fetch costs are negligible and the amount of work is similarly optimal: $\sum_{i=1}^{n} f_i(|b_i| \cdot O(1)) =$ $O(1) \cdot \sum_{i=1}^{n} f_i |b_i|$. Otherwise if they must be fetched from disk, I/O costs are non-negligible: $\sum_{i=1}^{n} f_i(|b_i| \cdot t(b_i)) = \sum_{i=1}^{n} f_i |b_i| \cdot$ $t(b_i)$, for some function $t(b_i)$.

We can model the incurred I/O costs using the average memory access time formula:

AMAT = hit time + miss rate × miss penalty

$$\implies t(b_i) = \text{mem latency} + \text{miss rate} \times \text{reauth latency}$$

 $\implies t(b_i) = H + mD = O(1) + mD$
(1)

where *H* is a fixed memory access cost, *m* is the miss rate of a node fetch in memory, and *D* is a fixed fetch/reauthentication cost. Substituting this in, the total amount of work is:

$$\sum_{i=1}^{n} f_i |b_i| \cdot t(b_i) = \sum_{i=1}^{n} f_i |b_i| \cdot (O(1) + mD)$$
$$= \underbrace{O(1) \cdot \sum_{i=1}^{n} f_i |b_i|}_{\text{base work}} + \underbrace{mD \cdot \sum_{i=1}^{n} f_i |b_i|}_{\text{I/O costs}}.$$
(2)

Remark. From our model, we see that higher miss rates for block hashes incur more work per edge, proportional to the expected number of hashes that must be computed per update or verification. Specifically, at a given miss rate, the incurred I/O costs follow the same distribution as the underlying access probability distribution: hotter data has a lower expected amount of base work and incurs lower I/O costs, while colder data has a higher expected amount and incurs higher I/O costs.

We also see that with an optimal cache (m = 0.0), the expected total amount of work is exactly optimal. However, it has been empirically observed that as cache size decreases, miss rates increase with a power law [14], and thus as the cache size decreases, expected I/O costs increase with a power law. This implies that the performance of hash trees is very sensitive to cache size. In particular, as cache memory can be financially costly on cloud servers, being able to synergize well with relatively smaller caches (w.r.t. larger disks) is critical to a practical hash tree deployment. Moreover, a Huffman tree is optimal under a fixed set of weights (cf. access probability distribution). If the symbol sequence (cf. block access sequence) observed while compressing a message (cf. during a program trace) exactly matches the one used to construct the tree, then the tree will be exactly optimal (i.e., provide optimal throughput). However, if the sequence deviates from the one used to construct the tree, the tree will not be exactly optimal. In this case, I/O costs will also increase at an amount proportional to the distance between the access probability distributions.

5 Optimal Tree Oracle

We now introduce a new method to instantiate an optimal hash tree in an offline setting. Our optimal definition provides that, if we have knowledge of a concrete block access sequence (i.e., workload trace), we can instantiate an optimal hash tree from the trace. In an *offline* setting, where we have access to workload traces (e.g., recorded with standard tools like blktrace), we can feasibly do so. Replaying the trace against the optimal tree will then determine the maximum performance achievable under the given workload. Replaying the trace against other hash tree designs will reveal how they perform with respect to the optimal.

We refer to this methodology as the optimal tree oracle, and it allows us to measure a concrete upper bound on performance. The primary purpose is to understand whether overheads over the baseline should be attributed to a fundamental scaling limit or to the structure of the tree itself. For example, a hash tree may be performing optimally, but have high overheads, which would suggest that complimentary optimizations (e.g., parallelization) may be the only way to break the performance ceiling. In contrast, a hash tree that does not perform optimally under a given workload may require a fundamental redesign.

We liken this approach to Belady's optimal page replacement algorithm [8], a clairvoyant algorithm that has a priori knowledge of future memory accesses and can make optimal page replacement decisions. This gives us the ability to make rigorously grounded conclusions about when a hash tree design performs well and when.

5.1 Workflow

The above procedure is composed of five steps (Figure 4).

- (1) Workload Generation Workload traces are first collected from applications or generated with standard benchmark tools like fio. The traces are composed of tuples of the form: (*op*, *offset*, *length*), where *op* is either read or write.
- (2) **Parameter Configuration** The system is then provisioned with the appropriate storage capacity, hash cache size, and read/write-ratio for workloads. The hash cache size is configured as a percentage of the total number of nodes in the hash tree. For example,

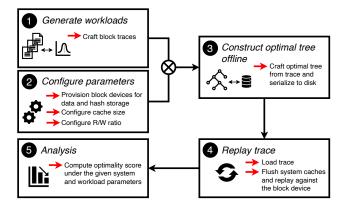


Figure 4. We rigorously evaluate performance by using an optimal tree oracle, which assumes knowledge of a workload trace and uses it to construct an optimal hash tree offline.

a 1 TB disk has approx. 268M 4 KB blocks and therefore 536M tree nodes. A cache size of 10% would hold 53.6M nodes, and with 72 B nodes (Section 7.1), would occupy 3.8 GB of memory.

- (3) Optimal Hash Tree Construction The generated workloads are run through Huffman's algorithm offline to produce an optimal hash tree. The tree is then serialized to disk to prepare to run the traces against it.
- (4) Trace Replay A trace is then loaded into memory and replayed against each hash tree construction in a serial fashion. System caches are flushed before each experiment to reduce interference between experiments.
- (5) Analysis Examining the performance of each hash tree design across a design space parameterized by capacity, cache size ratio, read/write ratio, and workload skewness allows us to understand where certain design points perform well or break down.

We defer analysis with the optimal tree oracle to Section 7.

6 Dynamic Hash Trees

State-of-the-art hash tree designs rely on static, balanced tree structures [1, 45], and balanced trees are specifically optimized for uniform access patterns. However, real-world storage workloads most often exhibit skewed access patterns [3, 16, 30, 47, 50]. Consequently, state-of-the-art designs leave a significant amount of performance on the table (Section 7). We hypothesize that we can use reference locality as a lever to achieve higher performance. This section builds on our observations of optimal trees to explore a novel hash tree design that exploits reference locality by learning and adapting to workload patterns on-the-fly.

6.1 Challenges

Finding a Suitable Tree Structure. Unlike the balanced hash trees used in state-of-the-art designs, optimal hash trees

Conference'17, July 2017, Washington, DC, USA

Quinn Burke, Ryan Sheatsley, Rachel King, Michael Swift, and Patrick McDaniel

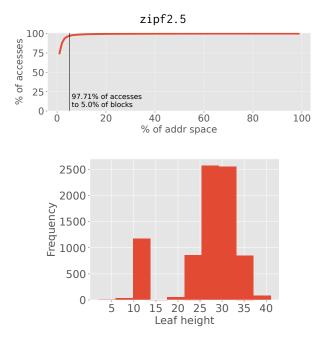


Figure 5. Storage workloads are skewed (top) [30], which suggests that the operations on the hash tree are also heavily skewed towards particular regions. This manifests in optimal hash trees (bottom) often being from balanced: under a Zipf(2.5) access probability distribution, the leaf heights show distinct regions of relatively hotter and colder data.

produced by Huffman codes are often far from balanced. Figure 5 shows an example under a Zipf(2.5) probability distribution over 8192 blocks (32 MB disk). In a balanced tree, leaf node heights should be constant at 13 levels. We see two distinct regions representing hotter (height \approx 10) and colder data (height \approx 30).

Yet, workloads characteristics can also vary over time: access patterns may still be skewed but regions of interest may change, or some periods of time may be characterized by more uniform access patterns. This is particularly true for storage that is shared by multiple cooperating applications or users. Thus, a tree that is optimal at one point in time may not be optimal for another (i.e., dynamically optimal). An online solution therefore must not only be able to *capture* hot data by placing more frequently accessed nodes higher in the tree, but also be able to dynamically *adapt* to changes in what particular data is deemed hot or cold over time.

Online tree optimization solutions have been widely studied, particularly for search. Most algorithms focus on keeping trees balanced to reduce worst-case running time. We explicitly aim to remove the balance constraint; commonly used self-balancing trees such as AVL trees are therefore ill-fit for our use case. Instead, we aim for a more aggressive optimization: to allow the tree to become unbalanced as necessary, but be driven by the workload. **Managing Restructuring Costs.** While intuitively it makes sense that unbalanced trees should be able to exploit skewed patterns by placing more frequently accessed leaf hashes closer to the root, realizing this is in a real system is a nontrivial problem. The mechanics of adapting trees involve a series of rotations. While rotations are cheap for search trees, consisting of a series of pointer updates, they are expensive for hash trees, as we have to recompute hashes for all nodes from the rotation point up to the root; this applies when nodes are rotated during either verifications or updates.

The costs of rotating nodes in the tree may therefore quickly outweigh any expected benefits of moving frequent nodes closer to the root. The cost of a rotation itself is also not constant, but proportional to the current height of the nodes involved in the rotation. Further, search trees permit all nodes to be searchable, but as mentioned, only leaf nodes are searchable in a hash tree. We therefore must maintain the invariant that during a rotation, a leaf remains a leaf and an internal node remains an internal node. Otherwise, a rotation will result in an invalid tree structure.

6.2 Randomized Splaying

We draw a connection to a widely used data structure in garbage collection and IP routing lookup: splay trees [43]. Splay trees are a type of binary search tree that brings an accessed leaf to the root through a series of rotations. Importantly, splay trees capture temporal locality by keeping frequently accessed nodes closer to the root (Figure 6). However, naively used, the cost of splaying can be extremely expensive, and splaying too frequently or opportunistically may keep the tree more balanced than desired. We adapt the conventional splay tree design to meet the constraints of a hash tree. Our heuristic algorithm consists of three parameters and is performed in two steps.

Heuristic Parameters. We define three parameters: a splay window flag *w*, splay probability *p*, and splay distance *d*. The splay window flag can be toggled on or off to indicate whether or not the splay window is active (i.e., whether or not we should consider a tree node to be splayed). This notion is useful because there may be certain periods at runtime where splaying should necessarily not occur. This may be the case, for example, if the system administrator has knowledge of current application access patterns or profiles them periodically, or if other background storage tasks may be in progress that require stability of data (e.g., health checks).

If the splay window is active, the splay probability denotes the probability that an accessed node should be splayed. The key intuition is that splaying is an expensive operation, but certain workload characteristics may be discernible by only examining and splaying nodes on a random subset of accesses. Finally, if a node is decided to be splayed, the splay distance defines the maximum number of levels that the

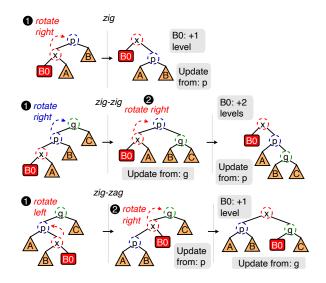


Figure 6. Splay trees are a type of binary search tree that capture temporal locality by bringing an accessed leaf closer to the root. We use a splay-based hash tree design to similarly capture temporal locality in cloud block storage workloads.

node should be splayed (i.e., *promoted*) up the tree. This entire process occurs at the end of each verification or update call and before anything is returned to the caller. We note that this task could be offloaded to a background thread, but would trade-off giving the caller a timely integrity check, which may violate integrity guarantees; we defer closer examination of this issue to future work.

6.3 Technical Approach

Analyzing Data Hotness. The splay distance is the central parameter that determines the effectiveness of a splay operation. Determining a suitable splay distance is challenging, as there is an inherent risk vs. reward trade-off when splaying a node. Splaying any node all the way to the root may be very beneficial if a node is relatively hot, as future accesses to the data can quickly benefit from the promotion. However, doing so would be severely wasteful if the node is cold, as the tree will then require several *additional* rotations to eventually promote hotter data and demote the cold data from a higher position in the tree. Finding an accurate and practical hotness metric is critical to balancing this trade-off.

We define the hotness of any tree node as the relative access frequency of the node with respect to other nodes. We track hotness of both leaves (i.e., blocks) and internal nodes (which indicate the hotness of particular subtrees/blocks). We attach an integer hotness counter to each tree node that is incremented whenever a node is promoted in the tree and decremented whenever a node is demoted in the tree. Thus, the hotness counter serves as a proxy that not only captures the relative access frequencies of nodes, but also the relative height differences in the tree as nodes are rotated. The counter is initialized to zero after the node is authenticated and cached; the hotness of nodes that are not currently cached in memory is therefore not tracked. This allows us to localize our analysis of data hotness to the working set. Note that this approach can significantly affect performance for small caches, as it will be difficult to draw a contrast between relatively hotter, warmer, and colder data when counters are reset frequently. Nonetheless, the splay distance is a function of the hotness. The splay distance is computed in a straightforward manner: at a distance proportional to the hotness. For simplicity, we set the splay distance to be h levels, where h is the current hotness value of the accessed leaf.

Intuitively, so long as the hotness counters reflect the relative access frequencies of nodes, nodes accessed more frequently will be splayed further towards the root. Moreover, note that our initial exploration into this space could be expanded with sketching algorithms, machine learning, or other more sophisticated techniques [24].

Promotion & Demotion. After computing the splay distance, the final step is to execute the splay operation. Splaying a DHT is done in nearly the same way as it is in a search tree. There are three cases to consider when splaying a node: *zig, zig-zig,* and *zig-zag* (Figure 6). In a zig case, the node's parent is the root, and we rotate the node up to the root. In a zig-zig case, the node's parent is not the root, and the node and the node's parent are either both left or right children. In this case, we perform two rotations along the same direction to rotate the node up two levels. In the zig-zag case, the node's parent is not the root, and the node's parent are opposite-side children. Thus, we perform two rotations along opposite directions to rotate the node up two levels.

A consequence of splaying is that an accessed node will either be promoted two levels (or to the root). Neighboring nodes will similarly be promoted opportunistically as a sideeffect of the splay. This provides two benefits. Nodes that are accessed frequently will therefore have an increasingly shorter path to the root, making verifications and updates quicker. More subtly, nodes that are accessed in close temporal proximity will slowly accumulate in nearby regions of the tree, allowing to exploit spatial locality within the tree.

Maintaining Hash Tree Invariants. We make three key changes to the standard splay operation to maintain three tree invariants. First, during a splay, we must ensure that a leaf node remains a leaf node and an internal node remains an internal node. Otherwise, a rotation will result in an invalid tree structure. For example, if a leaf node is splayed to the root, the root will become a leaf node, which is invalid. Whenever a block is read or written, we therefore execute a splay on the accessed leaf's parent rather than the leaf.

Next, we propagate the child status (left/right) to the splay operation, and swap the children of the parent node and the

Parameter	Description
Capacity	Usable capacity for data blocks
Read/write ratio	Distribution of reads and writes
Cache size ratio	Cache size as % of tree size

Table 1. We evaluate scalability by varying key parameters.

accessed node where necessary. This preserves the structural constraint for a valid hash tree while still ensuring the maximum degree of promotion for the accessed node.

Finally, splaying naturally introduces inconsistency into the tree, as it alters parent-child relationships: altering the tree structure will cause any subsequent hash fetches on a cache miss to fail due to an inconsistent root hash. We must therefore ensure that the tree remains in a consistent state by preemptively fetching (and authenticating) all auxiliary hashes before performing a rotation, then using them to commit the change immediately after. That is, parent hashes up to the root are recomputed per rotation. While updates can be costly, splaying can reduce these costs over time.

7 Evaluation

Below we evaluate the performance of DHTs in comparison to two insecure baselines (encryption/no integrity, no encryption/no integrity) and two state-of-the-art hash tree designs (binary trees used by dm-verity [1, 12] and high-degree trees used by VAULT [45]). We also discuss performance in the context of the optimal hash tree introduced in Section 4. An overview of our parameters is shown in Table 1.

7.1 Experiment Setup

Implementation. We implement all three hash tree designs in 4 K lines of C++. We use the BDUS framework to implement custom virtual block devices [20]. BDUS provides a virtual block device abstraction layer for file systems or application software on standard Linux systems. It has a kernel module that exposes block layer hooks to userspace, and a userspace library that exposes a simple API to application code. The two primary functions of interest are read() and write(), which are invoked by the kernel whenever a block is read from or written to the block device, respectively. We perform a verify operation immediately after a block is read and an update operation immediately before a block is written to disk. Note that we consider a hash tree at the block layer like many prior works [10, 12, 28, 38]; our basic data unit therefore aligns with the disk I/O size (4 KB).

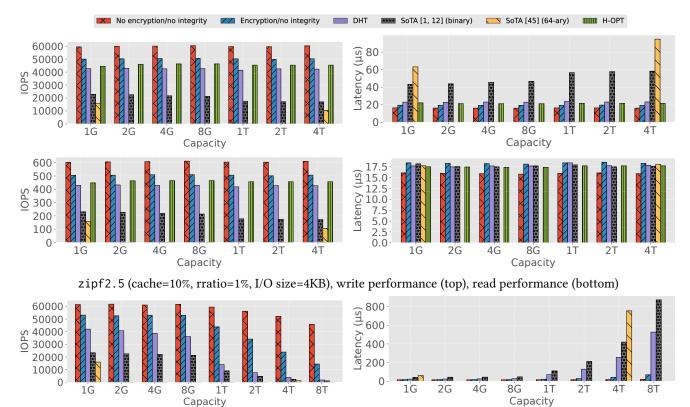
Testbed. We perform all experiments in a real cloud setting using AWS EC2 m6id.8xlarge instances, which are equipped with 32 logical cores, 128 GB memory, and 2 TB locallyattached NVMe SSDs operating at full bandwidth. We provision additional AWS EBS SSD volumes as necessary to match the capacity specified per experiment. We reinitialize hash trees between each experiment, use a standard LRU cache replacement policy, and we set the splay window flag w = True and splay probability p = 0.01 for DHTs.

Cryptographic Settings. While our focus is on integrity protection, our broader goal is trusted cloud storage, and we therefore also encrypt block data in addition to authenticating it. While there are many possible cipher modes and settings [10, 28], like similar works [5, 13, 45] we ensure deterministic authenticated encryption through AES running in GCM mode. We use a 128-bit encryption key for blocks. The MACs produced during the encryption process are used as the leaves in the hash tree. For internal nodes, we compute 256-bit HMACs using SHA-256 with a 256-bit key.

Workloads. Storage workloads are known to have a skewed shape [30]. Prior works benchmarking storage systems rely heavily on standard tool suites like fio or YCSB to generate skewed workloads, which primarily follow a Zipfian distribution [3, 16, 50]. Like these other works, we generate a set of Zipfian workloads with fio and record the traces such that we can compute an optimal tree and replay them against each hash tree design. We note that optimal trees and DHTs see qualitatively similar results across different Zipfian parameters, with larger speedups observed under increased skewness. For Zipfian workloads, we experiment with a parameter of 2.5, but note that prior measurement studies have characterized workloads as having Zipfian shape with parameters ranging from 1 to 5 [49]. We note that DHTs and balanced hash trees observe similar performance under uniform workloads and focus our analysis on non-uniform workloads, which are most often seen in practice.

We also supplement analysis of Zipfian workloads with a recent dataset of block-level traces published by Alibaba in 2023 [30]. The traces are recorded over a set of 1000 logical volumes with different capacities, and each record in a trace is a tuple of the form (*op*, *of f set*, *length*). We perform a preprocessing step to prepare the traces for use in our evaluation framework, which requires scaling the I/O offsets and lengths to the capacity specified per experiment. For our experiments, we randomly sample one device (logical volume ID 4) from the dataset, but note that the characteristics of each volume are qualitatively the same: the mean write ratio is >98% (due to higher-level caches likely handling reads, and only write requests causing I/O) and the traces are heavily skewed towards small regions of the disk. Note that we focus analysis of these traces on write performance, because there are too few read requests to draw any meaningful conclusions.

State-of-the-art & Insecure Baselines. We focus our analysis of the state-of-the-art and DHTs against the optimal and two insecure baselines (no encryption/integrity, no encryption/no integrity). We note that our focus is on storage, and the state-of-the-art for storage systems is dm-verity-style



alibaba_4 (cache=10%), write performance

Figure 7. Comparison of DHTs, balanced trees, the optimal, and two insecure baselines across various capacities. DHTs provide up to a 4.2× speedup over state-of-the-art designs.

trees-static, balanced, binary trees. The state-of-the-art for secure memories relies on static, balanced, high-degree (e.g., 64-ary) trees [45]. The intuition is that a larger node degree will reduce the tree height and thus the total hashing costs. Owing to their success in memory systems, we also examine high-degree trees for storage for juxtaposition.

Capacity

7.2 Results

We focus our analysis on three questions:

- 1. How well can state-of-the-art hash tree designs scale with capacity, cache size, and read/write ratio?
- 2. To what extent can DHTs or state-of-the-art designs deliver optimal performance?
- 3. What are the memory and storage overheads associated with implementing DHTs?

Scaling with Capacity. Figure 7 shows the IOPS and latencies observed across various capacities and under two workloads. The Zipfian experiment is configured with a read ratio of 1%, which reflects the read ratio observed in the Alibaba trace. We make three key observations.

First, both read and write performance of binary and 64ary hash trees decreases logarithmically with capacity. Under

the Zipfian workload, they observe up to 3.5× and 4× IOPS slowdowns over the no encryption/no integrity baseline, respectively. Under the Alibaba workload, they also incur increasing slowdowns as capacity scales, with up to a $40.1 \times$ slowdown at 8TB capacity. The average latencies also show the same pattern. Notably, 64-ary trees, which are stateof-the-art for secure memory systems, incur up to a $6.3 \times$ slowdown under the Zipfian workload and a 35.9× slowdown under the Alibaba workload. Note that 64-ary trees must be initialized with a capacity that is a power of 64. We also note that since the traces are scaled to our experiment capacity, IOPS generally decreases (due to scaled I/O sizes being larger) but the effective bandwidths remain the same.

In contrast, DHTs provide up to a $2.3 \times$ and $4.2 \times$ write IOPS speedup over binary and 64-ary hash trees, respectively. They also provide up to 2.7× and 4× write latency speedups over binary trees and 64-ary trees, respectively. Importantly, even as capacity increases, DHTs can reliably deliver the same amount of IOPS. These results show that static nature of state-of-the-art methods cannot capture patterns in workloads, and DHTs can more reliably scale to larger capacities. In fact, DHTs deliver >70% of the baseline throughput across all studied capacities under the Zipfian

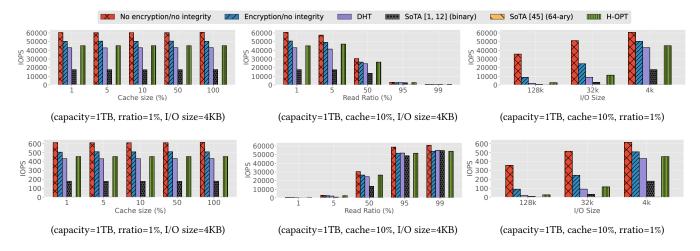


Figure 8. Write (top) and read (bottom) performance under the zipf2.5 workload w.r.t. cache size, read ratio, and I/O size.

workload. Although they also provide >1.7× speedups over the state-of-the-art under the Alibaba workload, overheads compared to the insecure baseline are still high in general, due to I/O sizes being larger. Future work could extend balanced trees and DHTs to support (safe) delaying/batching of writes to efficiently support large write requests. However, as reflected in the Zipfian workload, when workloads are mostly composed of small 4KB writes (which occurs most often in practice [30]), DHTs deliver the lowest overhead compared to the insecure baseline.

We now focus on the Zipfian traces to more broadly explore the parameter space.

Scaling with Cache Size. Figure 8 (left) shows performance with respect to cache size. Note that we specify cache size as a ratio of the tree size, and therefore the absolute cache size varies with the storage capacity. We make one key observation: small caches are very efficient. As the cache size increases beyond 1%, throughputs observed under each hash tree design do not increase. Yet, at a cache size ratio of 100% (which is unrealistic in practice, but is useful for modeling a perfect cache), DHTs still observe the same speedups. Thus, all hash tree designs make efficient use of available cache memory, but the structure of DHTs enables them to provide higher performance at a lower cache budget (we discuss this in more detail below). This shows that DHTs can provide large speedups at various operating points for cache size.

Scaling with Read/Write Ratio. Figure 8 (middle) shows how the performance changes with respect to the read/write ratio. We expect that at higher read ratios, DHTs, balanced, and optimal trees will all observe higher absolute throughputs, as reads can be quickly served by early returns due to caching. However, we see a very sharp performance drop for balanced trees when there is a significant proportion of writes. Note that writes are expensive becauase, unlike read requests, writes must always be serialized to the root to ensure consistency with the root hash and the data disk. At a read ratio of 50%, we see that writes become costly for balanced trees: DHTs are $1.7 \times$ faster.

At a read ratio of 1%, DHTs are $2.3 \times$ faster. The latter case is most often observed in practice, largely because higherlevel caches (e.g., application caches) can efficiently serve reads, leaving I/Os sent to storage to be mostly writes. Notably, even when workloads are read-heavy, DHTs deliver comparable performance to the state-of-the-art. We attribute this to the fact that DHTs inherit the theoretical guarantees of splay trees, which ensure O(logn) amortized lookup (i.e., verification or update) time. Thus, DHTs can perform at least as good as the balanced trees on average, for either read- or write-heavy workloads.

Scaling with I/O Size. Figure 8 (right) shows how performance changes with respect to I/O size. With increased I/O size, IOPS generally decreases, but bandwidth remains the same. We make two key observations. First, DHTs provide >2.3× speedups over balanced trees across each I/O size. With large 128K I/Os, the slowdowns of each hash tree design with respect to the insecure baseline increases due to increased per-I/O costs. In the context of the insecure baseline, the block layer in the kernel can mitigate per-I/O costs through optimizations like write buffering/batching. Balanced hash trees and DHTs could both be extended with (safe) write buffering/batching to reduce the gap with the insecure baseline. However, we note that the speedups observed by DHTs should scale proportionally.

Achieving Optimal Performance. Our optimal model helped informed the design of DHTs but also allows us to measure a concrete upper bound on performance. Figure 7 and Figure 8 also characterize the performance of balanced trees and DHTs with respect to the optimal. Note that we provide optimal results only for the Zipfian traces. The process of scaling the Alibaba traces (e.g., scaling a 1TB disk

	Memory Overhead	Storage Overhead
leaf nodes	0.44 imes	0.29×
internal nodes	0.80 imes	$0.75 \times$

Table 2. DHTs require additional memory/storage to cache/store each tree node. However, DHTs break even on this trade-off, because they can provide higher performance than balanced trees, at a smaller cache budget.

trace down to a trace for a 1GB disk) introduces a loss in fidelity in the traces and affects the Huffman algorithm in unpredictable ways. However, we note that constructing the tree under the original trace yields a tree that provides maximum throughput. For example, constructing our optimal hash tree over a 500GB disk from the original trace of volume #4 shown in Figure 7 (which was recorded on a 500GB disk) yields a tree that provides 23K IOPS.

With respect to capacity, we observe for the Zipfian workload that DHTs deliver >95% of optimal performance (>42K IOPS) as capacity scales up, while balanced trees provide only 55% of optimal performance in the best case at 1GB. With respect to cache size, read ratio, and I/O size, we observe similarly that DHTs deliver >95% optimal throughput across all experiments, while the slowdown factor between balanced trees and the optimal increases with capacity, writeheaviness, and I/O size. This shows that balanced hash trees do not provide a reliable guarantee on performance, while DHTs provide a stable performance guarantee. We attribute this to DHTs being based on splay-trees, which are conjectured to provide performance within a constant factor of the optimal tree structure under any access pattern.

Memory & Storage Overhead. While DHTs provide several advantages, they have higher memory and storage requirements than balanced trees. Table 2 shows the memory overheads for DHTs. DHTs cannot use implicit indexing like balanced trees, but instead require explicitly storing parent-child pointers (as integer node IDs) both for nodes in-memory and on-disk. This implies at least one additional integer field for leaf nodes, at most three additional integer fields for internal nodes, and one additional integer hotness counter field for all nodes.

This may have adverse affects on cache performance, since less nodes in a DHT can be stored within the same cache budget as a balanced tree. However, we show that cache hit rates are very high even for very small caches. Moreover, DHTs provide better performance at a smaller cache budget than balanced trees at a higher cache budget. For example, at a cache budget of *x* for balanced trees, DHTs would occupy (1.44x + 1.8x)/2 = 1.62x cache memory (and storage), but if DHTs provide a speedup > 1.62*x*, then we can conclude that, in terms of monetary cost, DHTs provide better performance per bit of cache memory purchased and thus make more efficient use of available cache memory. As we have shown, DHTs provide up to $4.2 \times$ speedups over balanced trees.

Key takeaway: Our experiments show that under a realistic set of system configurations and storage workloads, overheads incurred by state-of-the-art hash trees are prohibitive. Meeting the demands of large-scale, high-throughput, low-latency cloud storage requires a fundamental redesign of integrity mechanisms. Our observations of optimal tree structures and DHTs sheds light on how we can break the scalability limit of prior solutions.

8 Security Analysis

Below we analyze how DHTs remain resilient against the integrity violations outlined in Section 3.

Data Correctness. Like traditional balanced hash tree designs [45], DHTs authenticate block data with the MACs that serve as the leaves in the hash tree. The MACs ensure the correctness of data, and are checked whenever data is read or written by clients. Violating correctness guarantees would require a successful MAC forgery attack, which is infeasible under standard cryptographic assumptions.

Spatial Uniqueness. In DHTs, encryption and MACs are keyed to the block address by using the address as additional authenticated data (AAD). This ensures that data contents have not been corrupted, and also that the data is associated with the address intended by the client (i.e., blocks are not swapped before being returned to the client).

Temporal Uniqueness. Like balanced hash trees (Figure 2), DHTs prevent replay attacks at the block layer by authenticating all reads and writes against the root hash. The root hash is the trust anchor of the system. While the trees are structurally different, the root hash serves the same purpose.

9 Discussion

Below we discuss additional considerations regarding DHTs.

Leaf Order Consistency. The most significant difference from traditional balanced trees is that, in DHTs, nodes may be rotated to arbitrary locations in the tree. In some domains, such as blockchains, the leaf order carries meaning. For example, transactions represent leaves and must be organized in some well-defined order. DHTs would violate the integrity of such an ordering and would therefore not be suitable for such a context. In the context of cloud block storage, order does not matter. That is, nodes can be placed arbitrarily in the tree, insofar as the hash tree invariants outlined in Section 6 are met. Consistency in leaf ordering is thus a domain-specific property. For storage, the hash tree structure itself needs only provide the conduit to authenticate reads and writes

against the root hash. As nodes are moved to different locations in the tree, we still ensure spatial uniqueness by keying encryption and MAC generation to unique block addresses.

Block Size. Like other works, our basic unit of storage is a typical 4KB block. Some recent works have explored using larger block sizes to improve the performance of storage systems (e.g., 1 MB blocks for object storage). Evidently, using larger blocks can improve bandwidth utilization. However, there is no one-size-fits-all solution when choosing a suitable block size. For example, with larger blocks, if the application's I/O size does not align with the block size, then the system may suffer from I/O amplification. In the Alibaba dataset, we also found that a large majority I/Os (>90%) are small (4KB) for most volumes. We leave future work to exploring this trade-off in more detail.

10 Related Work

Hash trees have become a core component of many computing systems, including blockchains, secure memories, etc. [1, 3, 5, 11, 19, 23, 29, 32, 37, 42, 45]. We discuss these related works below.

Secure Memory Systems. Secure memories have been longstudied [21, 23, 41, 48]. Their central goal is to provide a secure environment in which the secrecy and integrity of application code and data can be assured. Recently, secure memories have seen widespread commercial success through implementations such as Intel SGX [13, 32, 40]. At the heart of a secure memory system is the hash tree, which ensures all three security properties discussed in Section 3. It is known that hash trees can severely impact performance, and optimizing them has thus been a central focus of recent research.

State-of-the-art approaches, such as Penglai [21], FastVer [3] and VAULT [45], have shown that various optimizations like caching, increasing tree fanout, and parallelization, can ensure low-overheads in some contexts (e.g., at small capacities). However, there are several key differences between these works and our work. First, we focus on persistent storage rather than main memory, which is subject to vastly different workload characteristics, capacities, and assumptions about cache memory size. We considered the state-ofthe-art for secure memories (high-degree trees[22, 41]) for juxtaposition, and show that such approaches are not applicable to storage. Notably, with larger fanouts, the number of auxiliary hashes that need to be fetched during an update or verification increases proportional to the fanout, thus requiring additional hash fetches (and reauthentications on misses). Moreover, some prior works have decidedly sidestepped the issue of writes by either suppressing caches during updates or limiting analysis to read-heavy or read-only workloads [3, 42]. Yet, storage workloads are known to be write-heavy, and we therefore closely examine write-heavy workloads to understand their implications on scalability.

DHTs take a fundamentally different approach to optimizing the hash tree: instead of increasing tree fanout, we remove the balance constraint to reduce the height of authentication paths. Specifically, high-degree trees trade-off increased overall fetch costs for reduced height, wheres DHTs trade-off increased cold-access fetch costs for reduced height.

Further, experiments in prior works have also been limited to simulation-based analysis and against small capacities (e.g., 16GB). We report experiments with an implementation on real block devices and consider a wide range of system settings: up to several TB capacity, with various cache sizes, with various read/write ratios. Other works using techniques such as lazy verification have sacrificed security guarantees for performance [3]. Because we focus on a more practical threat model, we do not compare against these works. However, we note that DHTs could be extended with such techniques, but leave such an analysis to future work.

Authenticated Data Structures. Hash trees have also been examined in the broader theoretical context of authenticated data structures—data structures that have strong integrity protections [35, 46]—for a variety of real-world problems. They become a central component of mobile and embedded device storage: dm-verity has played a pivotal role in providing verified boot for Android smartphones [1]. Other works have also examined hash trees in the context of blockchains [11], certificate revocation systems [33], and provable data possession schemes [18, 19].

These works have highlighted the theoretical efficiency of different approaches to ensuring integrity of arbitrary datasets, but there is consensus between the theory and systems communities that Merkle hash trees are state-ofthe-art method [17]. Our work builds on these efforts by showing that, while efficient in theory, traditional static, balanced hash trees still incur substantial overheads in real systems, and this motivates the design of DHTs.

11 Conclusion

We showed that state-of-the-art hash tree designs incur significant performance overheads and cannot scale to meet the demands of cloud storage systems. We addressed this problem by introducing a definition of an optimal hash tree, an oracle methodology to measure whether a hash tree design performs optimally, and a novel hash tree design called DHTs that exploits characteristics of optimal trees to provide up to a 4.2× speedup on read and write performance over the state-of-the-art. Our contributions provide a new foundation in the search for integrity mechanisms that can operate efficiently at scale. Notably, we re-characterize the integrity problem from a static one into a dynamic one, showing the viability of integrity structures that learn and exploit patterns in workloads to improve performance. Our code is plug-andplay into standard Linux systems and is open-sourced at [Anonymized link].

References

- Android. 2023. Implementing dm-verity. Google, Inc. Retrieved 2023-10-16 from https://source.android.com/docs/security/features/ verifiedboot/dm-verity
- [2] Sebastian Angel, Aditya Basu, Weidong Cui, Trent Jaeger, Stella Lau, Srinath Setty, and Sudheesh Singanamalla. 2023. Nimble: Rollback Protection for Confidential Cloud Services. In 17th USENIX Symposium on Operating Systems Design and Implementation (OSDI 23). 193–208.
- [3] Arvind Arasu, Badrish Chandramouli, Johannes Gehrke, Esha Ghosh, Donald Kossmann, Jonathan Protzenko, Ravi Ramamurthy, Tahina Ramananandro, Aseem Rastogi, Srinath Setty, et al. 2021. Fastver: Making data integrity a commodity. In *Proceedings of the 2021 International Conference on Management of Data*. 89–101.
- [4] Sergei Arnautov, Bohdan Trach, Franz Gregor, Thomas Knauth, Andre Martin, Christian Priebe, Joshua Lind, Divya Muthukumaran, Dan O'Keeffe, Mark L. Stillwell, David Goltzsche, Dave Eyers, Rüdiger Kapitza, Peter Pietzuch, and Christof Fetzer. 2016. SCONE: Secure Linux Containers with Intel SGX. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16). USENIX Association, Savannah, GA, 689–703. https://www.usenix.org/conference/ osdi16/technical-sessions/presentation/arnautov
- [5] Roberto Avanzi, Ionut Mihalcea, David Schall, Héctor Montaner, and Andreas Sandberg. 2022. Cryptographic Protection of Random Access Memory: How Inconspicuous can Hardening Against the most Powerful Adversaries be? Cryptology ePrint Archive (2022).
- [6] Amazon AWS. 2023. Amazon Elastic Block Store. Amazon Web Services, Inc. Retrieved 2023-05-16 from https://aws.amazon.com/ebs
- Microsoft Azure. 2023. Microsoft Azure Managed Disks. Google, Inc. Retrieved 2023-05-16 from https://learn.microsoft.com/en-us/azure/ virtual-machines/managed-disks-overview
- [8] Laszlo A. Belady. 1966. A study of replacement algorithms for a virtualstorage computer. *IBM Systems journal* 5, 2 (1966), 78–101.
- [9] Enrico Bocchi, Idilio Drago, and Marco Mellia. 2015. Personal cloud storage benchmarks and comparison. *IEEE Transactions on Cloud Computing* 5, 4 (2015), 751–764.
- [10] Milan Brož, Mikuláš Patočka, and Vashek Matyáš. 2018. Practical cryptographic data integrity protection with full disk encryption. In ICT Systems Security and Privacy Protection: 33rd IFIP TC 11 International Conference, SEC 2018, Held at the 24th IFIP World Computer Congress, WCC 2018, Poznan, Poland, September 18-20, 2018, Proceedings 33. Springer, 79–93.
- [11] Vitalik Buterin. 2016. Ethereum: platform review. *Opportunities and Challenges for Private and Consortium Blockchains* 45 (2016).
- [12] Anrin Chakraborti, Bhushan Jain, Jan Kasiak, Tao Zhang, Donald Porter, and Radu Sion. 2017. Dm-x: protecting volume-level integrity for cloud volumes and local block devices. In *Proceedings of the 8th Asia-Pacific Workshop on Systems*. 1–7.
- [13] Chia che Tsai, Donald E. Porter, and Mona Vij. 2017. Graphene-SGX: A Practical Library OS for Unmodified Applications on SGX. In 2017 USENIX Annual Technical Conference (USENIX ATC 17). USENIX Association, Santa Clara, CA, 645–658. https://www.usenix.org/conference/ atc17/technical-sessions/presentation/tsai
- [14] CK Chow. 1974. On optimization of storage hierarchies. IBM Journal of Research and Development 18, 3 (1974), 194–203.
- [15] Google Cloud. 2023. Google Cloud Persistent Disks. Google, Inc. Retrieved 2023-05-16 from https://cloud.google.com/persistent-disk
- [16] Brian F Cooper, Adam Silberstein, Erwin Tam, Raghu Ramakrishnan, and Russell Sears. 2010. Benchmarking cloud serving systems with YCSB. In *Proceedings of the 1st ACM symposium on Cloud computing*. 143–154.
- [17] Scott A Crosby and Dan S Wallach. 2011. Authenticated dictionaries: Real-world costs and trade-offs. ACM Transactions on Information and System Security (TISSEC) 14, 2 (2011), 1–30.

- [18] Rasmus Dahlberg, Tobias Pulls, and Roel Peeters. 2016. Efficient sparse merkle trees: Caching strategies and secure (non-) membership proofs. In Secure IT Systems: 21st Nordic Conference, NordSec 2016, Oulu, Finland, November 2-4, 2016. Proceedings 21. Springer, 199–215.
- [19] C Chris Erway, Alptekin Küpçü, Charalampos Papamanthou, and Roberto Tamassia. 2015. Dynamic provable data possession. ACM Transactions on Information and System Security (TISSEC) 17, 4 (2015), 1–29.
- [20] Alberto Faria, Ricardo Macedo, José Pereira, and João Paulo. 2021. BDUS: implementing block devices in user space. In *Proceedings of the 14th ACM International Conference on Systems and Storage*. ACM, Haifa Israel, 1–11. https://doi.org/10.1145/3456727.3463768
- [21] Erhu Feng, Xu Lu, Dong Du, Bicheng Yang, Xueqiang Jiang, Yubin Xia, Binyu Zang, and Haibo Chen. 2021. Scalable Memory Protection in the {PENGLAI} Enclave. In 15th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 21). 275–294.
- [22] Alexander Freij, Huiyang Zhou, and Yan Solihin. 2021. Bonsai merkle forests: Efficiently achieving crash consistency in secure persistent memory. In MICRO-54: 54th Annual IEEE/ACM International Symposium on Microarchitecture. 1227–1240.
- [23] Blaise Gassend, G Edward Suh, Dwaine Clarke, Marten Van Dijk, and Srinivas Devadas. 2003. Caches and hash trees for efficient memory integrity verification. In *The Ninth International Symposium on High-Performance Computer Architecture, 2003. HPCA-9 2003. Proceedings.* IEEE, 295–306.
- [24] Milad Hashemi, Kevin Swersky, Jamie Smith, Grant Ayers, Heiner Litz, Jichuan Chang, Christos Kozyrakis, and Parthasarathy Ranganathan. 2018. Learning memory access patterns. In *International Conference* on Machine Learning. PMLR, 1919–1928.
- [25] David A Huffman. 1952. A method for the construction of minimumredundancy codes. *Proceedings of the IRE* 40, 9 (1952), 1098–1101.
- [26] Mahesh Kallahalla, Erik Riedel, Ram Swaminathan, Qian Wang, and Kevin Fu. 2003. Plutus: Scalable Secure File Sharing on Untrusted Storage. In 2nd USENIX Conference on File and Storage Technologies (FAST 03). USENIX Association, San Francisco, CA. https://www.usenix.org/conference/fast-03/plutus-scalablesecure-file-sharing-untrusted-storage
- [27] Kimberly Keeton, Terence Kelly, Arif Merchant, Cipriano A Santos, Janet L Wiener, Xiaoyun Zhu, and Dirk Beyer. 2007. Don't Settle for Less Than the Best: Use Optimization to Make Decisions.. In *HotOS*.
- [28] Louiza Khati, Nicky Mouha, and Damien Vergnaud. 2017. Full disk encryption: bridging theory and practice. In *Topics in Cryptology– CT-RSA 2017: The Cryptographers' Track at the RSA Conference 2017, San Francisco, CA, USA, February 14–17, 2017, Proceedings.* Springer, 241–257.
- [29] Feifei Li, Marios Hadjieleftheriou, George Kollios, and Leonid Reyzin. 2006. Dynamic authenticated index structures for outsourced databases. In Proceedings of the 2006 ACM SIGMOD international conference on Management of data. 121–132.
- [30] Jinhong Li, Qiuping Wang, Patrick PC Lee, and Chao Shi. 2023. An indepth comparative analysis of cloud block storage workloads: Findings and implications. ACM Transactions on Storage 19, 2 (2023), 1–32.
- [31] Sinisa Matetic, Mansoor Ahmed, Kari Kostiainen, Aritra Dhar, David Sommer, Arthur Gervais, Ari Juels, and Srdjan Capkun. 2017. {ROTE}: Rollback protection for trusted execution. In 26th USENIX Security Symposium (USENIX Security 17). 1289–1306.
- [32] Frank McKeen, Ilya Alexandrovich, Alex Berenzon, Carlos V. Rozas, Hisham Shafi, Vedvyas Shanbhogue, and Uday R. Savagaonkar. 2013. Innovative instructions and software model for isolated execution. In Proceedings of the 2nd International Workshop on Hardware and Architectural Support for Security and Privacy - HASP '13. ACM Press, Tel-Aviv, Israel. https://doi.org/10.1145/2487726.2488368

- [33] Marcela S Melara, Aaron Blankstein, Joseph Bonneau, Edward W Felten, and Michael J Freedman. 2015. {CONIKS}: Bringing key transparency to end users. In 24th USENIX Security Symposium (USENIX Security 15). 383–398.
- [34] Ralph C Merkle. 1989. A certified digital signature. In Conference on the Theory and Application of Cryptology. Springer, 218–238.
- [35] Andrew Miller, Michael Hicks, Jonathan Katz, and Elaine Shi. 2014. Authenticated data structures, generically. ACM SIGPLAN Notices 49, 1 (2014), 411–423.
- [36] Alistair Moffat. 2019. Huffman coding. ACM Computing Surveys (CSUR) 52, 4 (2019), 1–35.
- [37] Moni Naor and Kobbi Nissim. 2000. Certificate revocation and certificate update. *IEEE Journal on selected areas in communications* 18, 4 (2000), 561–570.
- [38] NIST. 2023. Report on the Block Cipher Modes of Operation in the NIST SP 800-38 Series. NIST. Retrieved 2023-10-15 from https://nvlpubs.nist. gov/nistpubs/ir/2023/NIST.IR.8459.ipd.pdf
- [39] Ronald Perez, Reiner Sailer, Leendert van Doorn, et al. 2006. vTPM: virtualizing the trusted platform module. In Proc. 15th Conf. on USENIX Security Symposium. 305–320.
- [40] Christian Priebe, Divya Muthukumaran, Joshua Lind, Huanzhou Zhu, Shujie Cui, Vasily A. Sartakov, and Peter Pietzuch. 2020. SGX-LKL: Securing the Host OS Interface for Trusted Execution. arXiv:1908.11143 [cs] (Jan. 2020). http://arxiv.org/abs/1908.11143
- [41] Brian Rogers, Siddhartha Chhabra, Milos Prvulovic, and Yan Solihin. 2007. Using address independent seed encryption and bonsai merkle trees to make secure processors os-and performance-friendly. In 40th Annual IEEE/ACM International Symposium on Microarchitecture (MI-CRO 2007). IEEE, 183–196.

- [42] Rohit Sinha and Mihai Christodorescu. 2018. Veritasdb: High throughput key-value store with integrity. *Cryptology ePrint Archive* (2018).
- [43] Daniel Dominic Sleator and Robert Endre Tarjan. 1985. Self-adjusting binary search trees. *Journal of the ACM (JACM)* 32, 3 (1985), 652–686.
- [44] Aishwarya Srinivasan, Md Abdul Quadir, and V Vijayakumar. 2015. Era of cloud computing: A new insight to hybrid cloud. *Procedia Computer Science* 50 (2015), 42–51.
- [45] Meysam Taassori, Ali Shafiee, and Rajeev Balasubramonian. 2018. VAULT: Reducing paging overheads in SGX with efficient integrity verification structures. In Proceedings of the Twenty-Third International Conference on Architectural Support for Programming Languages and Operating Systems. 665–678.
- [46] Roberto Tamassia. 2003. Authenticated data structures. In Algorithms-ESA 2003: 11th Annual European Symposium, Budapest, Hungary, September 16-19, 2003. Proceedings 11. Springer, 2–5.
- [47] Weijie Wang, Yujie Lu, Charalampos Papamanthou, and Fan Zhang. 2023. The Locality of Memory Checking. *Cryptology ePrint Archive* (2023).
- [48] Chenyu Yan, Daniel Englender, Milos Prvulovic, Brian Rogers, and Yan Solihin. 2006. Improving cost, performance, and security of memory encryption and authentication. ACM SIGARCH Computer Architecture News 34, 2 (2006), 179–190.
- [49] Juncheng Yang, Yao Yue, and KV Rashmi. 2021. A large-scale analysis of hundreds of in-memory key-value cache clusters at twitter. ACM Transactions on Storage (TOS) 17, 3 (2021), 1–35.
- [50] Yue Yang and Jianwen Zhu. 2016. Write skew and zipf distribution: Evidence and implications. ACM transactions on Storage (TOS) 12, 4 (2016), 1–19.