

Efficient Hybrid Inline and Out-of-Line Deduplication for Backup Storage

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Backup storage systems often remove redundancy across backups via inline deduplication, which works by referring duplicate chunks of the latest backup to those of existing backups. However, inline deduplication degrades restore performance of the latest backup due to fragmentation, and complicates deletion of expired backups due to the sharing of data chunks. While out-of-line deduplication addresses the problems by forward-pointing existing duplicate chunks to those of the latest backup, it introduces additional I/Os of writing and removing duplicate chunks.

We design and implement *RevDedup*, an efficient hybrid inline and out-of-line deduplication system for backup storage. It applies coarse-grained inline deduplication to remove duplicates of the latest backup, and then fine-grained out-of-line reverse deduplication to remove duplicates from older backups. Our reverse deduplication design limits the I/O overhead and prepares for efficient deletion of expired backups. Through extensive testbed experiments using synthetic and real-world datasets, we show that *RevDedup* can bring high performance to the backup, restore, and deletion operations, while maintaining high storage efficiency comparable to conventional inline deduplication.

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1. INTRODUCTION

Deduplication is an established technique for eliminating data redundancy in backup storage. It treats data as a stream of fixed-size or variable-size *chunks*, each of which is identified by a *fingerprnt* computed by a cryptographic hash (e.g., MD5, SHA-1) of its content. Two chunks are said to be identical if their fingerprints are the same, while

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An earlier version of this article appeared in the 4th ACM SIGOPS Asia-Pacific Workshop on Systems (APSYS), 2013 [Ng et al. 2013]. This journal version extends our prior work in several aspects: (1) targeting general types of backup workloads, (2) addressing deletion of expired backups, (3) supporting variable-size chunking, (4) using containers to keep segments, (5) introducing the live window and archival window to flexibly decide how backups are deduplicated over their lifecycles, and (6) conducting more extensive experiments with synthetic traces.

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fingerprint collisions of two different chunks are very unlikely [Black 2006]. Instead of storing multiple identical chunks, deduplication stores only one unique copy of a chunk and refers any duplicate copies to the unique copy using smaller-size references. Since backups have high redundant content, it is reported that deduplication can help backup systems achieve effective storage saving by $20\times$ [Andrews 2013].

1.1. Inline versus Out-of-Line Deduplication

Deduplication can be realized *inline*, which removes duplicate chunks on the write path, or *out-of-line*, which first stores all data and later removes duplicates in the background. Today's production backup systems [Zhu et al. 2008; Wallace et al. 2012; Lillibridge et al. 2013], which mainly build on disk-based backends, often implement inline deduplication with average chunk size 4–8KB. However, inline deduplication poses several fundamental challenges to the basic operations of backup systems, including backup, restore, and deletion:

- Backup*: While inline deduplication avoids writing duplicates, its backup performance can be degraded by extensive metadata operations for chunk indexing, including fingerprint computations and index updates. The amount of metadata increases proportionally with the number of chunks stored. Thus, keeping all fingerprints and other metadata in main memory is infeasible. Instead, some indexing metadata must be kept on disk, but this incurs disk accesses for metadata lookups and degrades backup performance.
- Restore*: Inline deduplication introduces *fragmentation* [Rhea et al. 2008; Kaczmarczyk et al. 2012; Nam et al. 2012; Lillibridge et al. 2013], as backups now refer to existing data copies scattered in prior backups. This incurs significant disk seeks when restoring recent backups, and the restore performance degrades. Fragmentation becomes worse for newer backups, whose data is scattered across more prior backups. The gradual degradation is undesirable since the new backups are more likely to be restored during disaster recovery. A lower restore throughput of the latest backup implies a longer system downtime.
- Deletion*: With inline deduplication, expired backups cannot be directly deleted as they may be shared by newer, nonexpired backups. Deletion is often handled via a mark-and-sweep approach: In the mark phase, all chunks are scanned and any unreferenced chunks are marked for removal; in the sweep phase, all marked chunks are freed from disk in the background. However, the mark phase needs to search for unreferenced chunks across disk and incurs significant I/Os.

Extensive studies address the preceding challenges of inline deduplication (see Section 5). However, it remains an open issue of how to address the challenges *simultaneously* so as to enable deduplication-enabled backup systems to achieve high performance in backup, restore, and deletion operations.

Out-of-line deduplication addresses some aforementioned issues of inline deduplication. For example, it can reduce the disk I/O overhead of index lookups on the write path. It also mitigates fragmentation and preserves restore performance of the new backups by referring duplicate chunks of old backups to the chunks of new backups [Kaczmarczyk et al. 2012]. This forward-pointing approach also facilitates the deletion of old backups, since their chunks are no longer shared by new backups. However, out-of-line deduplication incurs extra I/Os of writing and removing redundant data, and hence gives poorer backup performance than inline deduplication. For example, writing duplicates can slow down the backup performance by around $3\times$ compared to inline deduplication based on the measurements in a commercial backup system [Kaczmarczyk et al. 2012]. Also, out-of-line deduplication needs extra storage space to keep redundant data before the redundant data is removed.

1.2. Contributions

Our position is that both inline deduplication and out-of-line deduplication complement each other if carefully used. We propose *RevDedup*, an efficient hybrid inline and out-of-line deduplication system for backup storage. Our work extends our prior work [Ng and Lee 2013] to aim for high performance in backup, restore, and deletion operations, while preserving storage efficiency as in conventional inline deduplication. RevDedup first applies coarse-grained inline deduplication at the granularity of large-size units, and further applies fine-grained out-of-line deduplication on small-size units to improve storage efficiency. Our out-of-line deduplication step, called *reverse deduplication*, shifts fragmentation to older backups by referring their duplicates to newer backups. To limit the I/O overhead of reverse deduplication, we compare only two consecutive backup versions derived from the same client, and we argue that it still effectively removes duplicates. Also, during reverse deduplication, we repackage backup data to facilitate subsequent deletion of expired backups.

We implement a RevDedup prototype and conduct extensive testbed experiments using synthetic and real-world workloads. We show that RevDedup maintains comparable storage efficiency to conventional inline deduplication, achieves high backup and restore throughput for recent backups (e.g., on the order of GB/s), and supports fast deletion for expired backups. To our knowledge, very few deduplication studies in the literature evaluate the actual I/O performance through prototype implementation.

The rest of the article proceeds as follows. In Sections 2 and 3, we present the design and implementation details of RevDedup, respectively. In Section 4, we report testbed experimental results. We review related work in Section 5, and finally conclude the article in Section 6.

2. REVDEDUP DESIGN

RevDedup combines inline and out-of-line deduplication and is designed for backup storage. It aims for the following design goals:

- comparable storage efficiency to conventional inline deduplication approaches;
- high backup throughput for new backups;
- high restore throughput for new backups; and
- low deletion overhead for expired backups.

2.1. Backup Basics

Backups are copies of primary data snapshotted from client systems or applications, and can be represented in the form of tar files or VM disk images (e.g., qcow2, vmdk, etc.). They are regularly created by a backup system, either as daily incremental backups or weekly full backups. Backup data is organized into *containers* as the units of storage and read/write requests, such that each container is of size on the order of megabytes. Today's backup solutions mainly build on disk-based storage, which achieves better I/O performance than traditional tape-based storage.

We define a *series* as the sequence of backups snapshotted from the same client at different times. Each backup series has a retention period [Wallace et al. 2012], which defines how long a backup is kept in storage. We define a *retention window* that specifies a set of recent backups that need to be kept in storage. The retention window slides over time to cover the latest backup, while the earliest backup stored in the system expires. The backup system later deletes the expired backups and reclaims storage space. Note that the retention window length may vary across different backup series.

Since backups share high redundancy, this work focuses on using deduplication to remove redundancy and achieve high storage efficiency. We can further improve storage

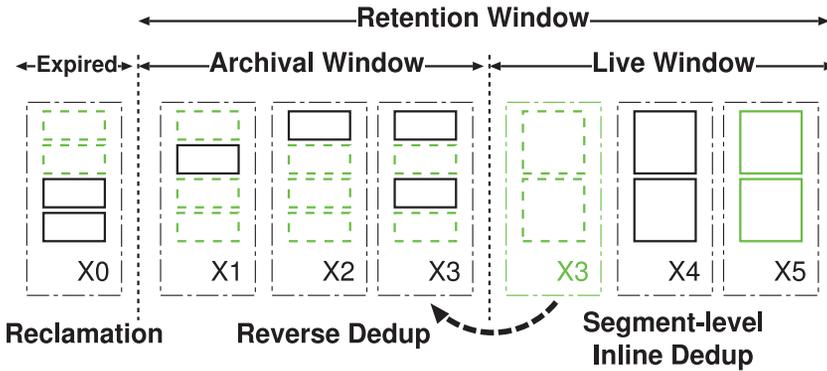


Fig. 1. Overview of RevDedup operations.

efficiency through local compression (e.g., Ziv-Lempel [Ziv and Lempel 1977]), yet we do not consider the effect of compression in this work.

2.2. RevDedup Overview

RevDedup performs deduplication in two phases. It first applies inline deduplication by dividing backup data into large-size units (e.g., on the order of megabytes) called *segments*, and removes duplicate segments of new backups on the write path. It packs the unique segments into containers and stores the containers on disk. Deduplication on large-size segments reduces both fragmentation and indexing overheads [Kruus et al. 2010]. See Section 2.3 for details.

RevDedup then reads the containers and applies out-of-line deduplication to small-size data units (e.g., on the order of kilobytes) called *chunks*. It further removes duplicate chunks of older backups and refers them to the identical chunks in newer backups. We call this *reverse deduplication*, which shifts fragmentation to older backups and hence maintains high restore throughput of newer backups. See Section 2.4 for details.

After reverse deduplication, RevDedup repackages segments into separate containers to facilitate later deletions of expired backups. See Section 2.5 for details.

We first describe how RevDedup prepares for the two-phase deduplication before explaining the design details.

2.2.1. Live and Archival Backups. RevDedup divides the retention window of a backup series into two subwindows: *live window* and *archival window*. Backups in the live window (called *live backups*) are those recently written and are more likely to be restored, while those in the archival window (called *archival backups*) serve for the archival purpose only and are rarely restored. RevDedup applies inline deduplication to the latest backup, which is first stored in the live window. The retention window then slides to cover the latest backup. The oldest live backup will move to the archival window, and RevDedup applies reverse deduplication to that backup out of line (e.g., when the storage system has a light load).

Figure 1 illustrates the lifecycles of six backups of the same series created in the following order: X0, X1, X2, X3, X4, and X5. Suppose that the retention window is set to five backups, the live window is set to two backups, and the archival window is set to three backups. When X5 is added, X0 expires and can be deleted to reclaim disk space. Also, the segments of X5 can be deduplicated with those of existing live backups (i.e., X4 in this example). Also, X3 moves to the archival window. We can perform reverse deduplication and remove duplicate chunks from X3.

2.2.2. Chunking. *Chunking* is the process of dividing a data stream into fixed-size or variable-size deduplication units (i.e., segments or chunks). Our discussion assumes variable-size chunking. Here, we consider the chunking approach based on Rabin Fingerprinting [Rabin 1981], whose idea is to compute a rolling hash of a sliding chunking window over the data stream and then identify boundaries whose lower-order bits of the rolling hash match a target pattern. An important property of Rabin Fingerprinting is that the new rolling hash value can be efficiently computed using the last rolling hash value.

RevDedup identifies both segment and chunk boundaries using the same target pattern. We define two bit lengths m and n , where $m > n$, which correspond to the average segment and chunk sizes, respectively. When the chunking window slides, we first check whether the lowest n bits of the rolling hash match the target pattern. If yes, the window endpoint is a chunk boundary, and we further check whether the lowest m bits of the rolling hash match the same target pattern; if yes, the window endpoint is also a segment boundary. Clearly, a segment boundary must also be a chunk boundary. The chunking process can be done in a single pass of the data stream, and hence preserves the chunking performance of Rabin fingerprinting.

In our discussion, the segment or chunk size configured in variable-size chunking actually refers to an average size. We also assume that the minimum and maximum segment or chunk sizes are half and twice the average size, respectively.

2.3. Segment-Level Inline Deduplication

RevDedup performs segment-level inline deduplication to the storage pool. As in conventional inline deduplication, RevDedup performs deduplication *globally* in different levels: within the same backup, across different backups of the same series, and across different series of backups. The main difference is the deduplication unit size: RevDedup uses large-size units (called segments) on the order of megabytes (e.g., 4–8MB), while conventional inline deduplication uses small-size units on the order of kilobytes (e.g., 4KB [Guo and Efstathopoulos 2011] or 8KB [Zhu et al. 2008]).

Choosing large deduplication units (segments) has two key benefits. First, it mitigates fragmentation [Srinivasan et al. 2012]. Since we put the entire segment in a container, we reduce the number of containers that need to be accessed with a large segment size. In addition, it keeps a small deduplication index (i.e., the data structure for holding the segment fingerprints and their locations), and hence mitigates the indexing overhead [Kruus et al. 2010]. For example, suppose that we store 1PB of data, the segment size is 4MB, and the index entry size is 32bytes. Then the index size is 8GB only, as opposed to 8TB when the deduplication unit size is 4KB.

Segment-level inline deduplication still achieves reasonably high deduplication efficiency, as changes of backups are likely aggregated in relatively few small regions, while several extended regions remain the same [Kruus et al. 2010]. Nevertheless, using large deduplication units cannot maintain the same level of deduplication efficiency as do conventional fine-grained deduplication approaches (see our evaluations in Section 4).

To keep track of the deduplication metadata for all stored segments, our current RevDedup design maintains an in-memory deduplication index. We can keep an on-disk index instead to reduce memory usage, and exploit compact data structures and workload characteristics to reduce on-disk index lookups [Zhu et al. 2008]. Another option is to keep the index on solid-state drives [Debnath et al. 2010; Meister and Brinkmann 2010]. The issues of reducing memory usage of indexing are posed as future work.

RevDedup packs the unique segments into a fixed-size container. To handle variable-size segments, we initialize a new container with a new segment (even the segment size

is larger than the container size). We then keep adding new segments to the container if it is not full. If adding a segment exceeds the container size, we seal and store the container, and create a new container for the segment being added.

2.4. Reverse Deduplication

After segment-level inline deduplication, RevDedup divides each segment into smaller-size chunks, each of which has size on the order of kilobytes, and applies chunk-level out-of-line deduplication to further improve storage efficiency. To mitigate fragmentation of the newer backups that are more likely to be restored, RevDedup performs reverse deduplication, i.e., removing duplicate chunks in older backups and referring them to identical chunks in newer backups.

However, we must address several issues of out-of-line deduplication. First, there are extra I/Os of identifying and removing duplicate chunks on disk. To reduce the I/O overhead, we limit the deduplication operation to two consecutive backups of the same series. Second, we can remove duplicate chunks only when their associated segments are no longer shared by other backups. We use two-level reference management to keep track of how segments and chunks are referenced and decide if a chunk can be safely removed. Third, we must support efficient removal of duplicate chunks. We argue that we only check the segments that are not shared by any live backups for chunk removal. In the following, we describe how we address the issues altogether.

2.4.1. Deduplication Operation. Our reverse deduplication works on two consecutive backups of the same series. When a live backup (call it X0) moves from the live window to the archival window, RevDedup loads the metadata of the following (live) backup of the same series (call it X1). It then removes duplicate chunks from X0 and refers them to those in X1.

The deduplication operation follows two principles and we provide justifications. First, we limit reverse deduplication to the *backups of the same series*. Due to repeated backups of the same client system, interversion duplicates of the same series are common [Kaczmarczyk et al. 2012]. Also, changes of a backup tend to appear in small regions [Kruus et al. 2010]. Thus, we can potentially remove additional interversion duplicates around the small change regions in a more fine-grained way [Kruus et al. 2010]. Second, reverse deduplication is applied to *consecutive backups*. Our assumption is that most duplicate chunks appear among consecutive backups.

Our current design focuses on only two consecutive backups, yet we can compare more backups to trade deduplication performance for storage efficiency.

Each backup keeps a list of references to all chunks. Each chunk reference is one of the two types: either (1) a *direct reference*, which points to a physical chunk, or (2) an *indirect reference*, which points to a reference of the following backup of the same series. Since the following backup may be further deduplicated with its own following backup, accessing a chunk may follow a chain of indirect references. Figure 2 shows an example of reverse deduplication for four backups created in the order X0, X1, X2, and X3. We see that X0 (the oldest backup) may access a chunk of X1 through an indirect reference, or a chunk of X2 or X3 through a chain of indirect references. Note that the latest backup must have direct references only.

To perform reverse deduplication between the old backup X0 and the following backup X1, RevDedup loads the chunk fingerprints of X1 from the metadata store (see Section 3) and builds an in-memory index on the fly. It then loads the chunk fingerprints of X0 and checks if they match any chunk fingerprints of X1 in the index. We quantify the worst-case memory usage as follows. Suppose that the raw size of a backup is 20GB, the chunk size is 4KB, and each chunk-level index entry size is 32bytes. The total memory usage is up to $20\text{GB} - 4\text{KB} \times 32\text{bytes} = 160\text{MB}$. Note that

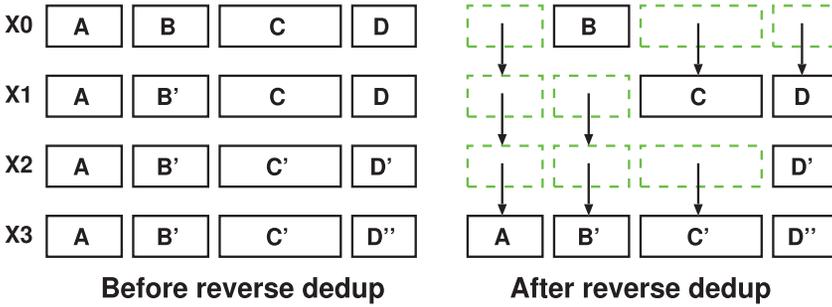


Fig. 2. Example of reverse deduplication for four backups of the same series created in the order X0, X1, X2, and X3.

the index only temporarily resides in memory and will be discarded after we finish reverse deduplication.

2.4.2. Two-Level Reference Management. After reverse deduplication, we can remove chunks that are not referenced by any backup from disk to reclaim storage space. RevDedup uses two-level reference management to keep track of how segments and chunks are shared.

RevDedup associates each segment with a reference count, which indicates the number of references from the live backups. Suppose that we now store a segment of a new backup. If the segment is unique, its reference count is initialized as one; if it is a duplicate, its corresponding reference count is incremented by one. When a live backup moves to the archival window, all its associated segments have their reference counts decremented by one. Reverse deduplication is only applied to segments that have zero reference counts, meaning that the segments are not shared by any live backup, and hence their chunks can be removed. To simplify our discussion, we call the segments with zero reference counts *nonshared*, and those with positive reference counts *shared*. We only check the nonshared segments for chunk removal.

A nonshared segment may belong to more than one series, so we need to check if each chunk in the nonshared segment can refer to another chunk in the next backup of the same series. If a chunk is found duplicate in the next backup of the same series, an indirect reference is recorded; if a chunk is unique, a direct reference is set. Each chunk is associated with a *direct reference flag*. Initially, the flag is set to false. If a direct reference is set for any one series, the flag is set to true. A chunk can be safely removed if both conditions hold: (1) its associated segment is nonshared, and (2) its direct reference flag remains false (i.e., it holds an indirect reference for every series to which its associated segment belongs).

Figure 3 shows how we manage the segment and chunk references. Suppose that we store the backups {X0, X1} and {Y0, Y1} of two separate backup series. Also, we assume that when X1 and Y1 are stored in the live window, both X0 and Y0 move to the archival window. Let the segment size be two chunks. From the figure, the segment AB is no longer shared by any live backup, so its reference count is zero. Also, since X0 and Y0 can refer to chunk A in X1 and Y1, respectively, chunk A can be removed from X0 by reverse deduplication. Since the segment CD is still shared by X1 and Y1, its reference count is two. Both segments AB' and AB'' have reference counts equal to one.

2.4.3. Chunk Removal. RevDedup loads the containers that have nonshared segments. It compacts all nonshared segments without the removed chunks in reverse deduplication, and repackages them into separate containers. It also rewrites the loaded containers with the remaining shared segments with positive reference counts back

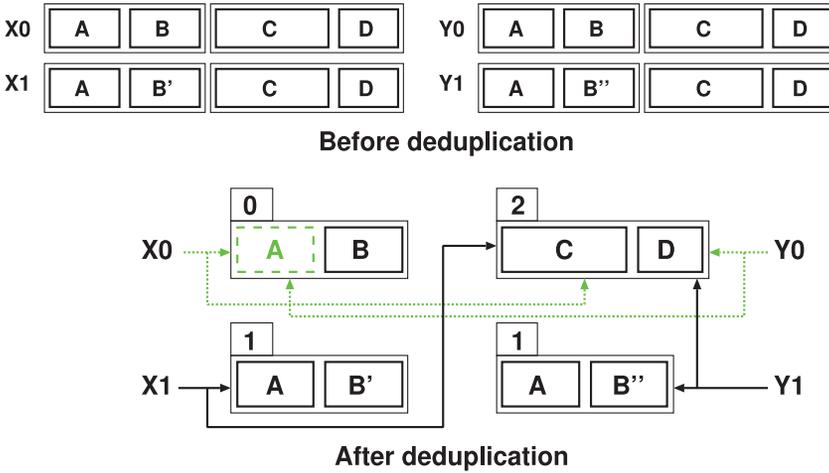


Fig. 3. Example of reference management in RevDedup for two backup series $\{X0, X1\}$ and $\{Y0, Y1\}$, where $X0$ and $Y0$ are in the archival window, while $X1$ and $Y1$ are in the live window.

to disk. Separating the nonshared and shared segments into different containers has two benefits. First, when we run the chunk removal process next time, the repackaged containers with nonshared segments are untouched. This saves the unnecessary I/Os. Second, it supports efficient deletion of expired backups, as described in Section 2.5.

2.5. Deletion of Backups

RevDedup supports efficient deletion of expired backups using *container timestamps*. When it removes chunks from nonshared segments and repackages them into a new container (see Section 2.4.3), it associates with the container a timestamp that specifies the creation time of the corresponding backup. Any segments whose backups are created at about the same time can be gathered and packed into the same container, even though the backups may be derived from different series. For containers with shared segments, their timestamps are set to be undefined.

To delete expired backups, RevDedup examines the well-defined timestamps of all containers and deletes the expired containers. Such containers must contain nonshared segments that belong to expired backups, and hence are safe to be deleted. We do not need to scan all segments/chunks as in the traditional mark-and-sweep approach, so the deletion time is significantly reduced.

3. IMPLEMENTATION

We have implemented a RevDedup prototype in C on Linux. The prototype mounts its storage backend on a native file system, which we choose to be Linux Ext4 in this work. In this section, we describe the components of the prototype, including metadata and executable modules. We also present techniques that further improve the prototype performance.

3.1. Metadata

We maintain deduplication metadata for each of the segments, chunks, containers, and backup series: (1) the metadata of each segment describes the segment fingerprint, the fingerprints of all chunks in the segment, the reference count (for chunk removal in reverse deduplication), and the segment offset; (2) the metadata of each chunk describes the chunk fingerprint and the chunk offset; (3) the metadata of each container describes

segments in the container and the timestamp (for reclamation); and (4) the metadata of each backup series describes which versions are in the live, archival, and retention windows. We store each type of the metadata as a log-structured file with fixed-size entries, each of which is indexed by a unique identifier. We map the metadata logs into memory using `mmap()`, so the entries are loaded into memory on demand.

In addition, we maintain an in-memory deduplication index for segment-level inline deduplication (see Section 2.3). We implement the index as a hash map using the Kyoto Cabinet library [FAL Labs 2012]. Each segment fingerprint is then mapped to an identifier in the segment metadata log. In our prototype, we compute the segment and chunk fingerprints with SHA-1 using the OpenSSL library [OpenSSL 2014].

Each backup is associated with a recipe that contains a list of references for reconstructing the backup. For a live backup, the recipe describes the references to the unique segments; for an archival backup, the recipe holds both direct and indirect references, which state the offsets of chunks on disk and the offsets of direct reference entries, respectively.

3.2. Executable Modules

We decompose the RevDedup prototype into executable modules that run as stand-alone programs. We can also run them as daemons and connect them via interprocess communication.

- `chunking`: It chunks a backup file into segments and chunks, and stores the fingerprints and offsets in a temporary file.
- `inlinededup`: It performs segment-level inline deduplication on the backup file, using the temporary file created from chunking. It first loads the in-memory segment deduplication index from the segment metadata log. For new unique segments, it adds them into containers, appends metadata to the segment metadata log, and adds new entries to the deduplication index. It also creates the backup recipe holding all the segment references for the backup.
- `revdedup`: It takes a backup of a series as the input and performs reverse deduplication on itself and its following backup of the same series. It also repacks segments with removed chunks into different containers.
- `restore`: It reconstructs the chunks of a backup given the series and version numbers as inputs. It reads the backup recipe, and returns the chunks by tracing the direct references or chains of indirect references.
- `delete`: It takes a timestamp as the input and deletes all backups created earlier than the input timestamp.

3.3. Further Improvements

We present techniques that improve the performance of RevDedup during deployment.

Multithreading: RevDedup exploits multithreading to parallelize operations. For example, during backup, multiple threads check the segments for inline deduplication opportunities and write segments into containers; during reverse deduplication, multiple threads read containers and check for chunk removal; during restore, multiple threads read containers and trace indirect reference chains to reconstruct the segments.

Prefetching: RevDedup reads containers during reverse deduplication and restore. It uses prefetching to improve read performance. Specifically, a dedicated prefetch thread calls the POSIX function `posix_fadvise(POSIX_FADV_WILLNEED)` to notify the kernel to prefetch the containers into cache and save future disk reads. While the prefetch thread issues the notification and waits for the response from the kernel, other threads work on metadata processing and data transmission so as to mitigate the notification

Table I. Details of All Synthetic Datasets

Traces	# Series	# Backups	$\alpha\%$	$\beta\%$	γ MB
<i>SG1</i>	1	78	2%	10%	10MB
<i>SG2</i>	1	78	4%	10%	10MB
<i>SG3</i>	1	78	2%	20%	10MB
<i>SG4</i>	1	78	2%	10%	20MB
<i>SG5</i>	1	78	10%	10%	10MB
<i>GP</i>	16	320	2%	10%	10MB

overhead. Note that prefetching is also used by Lillibridge et al. [2013] (known as the forward assembly area) to improve read performance of deduplication systems. Our prefetching approach differs in that it leverages the kernel support.

Handling of null chunks: Some backup workloads such as Virtual Machine (VM) images may contain a large number of null (or zero-filled) chunks [Jin and Miller 2009]. RevDedup skips writing null chunks. When a read request is issued to a null chunk, the restore module returns the null chunk on the fly instead of reading it from disk. This improves both backup and restore performance.

Tunable parameters: RevDedup makes performance trade-offs through configurable parameters, including the sizes of segments, chunks, and containers, as well as the lengths of retention, live, archival windows. For example, a longer live window implies that more backups are ready to be restored, while consuming more storage space; larger segments and chunks imply less indexing overhead and data fragmentation, while reducing deduplication efficiency. We explore the performance effects of different parameters in Section 4.

4. EXPERIMENTS

We conduct testbed experiments on our RevDedup prototype. We show that RevDedup achieves high storage efficiency, high backup throughput, high restore throughput of new backups, and low deletion overhead of expired backups.

4.1. Setup

Datasets: We evaluate RevDedup using both synthetic and real-world datasets. For synthetic datasets, we extend the idea by Lillibridge et al. [2013] to generate configurable workloads for stress-testing data fragmentation. We simulate a backup series by first creating a full backup using a Ubuntu 12.04 VM disk image configured with 8GB space. Initially, the image has 1.1GB of system files. On each simulated weekday, we randomly walk through the file system to pick $\alpha\%$ of files and modify $\beta\%$ of file contents, and further add γ MB of new files to the file system. The parameters α , β , and γ are configurable in our evaluation. We represent five simulated weekdays as one simulated week. At the start of each simulated week, we perform a full backup of the disk image using the `dd` utility. We generate 78 full backups to simulate a duration of 1.5 years. We configure the parameters to simulate five types of activities of a single backup series, as listed in Table I. We call the datasets *SG1-5*. In addition, we also simulate a scenario with a group of 16 backup series covering 20 weekly full backups each. We call the dataset *GP*.

We also consider a real-world dataset taken from the snapshots of VM images used by university students in a programming course. We prepared a master image of 7.6GB installed with Ubuntu 10.04 and assigned it to each student to work on three programming assignments over a 12-week span. We took weekly snapshots for the VMs. For privacy reasons, we only collected cryptographic hashes on 4KB fixed-size blocks. For

our throughput tests, we reconstruct each block by placing its block hash at the end of a null 4KB block. Any two identical (resp., different) block hashes will give identical (different, respectively) blocks. This preserves the characteristics of content similarities in the granularity of 4KB. Our evaluation selects a subset of 80 VMs covering a total of 960 weekly full backups. The total size is 7.2TB with 3.3TB of nonzero blocks. We call the dataset *VM*. Note that the dataset only presents a special real-world use case, and we do not claim its representativeness for general virtual desktop environments.

Testbed: We conduct our experiments on a machine with an Intel Xeon E3-1240v2 quad-core, eight-threaded processor, 32GB RAM, and a disk array with eight ST1000DM003 7200RPM 1TB SATA disks. By default, we configure a RAID-0 array as done in prior work [Guo and Efstathopoulos 2011] to maximize the disk array throughput for high-performance tests, while we also consider RAID-5 and RAID-6 in baseline performance tests (see Section 4.2). We fix the RAID chunk size at 512KB. The machine runs Ubuntu 12.04.3 with Linux kernel 3.8.

Default settings: We compare RevDedup and conventional inline deduplication. For RevDedup, we fix the container size at 32MB, the segment size at 4MB for inline deduplication, and the chunk size at 4KB for reverse deduplication. We also assume that the retention window covers all backups. We fix the live window length to be one backup and the archival window length to be the number of all remaining backups. For conventional inline deduplication, we configure RevDedup to fix the segment size as 4KB and disable reverse deduplication. The container size is also fixed at 32MB. We refer to conventional inline deduplication as *Conv* in the following discussion.

For the datasets *SG1-5* and *GP*, both RevDedup and *Conv* use variable-size chunking based on Rabin fingerprinting [Rabin 1981]; for the dataset *VM*, we use fixed-size chunking, which is known to be effective for VM image storage [Jin and Miller 2009]. We examine the effects of various parameters, including the container size, the segment size, and the live window length.

Evaluation methodology: Our experiments focus on examining the I/O performance of RevDedup. When we perform throughput and latency measurements, we exclude the overhead of fingerprint computations, which we assume can be done by backup clients offline before they store backup data. We precompute all segment and chunk fingerprints before benchmarking. In addition, for each write, we call `sync()` to force all data to disk. Before each read, we flush the file system cache using the command “`echo 3 > /proc/sys/vm/drop_caches`.” By default, we disable prefetching (see Section 3.3) to focus on the effect of disk accesses on I/O performance.

4.2. Baseline Performance

We measure the baseline performance of RevDedup using unique data (i.e., without any duplicates). We write 8GB of unique data, and then read the same data from disk. We also measure the raw throughput of the native file system. We obtain averages and standard deviations over 20 runs.

Table II shows the results. In RAID-0, RevDedup can achieve at least 95.9% and 88.6% of raw write and read throughputs, respectively. We also configure the testbed as RAID-5 and RAID-6. We observe throughput drops due to the storage of parities. Nevertheless, RevDedup achieves nearly the raw throughput.

4.3. Storage Efficiency

We calculate the percentage reduction of storage space with deduplication. We exclude the metadata overhead and null chunks in our calculation. We compare RevDedup and

Table II. Baseline Throughput of RevDedup with Segment Size 4MB and Container Size 32MB on Unique Data under RAID-0, RAID-5, and RAID-6 (values in brackets are standard deviations)

(GB/s)	Raw	RevDedup
W (R0)	1.060 (0.013)	1.017 (0.034)
R (R0)	1.235 (0.004)	1.094 (0.004)
W (R5)	0.913 (0.011)	0.81 (0.013)
R (R5)	1.004 (0.020)	0.85 (0.008)
W (R6)	0.793 (0.016)	0.734 (0.020)
R (R6)	0.935 (0.010)	0.726 (0.029)

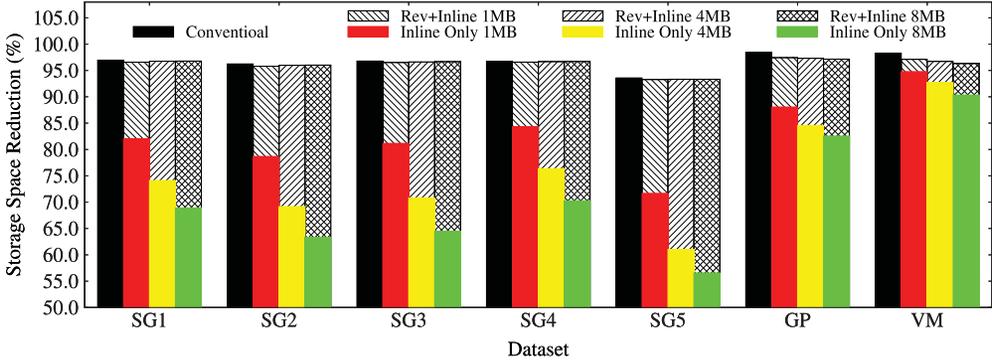


Fig. 4. Percentage reduction of storage space of RevDedup and *Conv.*

Conv. For RevDedup, we vary the segment size and fix the chunk size at 4KB. We also provide a breakdown for segment-level inline deduplication and reverse deduplication.

Figure 4 shows the results. Consider the synthetic datasets *SG1-5* and *GP*. In RevDedup, segment-level inline deduplication itself also reduces storage space, but the saving drastically drops as the segment size increases. For example, when the segment size is 8MB, segment-level inline deduplication only gives 56.5%–68.9% of space saving for *SG1-5*. Nevertheless, reverse deduplication increases the saving to 93.6%–97.0%, which is comparable to *Conv.*

For the real-world dataset *VM*, RevDedup achieves a saving of 96.3%–97.1%, which is close to 98.3% achieved by *Conv.* In particular, segment-level inline deduplication saves at least 90% of space, since most system files remain unchanged in the VM images. We emphasize that the findings are specific to our dataset and may not hold in general.

4.4. Throughput

We evaluate the backup and restore throughput of RevDedup, and compare the results with *Conv.* We study how the different segment sizes and container sizes affect the backup and restore throughput. We only focus on the datasets *SG1*, *GP*, and *VM*. We also study the overhead of reverse deduplication, the gains of prefetching, and the effect of live window length, where we focus on the dataset *SG1*. The results for *SG1* are plotted every three weeks for clarity of presentation. All results are averaged over five runs.

4.4.1. Backup. To evaluate the backup throughput of RevDedup, we only measure the backup performance due to segment-level inline deduplication, since reverse deduplication is assumed to be done out of line. We will measure the overhead of reverse deduplication in Section 4.4.3.

Before each experimental run of a dataset, we format the file system without any data. We submit each backup using `inlinededup` (see Section 3.2), and measure the

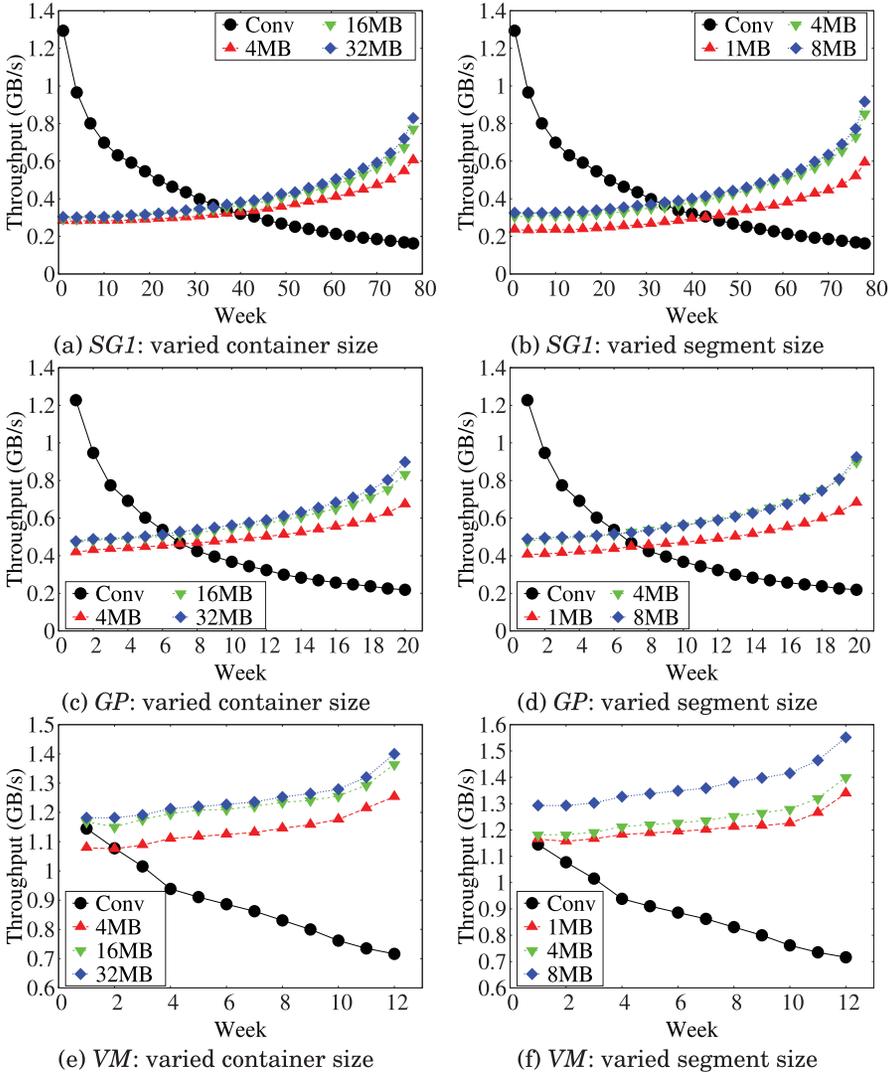


Fig. 5. Backup throughput of RevDedup and *Conv* for different datasets. We vary the container and segment sizes of RevDedup: (a), (c), and (e) fix the segment size at 4MB and vary the container size; (b), (d), and (f) fix the container size at 32MB and vary the segment size. The plots start from the second week to take into account interversion redundancy.

duration starting from when the in-memory deduplication index is built until all segments are packed into containers and written to disk. The backup throughput is calculated as the ratio of the original backup size to the measured duration. Figure 5 shows the backup throughput results, which we elaborate next.

Performance trends of *Conv* and RevDedup: At the beginning, RevDedup has significantly higher backup throughput than the raw write throughput [e.g., 4× for *SG1* as shown in Figure 5(a)]. The throughput decreases over time, as we make more content changes to the backups and hence introduce more unique data. Both synthetic datasets *SG1* and *GP* show similar trends, due to the ways of how we inject changes to the backups.

Table III. Time Breakdown of Writing the Second Backup of *SG1* for *Conv* with Segment Size 4KB and RevDedup with Varying Segment Sizes, Where the Container Size is Fixed at 32MB

	<i>Conv</i>	RevDedup		
		1MB	4MB	8MB
Index lookups (s)	2.562	0.032	0.012	0.008
Data writes (s)	0.961	0.501	0.617	0.646

The real-world dataset *VM* shows throughput fluctuations because of the varying usage patterns. For example, week 4 shows a sudden throughput drop because there was an assignment deadline and students made significant changes to their VMs. Despite the fluctuations, RevDedup still achieves much higher backup throughput than the raw write throughput. We note that RevDedup can reach an exceptionally high throughput of up to 30GB/s. The reason is that our *VM* dataset contains a large volume of duplicate segments and null segments, both of which can be eliminated on the write path.

Although *Conv* has higher reduction of storage space than RevDedup with only segment-level inline deduplication (see Figure 4), it has much lower backup throughput, and its throughput is fairly stable. To explain the results, we measure two suboperations of a backup operation: index lookups and data writes (note that data writes include packing segments to containers and writing containers to disk). With multithreading (see Section 3.3), both suboperations are carried out simultaneously, and hence the backup performance is bottlenecked by the slowest suboperation. We consider a special case when we store the backup of the second week for *SG1*. We configure *Conv* with segment size 4KB and RevDedup with varying segment sizes, while both schemes have container size fixed at 32MB. Table III provides a time breakdown for the two suboperations. We observe that for *Conv*, although its deduplication index is kept in memory, its small deduplication units significantly increase the lookup time and make the index lookups become the bottleneck. Even though we inject more unique data to the backups over time, the backup throughput remains bottlenecked by index lookups. On the other hand, RevDedup has much less index lookup overhead with larger segments. We also note that *Conv* has higher data write time than RevDedup, because it adds a much larger number of small segments into containers.

We emphasize that as more unique data is added, RevDedup eventually has its backup throughput dropped below *Conv*. Nevertheless, the backup throughput of RevDedup is lower bounded by the baseline for unique data (see Section 4.2).

We can reduce the index lookup overhead of inline deduplication by maintaining the temporal locality of fingerprints [Zhu et al. 2008], so as to improve the backup performance of *Conv*. Our current prototype does not implement this enhanced indexing scheme, and we consider this issue in future work.

Effect of container size: While a larger container size implies fewer write requests and hence better data write performance, the gains in backup throughput is insignificant due to the inevitable indexing overhead in deduplication. For example, for *SG1* in Figure 5(a) and *GP* in Figure 5(c), the backup throughput of RevDedup increases by only 9% and 16% (averaged over all weeks) when the container size increases from 4MB to 16MB, respectively.

Effect of segment size: A large segment size reduces the deduplication opportunity, and hence RevDedup writes more data to disk. Since the data write dominates the backup performance of RevDedup (see Table III), its backup throughput drops as the segment size increases. For example, for *SG1* in Figure 5(b), the backup throughput drops by 38% (averaged over all weeks) when the segment size increases from 1MB to 8MB.

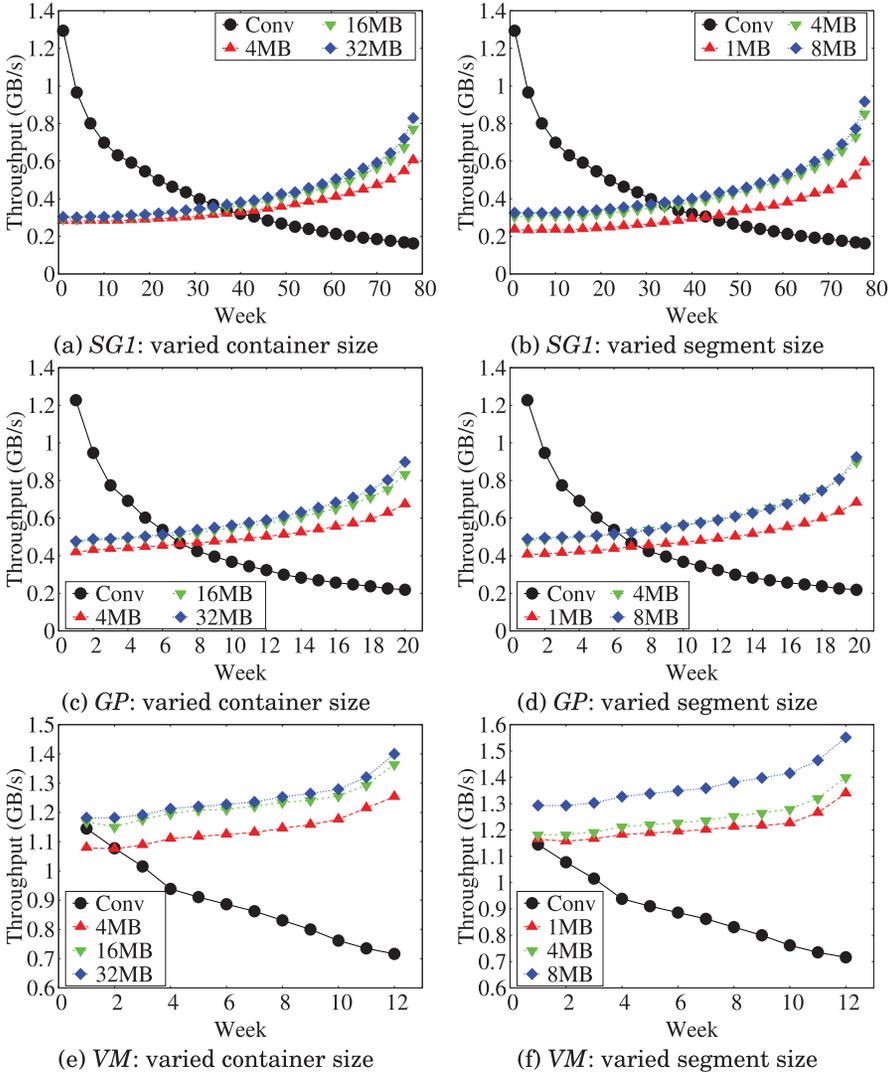


Fig. 6. Restore throughput of RevDedup and *Conv*, corresponding to the settings in Figure 5.

4.4.2. Restore. After writing all backups, we restore each backup using the module *restore* (see Section 3.2). We measure the restore throughput of RevDedup and *Conv* as the ratio of the original backup size to the restore time. For RevDedup, we first perform out-of-line reverse deduplication on the backups, so that the restore performance of both RevDedup and *Conv* is measured when they have comparable storage efficiency (see Section 4.3). Figure 6 shows the restore throughput results for various container sizes and segment sizes, corresponding to the settings of Figure 5. The results are elaborated as follows.

Performance trends of *Conv* and RevDedup: *Conv* suffers from data fragmentation and hence its restore throughput decreases for more recent backups (e.g., by 86% from week 2 to week 78 in Figure 6(a)), while RevDedup shifts data fragmentation to older backups and maintains high restore throughput for the latest backups. For instance,

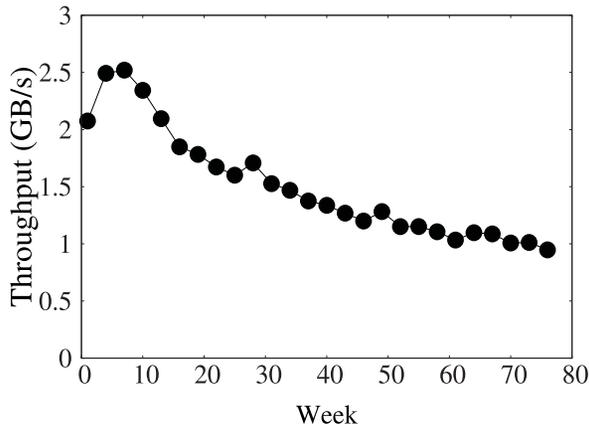


Fig. 7. Reverse deduplication throughput of RevDedup.

from Figures 6(a) and 6(c), the restore throughput for the latest backup of RevDedup is $5\times$ and $4\times$ that of *Conv* for *SG1* and *GP*, respectively. The throughput values are smaller than the raw read throughput, mainly due to data fragmentation caused by segment-level inline deduplication.

For the real-world dataset *VM*, we see similar trends of restore throughput for both RevDedup and *Conv*. However, the restore throughput of RevDedup goes beyond the raw read throughput (see Figures 6(e) and 6(f)). The reason is that the VM images contain a large number of null chunks, which are generated on the fly by RevDedup rather than read from disk. We expect that the restore throughput drops as the number of null chunks decreases.

Effect of container size: The restore throughput increases with the container size as the number of read requests decreases. For example, for *SG1* in Figure 6(a) and *GP* in Figure 6(c), the restore throughput of RevDedup increases by 11.8% and 14.4% (averaged over all weeks) when the container size increases from 4MB to 16MB, respectively. However, further increasing the container size from 16MB to 32MB shows only marginal gains.

Effect of segment size: A larger segment size increases the restore throughput, as it mitigates data fragmentation. For example, for *SG1* in Figure 6(b), the restore throughput for the latest backup of RevDedup increases by 39.3% (averaged over all weeks) when the segment size increases from 1MB to 8MB. The trade-off of using larger segments is that it reduces both storage efficiency and backup throughput.

4.4.3. Reverse Deduplication Overhead. We now evaluate the reverse deduplication throughput, defined as the ratio of the original backup size to the reverse deduplication time. Recall that we set the default live window length as one backup. After we submit a new backup, we perform reverse deduplication on its previous backup. We measure the time of reading the containers that have nonshared segments of the previous backup and writing the compacted segments without removed chunks to disk.

Figure 7 shows the reverse deduplication throughput for *SG1* starting from Week 1. Week 1 has lower throughput than the next few weeks, due to the following reason. Initially, many containers are mixed with shared and nonshared segments, so we load such containers and separate the shared and nonshared segments into different containers (see Section 2.4.3). Later we only load the containers whose segments change from shared to nonshared, plus the containers that have nonshared segments

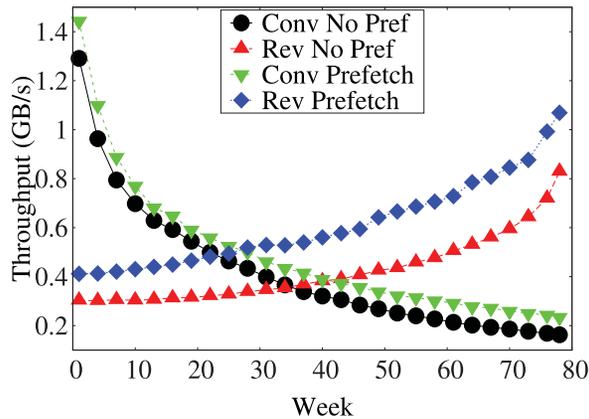


Fig. 8. Restore throughput of *Conv* and *RevDedup* with and without prefetching.

associated with the backup on which we apply reverse deduplication. We also see that the throughput drops as the amount of unique data increases, yet it is lower bounded by about half of the baseline read/write throughput (see Section 4.2) because the whole backup is read for chunk removal and rewritten to disk (assuming that the baseline read and write throughputs are about the same).

4.4.4. Gains of Prefetching. We disable prefetching in the previous experiments. We now evaluate the restore throughput increases with prefetching enabled. We focus on *SG1*. For *RevDedup*, we fix the segment size at 4MB and the container size at 32MB. Figure 8 shows the results. We see that prefetching improves the restore throughput by 23.9% and 45.8% (averaged over all weeks) for *Conv* and *RevDedup*, respectively. Note that the data fragmentation problem, while being mitigated, still manifests in *Conv*, which still has around 82% drop in restore throughput from the first week to the last one.

4.4.5. Effective Live Window Length. The live window length defines the number of backups that remain coarsely deduplicated by segment-level inline deduplication, and determines the trade-off between storage efficiency and restore performance. Here, we study the effect of live window length for the dataset *SG1*. We first store all backups of *SG1* and perform reverse deduplication using *RevDedup*. We then measure the restore throughput for each backup. We vary the live window length to be 1, 5, and 17 backups (i.e., the archival window lengths are 77, 73, and 61 backups, respectively).

Figure 9 shows the restore throughput results. The restore throughput increases over time for backups within the archival window, since *RevDedup* shifts data fragmentation to old backups. On the other hand, the restore throughput decreases over time for the backups within the live window (e.g., when the live window is 17 backups), due to data fragmentation caused by segment-level inline deduplication. Nevertheless, the drop is slower than conventional deduplication as the large segment size limits the overhead of data fragmentation.

Setting a larger live window increases the restore throughput of backups in the archival window. Recall that an archival backup has indirect reference chains to the oldest live backup. A larger live window implies that an archival backup has shorter indirect reference chains. This reduces the tracing time when restoring the archival backups.

The trade-off is that a larger live window length increases the storage space. For example, the percentage reductions of space saved due to deduplication drop from

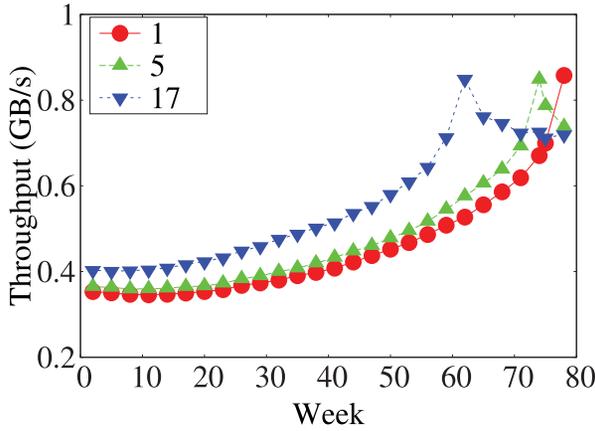


Fig. 9. Restore throughput of RevDedup with different live window lengths.

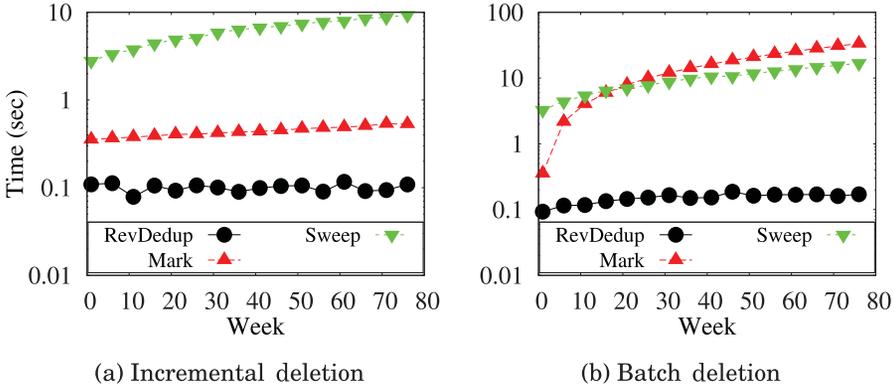


Fig. 10. Deletion times of RevDedup and mark-and-sweep.

96.6% to 93.2% (averaged over all weeks) when the live window length increases from 1 to 17 backups.

4.5. Deletion Overhead

We evaluate the deletion overhead of RevDedup and compare it with the traditional mark-and-sweep approach. We consider two types of deletion operations: incremental deletion of the earliest backup and batch deletion of multiple expired backups. We first store 78 weeks of backups and perform reverse deduplication using RevDedup, and then run each type of deletion. Figure 10 shows the average results over five runs for the dataset *SG1*. We elaborate the results next.

Incremental deletion: In this test, we keep deleting a backup from the series one by one, starting from the earliest backup. RevDedup simply deletes the metadata of the deleted backup and the containers whose timestamps are equal to the creation time of the deleted backup. On the other hand, in the mark-and-sweep approach, the mark phase loads the metadata of the backup and decrements the reference count of each associated segment, and the sweep phase scans through all containers to delete the nonreferenced segments and reconstruct the containers with the remaining segments that are not deleted. Figure 10(a) shows the time breakdown. The mark

phase incurs small running time as it only processes metadata, while the sweep phase incurs significant running time as it needs to read and reconstruct the containers. RevDedup has significantly smaller deletion time than each of the mark-and-sweep phases.

Batch deletion: In this test, we delete the n earliest backups, with n ranging from 1 (only the earliest one) to 77 (all except the most recent one). To measure the time of deleting n backups, we first take a snapshot of the storage partition and store the snapshot elsewhere, perform the deletion and record the time, and finally restore the snapshot to prepare for the next deletion. The deletion processes of both RevDedup and mark-and-sweep are similar to those in individual deletion. Figure 10(b) shows the time breakdown. The running time of the mark phase increases with n since it reads the metadata of more backups, while the sweep phase has similar running time as in incremental deletion as it scans through all containers once only. The deletion time of RevDedup remains very small.

Summary: The two tests show that RevDedup incurs small overhead in both incremental and batch deletion operations. The deletion overhead is amortized over the chunk removal process during reverse deduplication. The small batch deletion overhead of RevDedup provides flexibility for administrators to defer the deletion of expired backups as long as the storage space remains sufficient.

5. RELATED WORK

Backup: Most existing deduplication studies for backup storage focus on achieving high backup performance. Deduplication is first proposed in Venti [Quinlan and Dorward 2002] for data backup in content-addressable storage systems. DDFS [Zhu et al. 2008] and Foundation [Rhea et al. 2008] maintain fingerprints in a Bloom filter [Bloom 1970] to minimize memory usage for fingerprint indexing. Data Domain File System (DDFS) further exploits spatial locality to cache the fingerprints of blocks that are likely written later. Other studies [Bhagwat et al. 2009; Lillibridge et al. 2009; Kruus et al. 2010; Guo and Efstathopoulos 2011; Xia et al. 2011; Meister et al. 2013] exploit workload characteristics to further improve backup performance while limiting the memory overhead for indexing. ChunkStash [Debnath et al. 2010] and Dedupv1 [Meister and Brinkmann 2010] store fingerprints in solid-state drives to achieve high-speed fingerprint lookup. All previous approaches build on inline deduplication, while RevDedup uses out-of-line deduplication to address both restore and deletion performance. In particular, Bimodal [Kruus et al. 2010] uses a hybrid of large and small chunk sizes. Although seemingly similar to RevDedup, it dynamically switches between the chunk sizes in inline deduplication, while RevDedup uses out-of-line deduplication on small-size chunks.

Restore: To mitigate chunk fragmentation in inline deduplication and hence improve restore performance, Kaczmarczyk et al. [2012] propose context-based rewriting, which selectively rewrites a small percentage of data for the latest backups. Nam et al. [2012] measure the fragmentation impact given the input workload and activate selective deduplication on demand. Lillibridge et al. [2013] use container capping to limit the region of chunk scattering, and propose the forward assembly area (similar to caching) to improve restore performance. Note that the studies [Kaczmarczyk et al. 2012; Nam et al. 2012; Lillibridge et al. 2013] only conduct simulation-based evaluations, while we implement a prototype to experiment with the actual I/O throughput. SAR [Mao et al. 2014] leverages Solid-State Drives (SSDs) to store the chunks referenced by many duplicate chunks and absorb the random reads to hard disks. In contrast, RevDedup does not rely on the use of SSDs.

The previous approaches are designed for backup storage, while iDedup [Srinivasan et al. 2012] is designed for primary storage and it limits disk seeks by applying deduplication to chains of continuous duplicate chunks rather than individual chunks.

Reclamation: Several approaches focus on reducing the reclamation overhead in in-line deduplication systems. Guo and Efstathopoulos [2011] propose a grouped mark-and-sweep approach that associates files into different backup groups and limits the scanning to only a subset of backup groups. Botelho et al. [2013] propose a memory-efficient data structure for indexing chunk references. Strzelczak et al. [2013] extend HYDRAsTOR [Dubnicki et al. 2009] with concurrent deletion to minimize the interference of background sweeping to ongoing writes. Simha et al. [2013] limit the number of reclaimed chunks and ensure that the reclamation overhead is proportional to the size of incremental backups.

6. CONCLUSIONS

We explore the problem of achieving high performance in essential operations of deduplication backup storage systems, including backup, restore, and deletion, while maintaining high storage efficiency. We present RevDedup, an efficient hybrid inline and out-of-line deduplication system for backup storage. The key design component of RevDedup is reverse deduplication, which removes duplicates of old backups out of line and mitigates fragmentation of latest backups. We propose heuristics to make reverse deduplication efficient: (1) limiting the deduplication operation to consecutive backup versions of the same series, (2) using two-level reference management to keep track of how segments and chunks are shared, and (3) checking only nonshared segments for chunk removal. We extensively evaluate our RevDedup prototype using synthetic and real-world workloads and validate our design goals. The source code of our RevDedup prototype is available for download at <http://ansrlab.cse.cuhk.edu.hk/software/revdedup>.

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