Improving Restore Performance in Deduplication Systems via a Cost-efficient Rewriting Scheme

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Abstract—In chunk-based deduplication systems, logically consecutive chunks are physically scattered in different containers after deduplication, which results in the serious fragmentation problem. The fragmentation significantly reduces the restore performance due to reading the scattered chunks from different containers. Existing work aims to rewrite the fragmented duplicate chunks into new containers to improve the restore performance, which however produces the redundancy among containers, decreasing the deduplication ratio and resulting in redundant chunks in containers retrieved to restore the backup, which wastes limited disk bandwidth and decreases restore speed. To improve the restore performance while ensuring the high deduplication ratio, this paper proposes a cost-efficient submodular maximization rewriting scheme (SMR). SMR first formulates the defragmentation as an optimization problem of selecting suitable containers, and then builds a submodular maximization model to address this problem by selecting containers with more distinct referenced chunks. Moveover, this paper further leverages the grouped form, i.e., GSMR, to reduce the fragmented chunks caused by the accumulated differences among backup versions. We implement SMR in the deduplication system, which is evaluated via three real-world datasets. Experimental results demonstrate that SMR is superior to the state-of-the-art work in terms of the restore performance as well as deduplication ratio, and GSMR further improves the restore performance. We have released the source code of SMR in Github for public use.

Index Terms—Data Deduplication, Restore Performance, Rewriting Scheme.

1 Introduction

Data deduplication has been widely used in backup systems to save storage space [1], [2], [3], [4], [5], [6]. It divides incoming data stream into small and variable pieces, called chunks [7], and identifies each chunk by its small-size signature, called fingerprint, via hash functions, such as SHA-1, SHA-256 and MD5 [7], [8]. A fingerprint index maps fingerprints of the stored chunks to their physical addresses [9], [10]. These chunks are stored into several large fixed-size storage units called containers, to preserve the spatial locality of the backup data stream [2], [9], [11], [12], [13]. A container is the basic unit of reads and writes. Based on the redundancy of incoming chunks, a data deduplication system needs to carry out different operations. Specifically, duplicate chunks are replaced with the references to existing identical copies stored in old containers, and unique chunks are written into new containers. Each backup has a recipe to record the reference to the container of each backup chunk. In a restore phase, the restore algorithm scans down the recipe of the backup to determine which containers need to be retrieved from disks to the restore cache, which contains the prefetched containers, to restore the target chunks of the backup stream.

Although data deduplication is space-efficient, logically consecutive chunks have to be physically scattered in different containers, thus causing chunk fragmentation [9], [11], [14], [15], [16]. The fragmentation severely degrades the restore performance, while the infrequent restore is very important and becomes the main concern from users [17]. First, original sequential disk accesses of reading logically consecutive chunks become many random ones, while random accesses perform poorly in disks due to the penalty of disk seeks [11], [18]. Second, due to the fragmentation, some containers, containing a few referenced chunks (defined as the chunks referenced by the backup), are retrieved to restore the backup. The remaining unreferenced chunks in the retrieved containers are not accessed by the data stream, thus causing the waste of limited disk bandwidth and decreasing restore speed.

To address the fragmentation problem, several schemes propose rewriting algorithms to rewrite fragmented duplicate chunks during the backup, such as Capping [11] and NED [12]. They aim to obtain a suitable trade-off between deduplication efficiency and restore performance via selective deduplication upon containers with more referenced chunks.

We observe that more versions of the backup data are backed up, and more duplicate chunks are rewritten into new containers, as described in Section 2. Thus, multiple identical copies of these chunks are stored in different containers, causing redundancy among containers. However, the containers selected by existing schemes [11], [12] are suboptimal due to overlooking the redundancy among the containers. Hence, some containers with many redundant chunks, which are not referenced by the backup, are selected, thus wasting some disk bandwidth and slowing down the restore speed.

To address this problem, we propose a submodular maximization rewriting scheme (SMR) to efficiently select containers for deduplication, and judiciously rewrite duplicate

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fragmented chunks. SMR aims to select a limited number of containers which offer more distinct referenced chunks for the backup, thus reducing the number of redundant or unreferenced chunks in the selected containers, to gain a better trade-off between deduplication efficiency and restore performance. If more distinct referenced chunks are offered for the current backup stream, more chunks in the backup stream can be deduplicated, thus saving storage space. Since less chunks are rewritten into new containers, SMR decreases the number of containers retrieved for restore. In addition, SMR also reduces the disk accesses of redundant and unreferenced chunks fetched in the restore phase. Hence, SMR achieves better restore performance as well as deduplication ratio.

Though consecutive backup versions are similar under most situations, we observe that the differences among versions are accumulated with the increasing number of versions, as described in Section 4. As a result, there are more and more fragmented chunks which jeopardize the restore performance. Therefore, we further propose a grouped deduplication scheme of SMR to improve the restore performance further. We divide the sequential backup versions into groups, and each version only deduplicates chunks with the versions in its own group. Hence, the differences among versions are limited to each group, reducing the number of fragmented chunks of backup versions.

In summary, the paper makes the following contributions.

- We observe that due to overlooking the redundancy among containers, existing solutions [11], [12] potentially choose suboptimal containers with many redundant chunks, which decreases the restore performance. This is an important problem for improving entire system performance.
- We propose a submodular maximization rewriting scheme, i.e., SMR, to select containers with more distinct referenced chunks for the backup, reducing the waste of disk accesses caused by redundant and unreferenced chunks in the restore phase. It can deduplicate more chunks and rewrite less chunks, and less containers are retrieved during the restore, gaining a better trade-off between deduplication efficiency and restore performance.
- We propose a grouped deduplication scheme to optimize SMR, i.e., GSMR, which mitigates the fragmentation caused by the accumulated differences among versions. GSMR improves the restore performance further compared with SMR, without significantly decreasing the deduplication ratio.
- We implement our scheme in the deduplication system and evaluate the performance via three real-world backup datasets. Compared with the state-of-the-art schemes [11], [12], experimental results demonstrate that our scheme obtains higher deduplication ratio as well as restore performance. We have released the source code of SMR for public use at https://github.com/courageJ/SMR.

The rest of this paper is organized as follows. In Section 2, we describe the background and motivation. We present the design of SMR and grouped deduplication respectively in Sections 3 and 4. Section 5 presents the evaluation methodology and results. Related work is discussed in Section 6. We conclude our paper in Section 7.

2 Background and Motivation

2.1 Chunk Fragmentation

Data deduplication saves storage capacity by storing one copy of the duplicated data. But the logically contiguous chunks of each backup are scattered all over different containers, called chunk fragmentation [9], [11], [14], [15], [16]. Thus the restore of each backup needs many random I/Os to the containers, which perform poorly in disks. Hence, chunk fragmentation significantly decreases the restore performance.

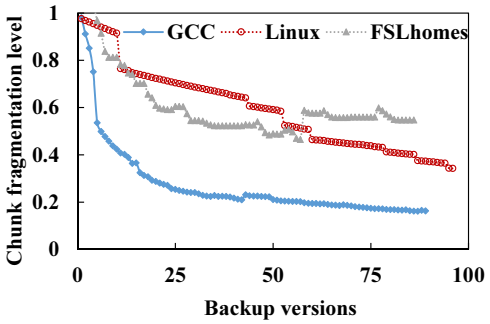


Fig. 1. The chunk fragmentation over time.

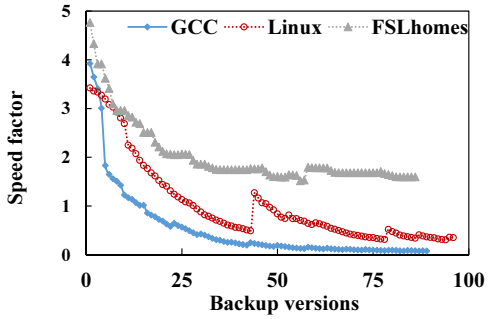


Fig. 2. The speed factor over time.

We simulate the baseline deduplication without rewriting on three real-world datasets, including GCC [19], Linux [20] and FSLhomes [21] (detailed in Section 5) to explore the degree of chunk fragmentation and the restore performance. The chunk fragmentation level (CFL) [15], [16] is a quantitative metric to measure the level of chunk fragmentation per data stream, which is defined as a ratio of the optimal number of containers without any deduplication scheme with respect to the number of containers after deduplication to store the backup data stream. The CFL ranges from 0 to 1. The smaller CFL indicates that the physical distribution of the data stream is more scattered, resulting in lower restore speed. The speed factor [11] (detailed in Section 5) is a metric to evaluate the restore performance. The higher speed factor indicates the better restore performance. As shown in Figure 1, the fragmentation level is mainly in a downward trend, indicating that the physical dispersion becomes more severe. As shown in

Figure 2, the speed factor declines severely with the increasing number of backup version, indicating the decrease of restore performance when more versions are backed up. A few exceptions in the Linux datasets are the major revision updates, which have more new data stored consecutively. When more backups arrive, more shared chunks appear, which exacerbates the backup fragmentation and decreases the restore performance. Hence, how to mitigate the large slowdown of restore performance over time caused by the increasing degree of chunk fragmentation is an important problem to be concerned.

2.2 The Selective Container Deduplication Schemes

In order to address the fragmentation problem and improve restore performance, some schemes about selective container deduplication have been proposed, e.g., Capping [11] and NED [12]. They define the fraction of chunks referenced by the backup in a container as the container's utilization and try to select containers with higher utilization for a backup to deduplicate. These schemes rewrite the duplicate chunks which refer to lower-utilization containers, to alleviate the waste of disk bandwidth caused by the unreferenced chunks in these containers in the restore phase. Hence, the restore performance has been improved with the cost of decreasing storage efficiency.

Specifically, Capping splits the backup data stream into fixed-length segments, and uses a buffer to temporarily store them. The fingerprint index is further queried to conjecture which containers can be referenced by the chunks in the current segment. In fact, this is a trade-off between deduplication ratio and restore performance by setting the amount limit CAP_T of selected containers for deduplication. If the amount N of the containers which contain referenced chunks for the current segment is more than CAP_T, the top CAP_T containers are selected and used in deduplication according to their utilization. The chunks of the segment are deduplicated if having identical copies in the selected containers. Otherwise, they are rewritten into new containers. Capping improves restore performance by limiting the amount of containers that a segment can refer to, and selects the containers with higher utilization. Moreover, NED computes the ratio of the sum size of referenced chunks to that of the stored chunks in each container for the current backup segment. If the ratio of a container is lower than a threshold NED_T, the chunks in the segment that can refer to this container are regarded as fragmented chunks, which are further rewritten into new containers. NED aims to select some containers with utilization over the threshold for deduplication, which improves restore performance and mitigates data fragmentation.

2.3 Problem Statement

Multiple rewriting schemes, e.g., Capping [11] and NED [12], have been proposed to rewrite fragmented duplicate chunks to improve restore performance. However, with the increase of the number of backup versions, more and more duplicate chunks are rewritten into new containers. In consequence, many identical chunks are stored in different containers, thus increasing the redundancy among containers. Due to overlooking the redundancy among containers, existing schemes [11], [12] need to count some redundant chunks, which are not referenced by the backup, in computing the utilization of containers. Hence, some suboptimal containers are selected for the backup, which exacerbates disk accesses and slows down the restore speed.

Specifically, there exist multiple identical chunks among the selected containers referenced by the backup. One of these identical chunks can be referenced to deduplicate and restore all chunks with identical context of the backup. Due to playing the same function, other redundant chunks are not needed to be referenced by the backup. These redundant chunks in the selected containers hence fail to be regarded as referenced chunks in computing the utilization for these selected containers that are mistakenly considered to achieve higher utilization.

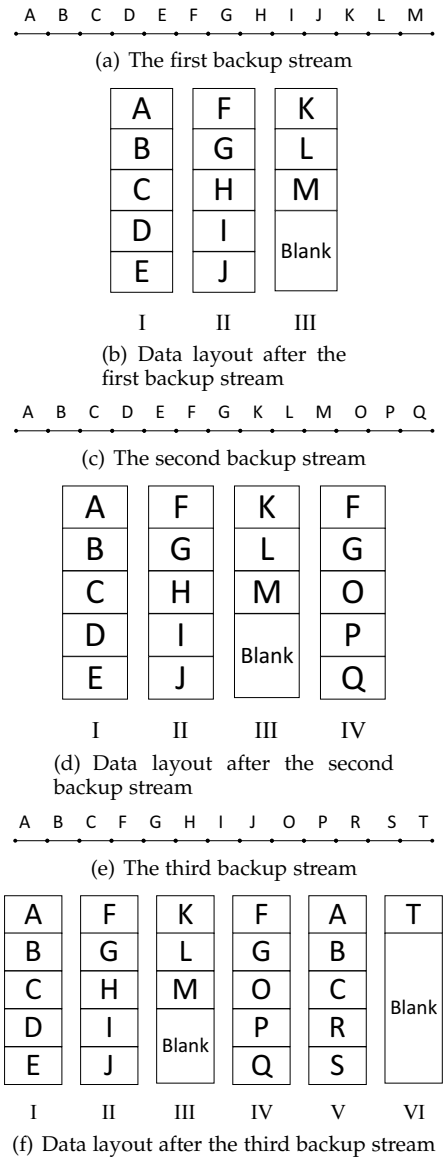
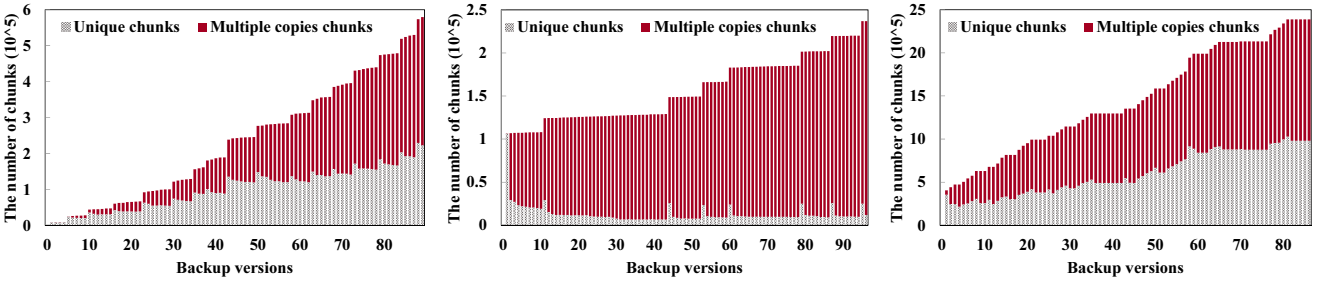


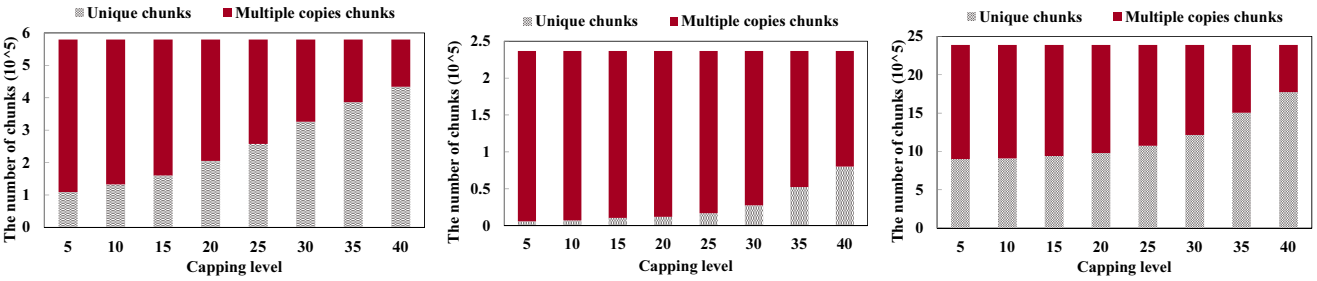
Fig. 3. An example of three consecutive backups with the Capping rewriting scheme.

We take Capping [11] as an example to show the effects of the redundancy among containers on the restore performance. As shown in Figure 3, three data streams with thirteen chunks are backed up and the amount of the



(a) GCC (b) Linux (c) FSLhomes

Fig. 4. The redundancy among containers in consecutive versions backups with the Capping rewriting scheme.



(a) GCC (b) Linux (c) FSLhomes

Fig. 5. The observations of redundancy among containers in various CAP_T levels.

selected containers in Capping, CAP_T, is set as 2. The number of chunks stored in each container is fixed as 5. The chunks in the first stream are stored in containers I, II, and III. When the second stream arrives, the utilizations are computed for each container: I is 5, II is 2 and III is 3. The containers I and III are the top 2 selected containers. Two chunks F and G referring to the container II and the remaining three unique chunks are written into the new container IV. Moreover, when the third stream arrives, the utilizations for each container are also computed: I is 3, II is 5, III is 0 and IV is 4. Thus top 2 selected containers are II and IV. 7 chunks are deduplicated. 6 remaining chunks which do not refer to the two containers are stored in new containers. As shown in the third stream backup, both containers II and IV have chunks F and G. Thus, in a restore phase, fetching the container IV only restores the chunks O and P, since the chunks F and G have been already restored by the container II. This scheme deduplicates less data due to selecting the container IV to deduplicate the chunks F and G that have been deduplicated by the container II. Thus, the chunks F and G in the container IV are considered to be referenced chunks when the Capping scheme counts the utilization for the container IV to select container IV, but the chunks F and G actually are not, wasting disk accesses.

As shown in the example above, more backups lead to more rewritten chunks in the new containers. Hence, there are more identical chunks stored in different containers, increasing the redundancy among containers. Existing schemes [11], [12] determine a chunk as the referenced chunk as long as it can be referenced by the backup. But considering all chunks in the selected containers, some chunks are redundant to be referenced, leading to extra disk accesses in a restore phase.

2.4 Observations and Motivations

2.4.1 The Redundancy among Containers

More and more chunks are rewritten into new containers in a backup for better restore performance, and thus multiple copies are stored in different containers for identical chunks, increasing the redundancy among containers. We explore the redundancy among containers in three real-world datasets, including GCC [19], Linux [20] and FSLhomes [21] (detailed in Section 5). We use Capping [11] as the example of the rewriting algorithm to back the consecutive versions of each dataset up in two experiments. One is to back the datasets up under the constant Capping level, i.e., CAP_T. The other is to back up under different CAP_T values. The default size of segment in Capping is 20MB, which is recommended in the Capping paper [11]. The constant Capping level in the first experiment is set as 20 containers per 20MB segment.

We classify the stored chunks into two categories: unique chunks (i.e., chunks only stored in one container) and redundant chunks (i.e., chunks with multiple copies stored in different containers). We count the amount of the two kinds of chunks respectively.

As shown in Figure 4, the amount of redundant chunks becomes far more than that of unique chunks when the backup version number grows. The reason is that original unique chunks become chunks with multiple copies since incoming identical chunks are rewritten into new containers. More and more containers have identical chunks. As shown in Figure 5, CAP_T values vary from 5 to 40 per segment. Smaller CAP_T indicates that less containers are selected for segments, achieving better restore performance, and more chunks are rewritten into new containers, which results in more redundant chunks. As shown in the two experiments, more and more chunks are rewritten into new

containers to reduce data fragmentation, however increasing the redundancy among containers.

2.4.2 Motivations

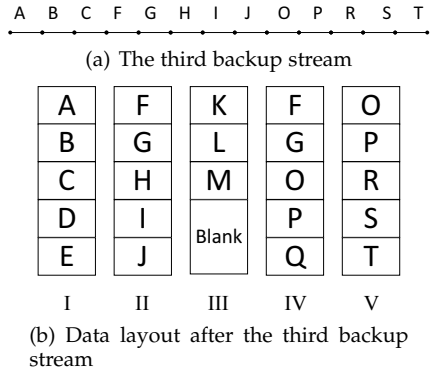
Although existing selective container deduplication schemes improve restore performance by limiting the amount of the selected containers with less referenced chunks for deduplication, the redundancy among containers results in multiple identical chunks to be selected for deduplication and fetched to restore the same chunks, wasting disk accesses. In essence, the wasted disk accesses in the restore phase are caused by selecting different containers with redundant chunks to deduplicate. Thus, when fetching containers to restore data stream, both unreferenced and redundant chunks in containers cause the waste of disk bandwidth and decrease the restore performance.

TABLE 1
The amount of distinct referenced chunks for every 2 containers.

Container ID	Distinct Referenced Chunks	Chunks Amount
I, II	A B C F G H I J	8
I, III	A B C	3
I, IV	A B C F G O P	7
II, III	F G H I J	5
II, IV	F G H I J O P	7
III, IV	F G O P	4

We aim to improve the restore performance by selecting a subset of containers with more distinct referenced chunks for deduplication under the limits of selected containers to reduce the number of unreferenced and redundant chunks in the selected containers. For example, we perform our selection strategy on the three backup streams as shown in Figure 3. The amount of the selected containers is also set as 2, which is the same as Capping level, i.e, CAP_T in Figure 3. The backup processes and containers distributions after the first two stream backup are the same as those in Figure 3. For the third data stream, when selecting 2 containers to deduplicate, we first count the amount of distinct referenced chunks for every 2 containers, as shown in Table 1. The number of distinct referenced chunks in the subset, consisting of the containers I and II, is more than any other subsets. Selecting the containers I and II can deduplicate 8 chunks and write 5 chunks. The distributions of containers after the third backup stream are shown in Figure 6.

Compared with Capping in Figure 3, we deduplicate 8 chunks A, B, C, F, G, H, I and J while Capping deduplicates 7 chunks F, G, H, I, J, O and P. We rewrite 2 duplicate fragmented chunks O and P into new containers while Capping rewrites 3 duplicate fragmented chunks A, B and C. Hence, we deduplicate more chunks and rewrite less chunks, saving more storage space. In the restore phase, we only fetch three containers I, II, V to restore the third data stream while Capping needs to retrieve four containers II, IV, V, VI. The reason is that we select two containers I and II, which have the largest number of distinct referenced chunks and no redundant chunks. Capping selects containers II and IV, which have higher utilizations and however contain two redundant chunks. The redundancy causes the actual number of referenced chunks in container IV to be much smaller than that in container I. Capping mistakenly considers the utilization of container IV to be the one of top 2 containers, which is selected for deduplication. Therefore, selecting containers with more distinct referenced chunks can deduplicate more chunks, rewrite less chunks and reduce the number of redundant and unreferenced chunks in the selected containers, achieving higher deduplication ratio and also improving restore performance.



(a) The third backup stream

(b) Data layout after the third backup stream

Fig. 6. The distributions of containers after the third backup.

3 The Design of SMR

3.1 An Architectural Overview

To reduce data fragmentation, our proposed Submodular Maximization Rewriting Scheme (SMR) selectively rewrites some fragmented duplicate chunks into new containers, and deduplicates the remaining duplicate chunks. SMR aims to trade the slight decrease of deduplication ratio for the high restore performance via efficiently selecting a limited number of old containers with more distinct referenced chunks for deduplication by a submodular maximization model. Specifically, in an old container, if there are many unreferenced and redundant chunks which are not needed to be referenced by the backup, there are few referenced chunks in the container. Thus, SMR rewrites the few referenced chunks of the old containers to reduce disk accesses caused by the unreferenced and redundant chunks in the restore phase. In a backup phase, there are many old containers sharing the duplicate chunks with the backup data stream. How to select the containers to perform deduplication is a trade-off between the restore performance and the deduplication ratio. Hence, SMR selects a suitable subset of containers to obtain better restore performance while ensuring the high deduplication ratio.

Figure 7 illustrates the architecture of SMR in a deduplication system. The grouping operation is optional, which is a part of grouped deduplication and detailed described in Section 4. In the main memory, the system splits the input data streams into chunks and uses hash functions to identify them, then the data stream is divided into segments which consist of some continuous chunks. For each segment, after redundancy identification, in order to gain a suitable trade-off between deduplication ratio and restore performance, SMR determines which chunks are deduplicated or rewritten according to the redundancy information of segments.

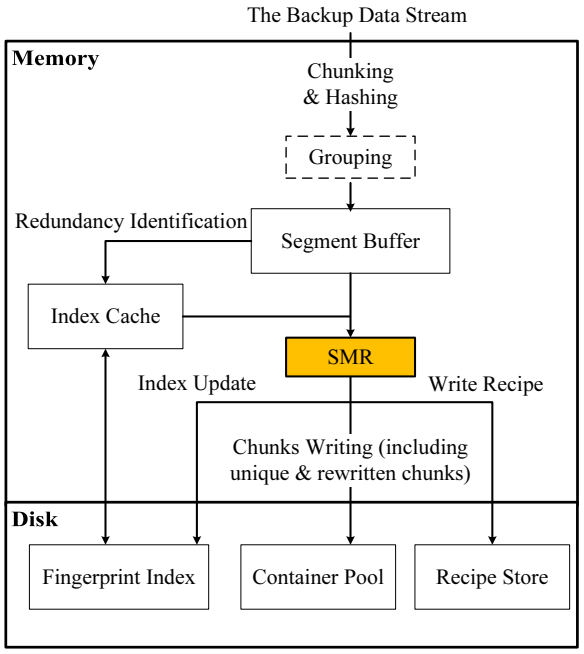


Fig. 7. The Architecture.

Finally, these rewritten and unique chunks are stored into the container pool. Meanwhile, the index and recipe are updated according to the fingerprints and addresses of these chunks.

Specifically, before a backup, the SMR level, i.e., T old containers selected for the deduplication of every S MB segment, is configured and the backup stream is split into chunks, which are further grouped into segments. For each segment, we first read each chunk of the segment, and then determine which chunks have identical copies stored in containers and their located container IDs by inquiring the fingerprint index. In detail, the complete fingerprint index is stored on disks while the hot part is stored in memory to accelerate the indexing of fingerprints. Afterwards, we select T old containers with the largest number of distinct referenced chunks to perform deduplication. Finally, for each chunk in the segment, if finding an identical copy in the selected containers, the chunk is deduplicated. Otherwise, it is treated as new chunks to be stored in new containers.

3.2 The Submodular Maximization Rewriting Scheme

In a restore phase, the containers containing the target chunks of the restored data stream are read from disks to the memory. One way to improve restore performance is to reduce the number of the retrieved containers.

In order to achieve this goal, SMR limits the number of old containers that referenced by the backup and reduces the amount of new containers storing the rewritten and unique chunks. Limiting the number of old containers means selecting a subset of old containers for the backup in deduplication. Reducing the amount of new containers means reducing the number of rewritten chunks, which depends on the old containers selection. Considering that the unreferenced and redundant chunks in old containers waste disk accesses in a restore phase, if a set of old containers with more distinct referenced chunks are selected for the backup to perform deduplication, we are able to deduplicate more chunks and reduce the number of the chunks to be rewritten into new containers. Thus, the number of the retrieved containers is reduced while alleviating the waste of disk accesses caused by unreferenced and redundant chunks, improving the restore performance.

We formulate the problem of container selection as a *subset selection problem*.

Definition 1. (Subset Selection Problem) Given a set of old containers to be selected $V = (C_1, C_2, ..., C_{|V|})$ and the amount of selected containers T, we aim to find a container subset $S \subseteq V$, $|S| \leq T$, which can offer the largest number of distinct referenced chunks for the backup to perform deduplication under the constraints of the container amount.

Here, we set the SMR level metric as the maximum amount of selected containers T to limit the amount of old containers to be selected, which constrains the number of containers that need to be read in the restore phase to accelerate restore speed.

The number of deduplicated chunks depends on the number of distinct referenced chunks in the selected containers. Hence, the container subset with the largest number of distinct referenced chunks can deduplicate the maximum number of chunks, and new containers ideally store the minimum number of rewritten chunks, which decreases the storage consumption. Moreover, we determine which subset of containers can be selected, rather than determining whether to be selected for each container, thus preventing redundant chunks from being counted into the number of the referenced chunks.

To address the problem of container subset selection, we build a submodular maximization model [22]. We first design a scoring function $F : 2^V \rightarrow \mathbb{R}$ to indicate the amount of distinct referenced chunks in a subset. Thus the subsets offering more distinct referenced chunks are mapped to higher scores and the subsets offering less distinct referenced chunks are mapped to lower scores. The subset selection can be performed by the following computation:

$$S^* \in \underset{S \subseteq V}{\operatorname{argmax}} F(S) \quad s.t. |S| \leq T.$$

In order to describe the distinct referenced chunks in containers, the scoring function F is designed as:

$$F(S) = \left| \bigcup_{C_i \in S} w(C_i) \right|.$$

Specifically, $w(C_i)$ represents all referenced chunks in the container C_i. $\bigcup$ denotes the union of a collection of sets, indicating the set of all distinct elements in the collection. The $|\cdot|$ denotes the number of all elements in the set. Hence, F(S) denotes the number of all distinct referenced chunks that all containers $C_i \in S$ can offer.

In general, for arbitrary set functions, computing S^* is intractable [23]. Moreover, in the subset selection problem, there are $\binom{N}{M}$ possible cases of selecting M containers from N containers, which is exponentially large for any reasonable M and N [24]. Hence, it is inefficient to compute all

possible cases. However, the maximization for any monotone submodular functions under some constraints can be efficiently solved by the greedy algorithm in a constant-factor mathematical quality guarantee [25]. The scoring function F is exactly a monotone submodular function, which is proved below. Thus, we can address the subset selection problem efficiently via the greedy algorithm [22].

We first introduce the definition and property of submodular functions [26].

Definition 2. (Submodular) Given a finite set, a set function $f : 2^V \rightarrow \mathbb{R}$ that maps subset $S \subseteq V$ of a finite ground set V to real numbers, is submodular if it satisfies: for any $S \subseteq T \subseteq V$ and $a \in V \setminus S$,

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T)).$$

This states that the incremental benefit of adding an element to a smaller set is not less than that of adding an element to a larger set.

Definition 3. (Monotone) A set function $f : 2^V \rightarrow \mathbb{R}$ is monotone if for every $S \subseteq T \subseteq V$, $f(S) \leq f(T)$.

Based on the definition and property, we prove the scoring function F is a monotone submodular function. The operation $\cap$ in the formulation, e.g, $A \cap B$ denotes the intersection of two sets A and B, indicating a set that contains all elements of sets A and B.

Statement 1. The scoring function $F(S) = \left|\bigcup_{C_i \in S} w(C_i))\right|$ is submodular.

Proof 1. Given any set $S \subseteq T \subseteq V$ and element $C_a \in V \setminus S$, we have

$$F(S \cup \{C_a\}) - F(S) = |w(C_a)| - \left| w(C_a) \cap \left(\bigcup_{C_i \in S} w(C_i) \right) \right|,$$

indicating the number of chunks in container C_a but not in any containers $C_i \in S$, and

$$F(T \cup \{C_a\}) - F(T) = |w(C_a)| - \left| w(C_a) \cap \left(\bigcup_{C_i \in T} w(C_i) \right) \right|,$$

indicating the number of chunks in container C_a but not in any containers $C_i \in T$. Thus we have

$$\begin{aligned} & F(S \cup \{C_a\}) - F(S) - (F(T \cup \{C_a\}) - F(T)) \\ &= \left| w(C_a) \cap \left(\bigcup_{C_i \in T} w(C_i) \right) \right| - \left| w(C_a) \cap \left(\bigcup_{C_i \in S} w(C_i) \right) \right| \\ &= \left| w(C_a) \cap \left(\bigcup_{C_i \in (T \setminus S)} w(C_i) \right) \right| \\ &\geq 0. \end{aligned}$$

This indicates the number of chunks in C_a, which are not in any containers $C_i \in T \setminus S$. The left expression is not less than 0 in any case. Specially, when the chunk intersection of containers C_a and $C_i \in T \setminus S$ is empty, the left expression is equal to 0. Thus,

$$F(S \cup \{C_a\}) - F(S) \geq F(T \cup \{C_a\}) - F(T),$$

indicating F is submodular according to Definition 2. That means when adding the new container C_a to the smaller set S, the incremental number of distinct referenced chunks is not smaller than that of adding C_a to the larger set T.

Statement 2. The scoring function $F(S) = \left|\bigcup_{C_i \in S} w(C_i))\right|$ is monotone.

Proof 2. Given any set $S \subseteq T \subseteq V$, we have

$$\begin{aligned} F(T) - F(S) &= \left| \bigcup_{C_i \in T} w(C_i) \right| - \left| \bigcup_{C_i \in S} w(C_i) \right| \\ &= \left| \bigcup_{C_i \in T \setminus S} \left(w(C_i) - w(C_i) \cap \left(\bigcup_{C_j \in S} w(C_j) \right) \right) \right| \\ &\geq 0. \end{aligned}$$

$F(T)$ is always not smaller than $F(S)$, indicating F is monotone according to Definition 3. That means the number of distinct referenced chunks in the larger set T is not smaller than that in the smaller set S. As shown above, the scoring function F is proved to be submodular and monotone.

Algorithm 1 The Greedy Selection Algorithm

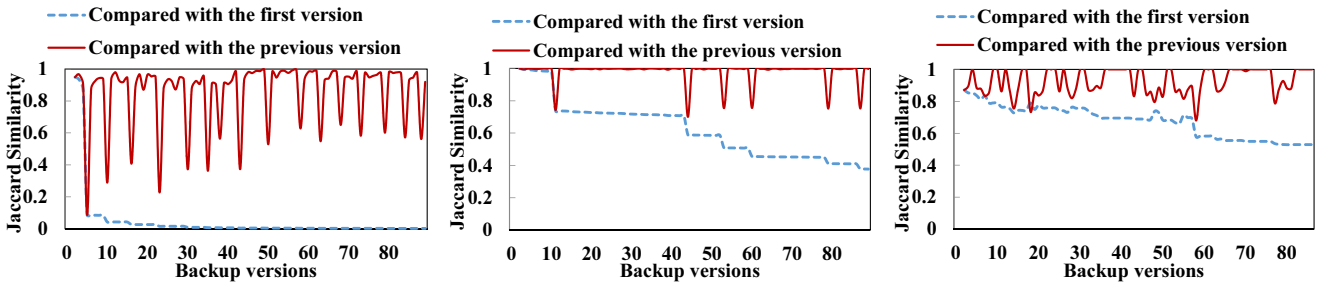
Input: A set of containers to be selected: V. Submodular monotone function: $F(\cdot)$. All chunks in each container: $w(\cdot)$. The amount of containers selected: T.
Output: A set of containers $S \subseteq V$, where $|S| \leq T$.

```
S_0 ← Ø, i ← 0
while |S_i| ≤ T do
    Choose c_i ∈ argmax_{c_i ∈ V \ S_i} (F(S_i ∪ {c_i}) − F(S_i))
    if (F(S_i ∪ {c_i}) − F(S_i) == 0) then
        Break
    end if
    S_{i+1} ← S_i ∪ {C_i}
    i ← i + 1
end while
return S_i
```

We design a greedy algorithm to select the subset of containers with the largest number of distinct referenced chunks effectively. As shown in Algorithm 1, the algorithm sequentially finds a container c_i in the remaining set $V \setminus S_i$ for each iteration. Moreover, c_i has the maximum quantity in offering the chunks which are different from chunks in S_i. Adding c_i to S_i offers more distinct referenced chunks for the segment than other containers. When adding the containers from the set $V \setminus S_i$ to S_i, if the increased number of distinct referenced chunks is not larger than 0, the iteration will stop, preventing containers without any referenced chunks from being selected and reducing disk accesses. When selecting b containers from a containers, the number of containers that the greedy algorithm needs to access is $N_{a,b}$.

$$N_{a,b} = \sum_{i=a-b+1}^{a} = (2 * a - b + 1) * b/2$$

The number of containers that traversing all possible cases needs to access is $\binom{a}{b}$, which is much larger than $N_{a,b}$. Hence, the greedy algorithm can figure out the selection problem efficiently.



(a) GCC (b) Linux (c) FSLhomes

Fig. 8. The similarity between two backup versions.

4 The Grouped Deduplication Scheme

4.1 The Observation of Differences among Backup Versions

To explore the variation of the difference degree among backup versions, we calculate the Jaccard Similarity Index [27] for backup versions of three real-world datasets, including GCC [19], Linux [20] and FSLhomes [21] (detailed in Section 5). For each version, we compare it with the first backup version and its previous version to compute the Jaccard Similarity Index. As shown in Figure 8, the similarity index between each version and its previous version is more than 0.8 except for some major version upgrades. However, the similarity between each version and the first version mainly decreases with the increasing of the version number. The similarity between two backup versions is time-sensitive according to its backup sequence. The differences may be slight between two consecutive versions, while those among versions are accumulated when the number of versions increases. As shown in Figure 1, the change regulation of the fragmentation level basically keeps pace with the Jaccard Similarity Index between each version and the first version. The accumulated differences result in the increasing number of the fragmented chunks, which hurt the restore performance. Specifically, the differences among versions allow some chunks which are referenced by older versions to become unreferenced for newer versions, and the referenced chunks to become fragmented chunks. Taking Figure 3 as an example, the chunks F, G, H, I, J are referenced by the first stream, while only chunks F and G are still referenced by the third stream. The chunks F and G, which are less than a half in the container II, become the fragmented chunks of the third backup stream. The increasing number of fragmented chunks has negative impact on restore performance. Hence, when larger differences appear, the latter version can choose not to share chunks with former versions at the cost of little deduplication ratio, which decreases fragmented chunks and significantly improves the restore performance of the newer ones.

4.2 The GSMR Design

Based on the observation, we propose a grouped deduplication scheme to further reduce the fragmented chunks. The main idea is to divide the consecutive versions into groups without intersections with each other. Each version only needs to share chunks with other versions in its group for deduplication. Hence, without sharing chunks with former backup versions, backup versions have less fragmented chunks, and the restore performance is improved. In detail, several consecutive versions are grouped as described in Algorithm 2. The amount of version in each group depends on the Jaccard Similarity Index between two consecutive versions. When backing up $Version_i$, if it is not the first version of the group $group_j$ and the Jaccard Similarity Index between it and its previous version is less than the assigned threshold T, i.e., $J_{Version_i,Version_{i-1}} < T$, $group_j$ is stopped and the system will first build a new group $group_{j+1}$ and $subindex_{j+1}$, then it puts $Version_i$ into the new $group_{j+1}$ and query $subindex_{j+1}$ to deduplicate the duplicate chunks in $Version_i$. Otherwise, the system will put $Version_i$ into $group_j$ and queries $subindex_j$ for the deduplication of $Version_i$. Hence, each group contains versions which are very similar with its previous version. For each group, the system builds a new subindex for the group for deduplication. Each version in this group identifies the redundancy of its chunks only based on the $subindex_j$ and

Algorithm 2 The Grouped Dedupliation Algorithm

Input: A set of versions to be backed up: $version_1$, ... ,$version_S$.
Versions overall amount: S.
Jaccard similarity index threshold for two consecutive versions: T.
Jaccard similarity index threshold between two consecutive versions: $J_{Version_i,Version_{i+1}}$

```
i ← 1, j ← 0, FirstVersion ← 1
while i ≤ S do
    if FirstVersion = 1 then
        j ← j + 1
        create subindex_j for group_j
        FirstVersion ← 0
    else if J_{Version_i,Version_{i-1}} < T then
        FirstVersion ← 1
        Continue
    end if
    query subindex_j to identify the redundancy of each chunks of version_i, if the chunk is duplicate, deduplicate it.
    write unique chunks of version_i into new containers
    update subindex_j
    i ← i + 1
end while
```

deduplicates duplicate chunks. Then unique chunks are stored into new containers and the $subindex_j$ is updated accordingly, which is used by the deduplication of the following backup version in this group. Each group has its own subindex for deduplication, and the versions from different groups are not sharing chunks, thus reducing the amount of fragmented chunks and improving the restore performance. We synergize SMR with the grouped deduplication scheme, i.e., GSMR, to improve the restore performance further. We only need to replace the conventional deduplication operation with SMR in Algorithm 2.

5 Performance Evaluation

5.1 Experiment Setup

We configure our experimental environment by extending a real-world open-source deduplication system, i.e., Destor [28], which has been used in multiple research schemes [9], [29], [30]. To examine the restore performance of SMR, we compare it with two state-of-the-art selective rewriting schemes that leverage containers in deduplication systems, i.e, Capping [11] and NED [12], described in Section II.

We implement our scheme in Destor [28] on the CentOS operating system running on a 4-core Intel E5620 2.40GHz system with 24GB memory and 1TB hard disk. As shown in Figure 7, the workflow of deduplication consists of several phases, such as chunking, hashing, indexing and rewriting. In the implementation of deduplication system, to fully use the sources of multi-core system, we pipeline the four phases mentioned above to speed up the deduplication process by using pthreads. Due to the lack of source code of Capping, we faithfully implement its idea and main components described in its paper [11], which is also released in our public source code.

Three real-world datasets, including GCC, Linux and FSLhomes, are used for evaluation, which have been evaluated for deduplication in the storage community [9], [31], [32], [33]. Their characteristics are listed in Table 2. Specifically, Linux [20] consists of 96 consecutive versions of unpacked Linux kernel sources from linux-4.0 to linux-4.7. Moreover, GCC [19] consists of the source code of the GNU Complier Collection. There are 89 consecutive versions from gcc-2.95 to gcc-6.1.0. The total size of the dataset is about 56GB. FSLhomes [21] dataset consists of snapshots of the home directories from students. We collect the data from several students' backups over 4 months in year 2014, which consists of 86 versions with the total size of 440GB.

TABLE 2
Workload characteristics of the three datasets used in performance evaluation.

Dataset name	GCC	Linux	FSLhomes
Total size	56GB	97GB	440GB
Amount of versions	89	96	86
Deduplication ratio	0.85	0.95	0.94
Average chunk size	6.17KB	4.97KB	8KB

In a deduplication system, each dataset is divided into variable-size chunks by using the content-based Rabin chunking algorithm [34]. The SHA-1 hash function [8] is used to generate the fingerprints of chunks. Since this paper mainly focuses on improving the restore performance rather than the fingerprint index access boosting, we simply store the complete fingerprint index in memory in these experiments. The restore cache stores the prefetched containers, in which the LRU replacement algorithm is used [11].

We use the speed factor [11] as the metric of the restore performance and the deduplication ratio and throughput to examine the deduplication efficiency. Specifically, speed factor [11] is to compute 1 divided by mean container read per MB of data restored, which is widely used to evaluate the restore performance [9], [11], [12]. Higher speed factor means that less containers are needed for the restored data per MB, thus indicating better restore performance. Moreover, deduplication ratio is the ratio of total size of the removed duplicate chunks to that of all backed up chunks. Furthermore, deduplication throughput is the amount of backed up data per second. The higher deduplication throughput indicates the faster backup speed.

5.2 The Configurations of Parameters

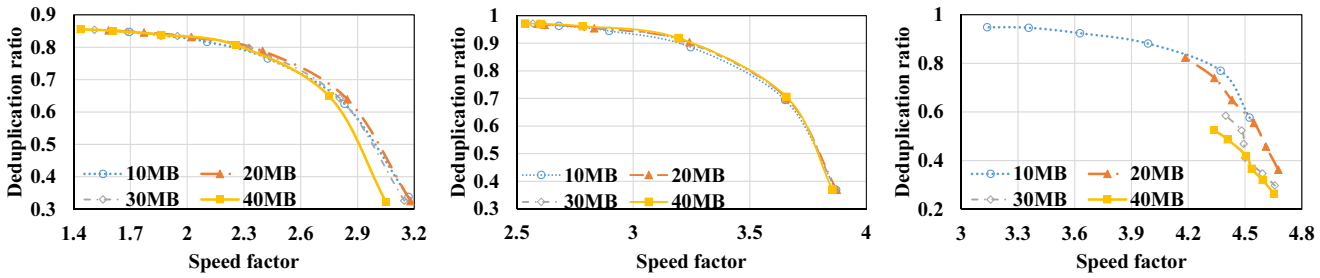
The segment size, cache size and container size are key parameters in deduplication and restore phases. We conduct many experiments to assign suitable values to these parameters, to achieve better performance of deduplication system. When exploring the possible setting of one parameter, other two parameters are set as their largest values in these experiments. For example, in the experiments the restore performance under various segment sizes, the cache size is fixed as 60 containers and the container size is 4MB.

5.2.1 The Segment Size

The chunks of a backup stream are grouped into fixed-sized segments in the backup and restore phases. The segment size sets the scale of fragment identification. Figure 9 shows the restore performance of SMR under various segment sizes. We observe that increasing the segment size makes little difference to the speed factor. Larger segment sizes fail to produce better results than smaller ones. For example, the deduplication and restore performance when the segment size is set as 20MB are better than that of the 40MB size. Hence, the segment size is set as 20MB by default, which is also the recommended setting in Capping and NED.

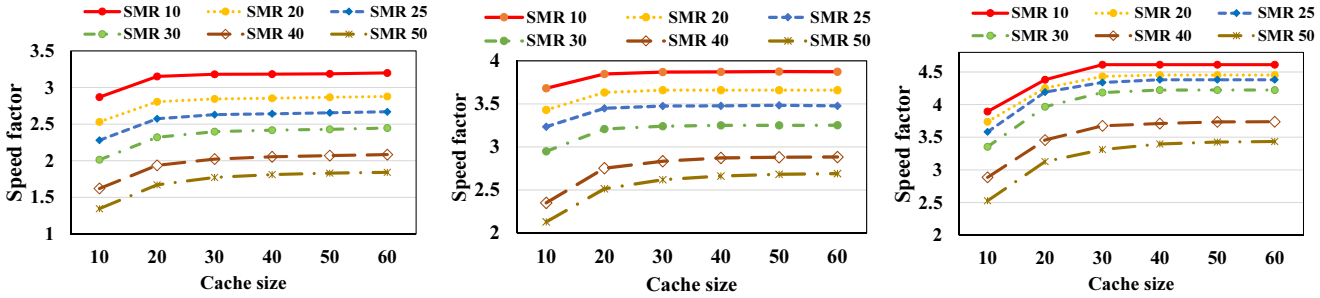
5.2.2 The Cache Size

Due to restoring the target data stream, the corresponding containers are retrieved to restore cache from disks. We consider the restore cache size for temporarily storing the containers in the restore phase. Figure 10 shows the restore performance of SMR under various cache sizes. Specifically, SMR T stands for a SMR level of T containers for each segment. For example, SMR 10 indicates that for each segment, 10 containers are selected for deduplication. We observe that if the cache size continuously increases, the restore speed is faster. The reason is that larger cache sizes allow more containers to be stored in the cache to restore chunks, reducing the time overhead of fetching containers when the cache misses occur. In addition, the increasing trend of speed factor becomes slower. We argue that for a large proportion of backup segments, about 20 containers



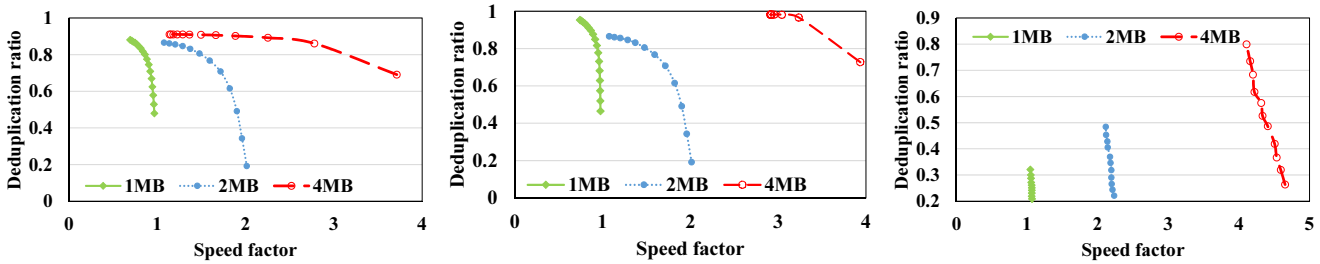
(a) GCC (b) Linux (c) FSLhomes

Fig. 9. The effect of segment sizes varies from 10MB to 40MB on deduplication and speed for selected SMR ratios (SMR level to the segment size). SMR ratios are 5/10, 10/10, 15/10, 20/10, 25/10, 30/10 containers per MB.



(a) GCC (b) Linux (c) FSLhomes

Fig. 10. The effect of various cache sizes on the restore performance. The cache size is the total size of # containers. SMR T denotes a SMR level of T containers per 20MB segment.



(a) GCC (b) Linux (c) FSLhomes

Fig. 11. The effect of various container sizes on the restore performance and speed factor. The container sizes are set to 1MB, 2MB, and 4MB respectively.

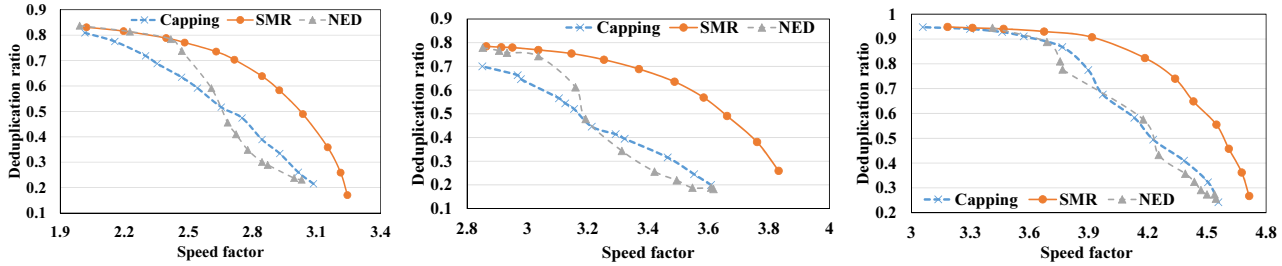
are sufficient to restore a segment. For most segments, when the cache size is over 20, all containers can be fetched into cache at once without replacement. But the speed factor still increases since the total size of containers needed by a few segments is larger than the cache size. Hence, we set the default cache size as the total size of 30 containers with LRU cache replacement scheme, which can cater to temporary store needs of most cases.

5.2.3 *The Container Size*

Figure 11 illustrates the restore speed and deduplication ratio results of SMR when the configured container sizes are set to be 1MB, 2MB, 4MB respectively. We use various SMR levels to conjecture the relationship between restore speed and deduplication ratio. Specifically, more containers can restore more chunks in one access, resulting in better restore performance under the same deduplication ratio. Hence, the default size of container is set as 4MB, which is also well-recognized in deduplication systems [2], [9], [11], [12], [28].

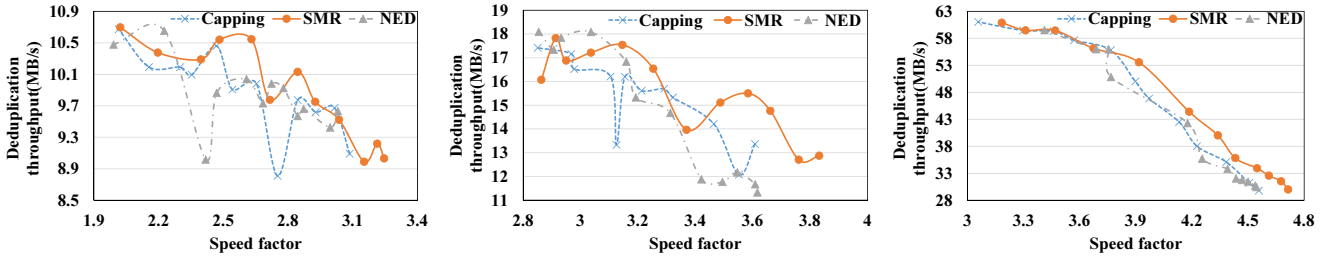
5.3 Experimental Results and Analysis

SMR aims to obtain a suitable trade-off between deduplication efficiency and restore performance. We compare our scheme with two state-of-the-art schemes, i.e., Capping and NED. The experimental settings of Capping and NED faithfully follow the recommended parameters of their publications [11], [12]. For example, the segment size is set as 20MB. We evaluate the overall speed factor, deduplication throughput and deduplication ratio under different rewrite thresholds in SMR and the two compared schemes. Specifically, for each 20MB segment, the Capping levels are 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55 and 60. The corresponding NED thresholds are 0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0 per 20MB segment. Moreover, the related SMR levels are 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55 and 60 per 20MB segment. We repeated the experiments of each rewriting level or threshold for three times, and the points in Figures 12 and 13 are the average results for each rewriting level or threshold.



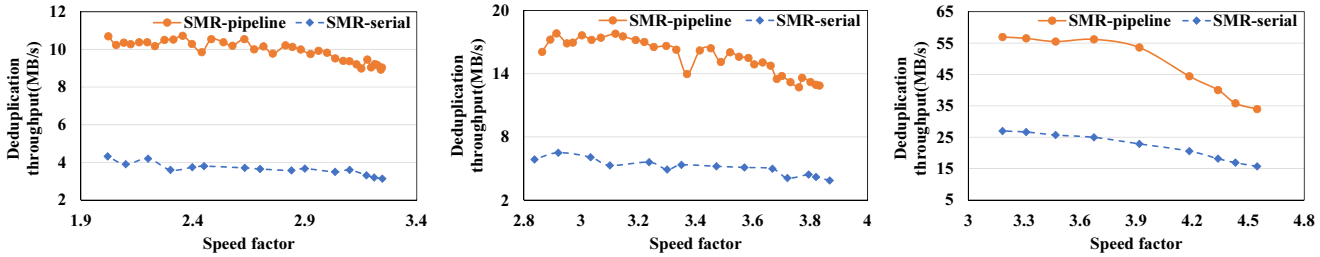
(a) GCC (b) Linux (c) FSLhomes

Fig. 12. Deduplication ratios versus speed factors for various thresholds in the Capping levels, SMR levels and NED thresholds in three datasets.



(a) GCC (b) Linux (c) FSLhomes

Fig. 13. Deduplication throughput versus speed factor as Capping levels, SMR levels and NED thresholds vary in three datasets.



(a) GCC (b) Linux (c) FSLhomes

Fig. 14. Deduplication throughput versus speed factor in serial and pipeline implemented SMR.

5.3.1 The Relationship between Deduplication Ratio and Speed Factor

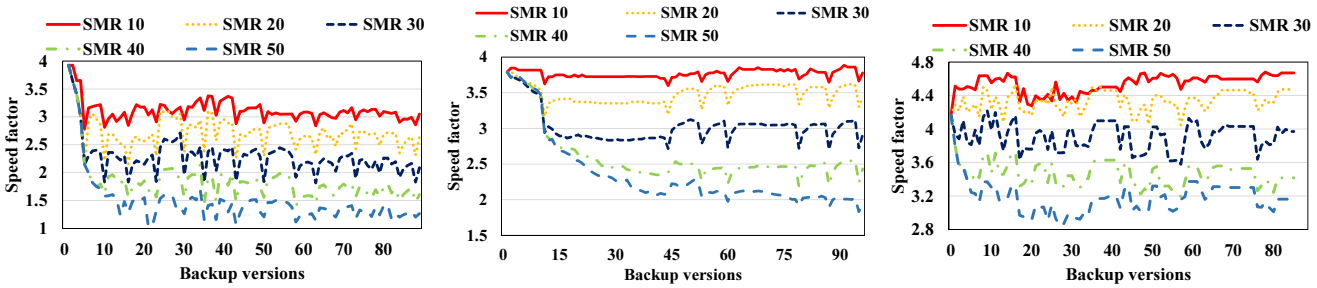
In general, higher speed factor results in lower deduplication ratio, since more duplicate fragmented chunks are rewritten. As shown in Figure 12, the speed factors of SMR are larger than those of Capping and NED in the same deduplication ratios. Similarly, the deduplication ratios of SMR are larger than those of Capping and NED in the same speed factors. SMR can deduplicate more data while gaining better restore performance. For example, Table 3 shows the detailed amount of unreferenced chunks and redundant chunks when three rewriting schemes achieve the same deduplication ratio as 0.49. SMR reduces the amount of redundant chunks by 20X and unreferenced chunks by 2X when restoring the GCC dataset, and achieves higher speed factor. Like our analysis in Section 2, our scheme improves restore performance by reducing the amount of unreferenced and redundant chunks fetched in the restore phase. Thus, more chunks are deduplicated by more distinct referenced chunks in the selected containers. Less chunks are rewritten into new containers and less containers are needed to be retrieved during the restore.

TABLE 3
The amount of unreferenced chunks and redundant chunks in the three rewriting schemes and detailed rewriting levels or thresholds. The dataset is GCC, and the deduplicatio ratio of the three rewriting schemes is 0.49.

Rewriting Scheme	Capping	SMR	NED
Speed factor	2.69714	3.03589	2.68622
Amount of unreferenced chunks	3884428	1782090	3234276
Amount of redundant chunks	4407953	194784	4632670

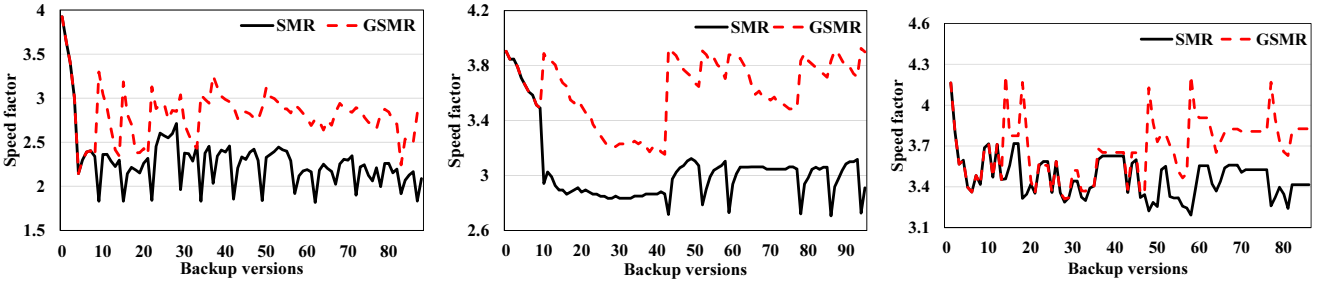
5.3.2 The Relationship between Deduplication Throughput and Speed Factor

Figure 13 presents the comparison among SMR, Capping and NED in terms of deduplication throughput and speed factor. When having the same restore performance, SMR can achieve better deduplication throughput than other approaches in most cases. The reason is when selecting b containers from a containers, Capping and NED need to sort all a containers by the number of referenced chunks in each container. SMR only needs to visit $N_{a,b} = (2 * a - b + 1) * b/2$ containers, while b is much smaller than a. The fluctuations in the curves of GCC and Linux are influenced



(a) GCC (b) Linux (c) FSLhomes

Fig. 15. The effects of various SMR levels on speed factor. SMR T denotes a SMR level of T containers per 20MB segment.



(a) GCC (b) Linux (c) FSLhomes

Fig. 16. The speed factor comparisons of GSMR and SMR. The Jaccard similarity index threshold for two consecutive versions is 0.8.

by flushing container into disks. The FSLhomes dataset is a trace, which consists of chunks metadata without real chunks data stored, and it is smoother than the other two curves.

5.3.3 The Effects of pipelined deduplication

In the multi-core system, the phases of deduplication are pipelined to backup data faster. We take the implemented SMR as an example to show the effects of pipelined deduplication workflow. The SMR is implemented in serial deduplication phases and pipelined deduplication phases. The serial deduplication phases run in a single thread sequentially. The pipelined deduplication phases use pthreads for each phase, and run as pipeline. The results are shown in Figure 14. The pipeline-based SMR improves deduplication throughput by 2.1X-3.2X compared with serial implemented SMR, which leverages the multi-core architecture to run phases in parallel.

5.4 The SMR Level Settings

In our scheme, the SMR level, defined as the number of old containers selected for deduplication, i.e., is adjustable to improve restore performance to meet the needs of different cases. Figure 15 shows the effects of various SMR-level settings on the speed factor. The smaller SMR level results in the higher speed factor. Because selecting less containers slows down the accumulation speed of data fragmentation. Less data fragmentation leads to better restore performance. Lower SMR level setting can alleviate the waste of disk accesses caused by unreferenced or redundant chunks in the retrieved containers. The SMR level is the key element to tradeoff deduplication efficiency and restore performance, and can be altered according to the demands of restore performance.

5.5 The Comparisons between SMR and GSMR

We compare the original SMR and GSMR in terms of restore performance. In the evaluation, we set the same SMR level for both schemes, and Jaccard similarity index threshold assigned for two consecutive versions is 0.8 according to the observations from Figure 8. As shown in Figure 16, the restore performance of each version in GSMR is not lower than SMR. On average, for GCC dataset, GSMR increases 26% of restore performance with only 1.5% decrease of deduplication ratio. For Linux dataset, GSMR increases 20% of restore performance and 0.2% of deduplication ratio. In FSLhomes dataset, GSMR improves restore performance by 6% with only 1% decrease of deduplication ratio. Though GSMR would hurt the deduplication ratio of the first version of each backup group, it increases the utilization of some containers and provides better selection for SMR. Hence, in some cases, both deduplication ratio and restore performance increase. GSMR hence improves restore performance without a significant decrease of deduplication ratio compared with SMR.

6 Related Work

In order to address the fragmentation problem, existing schemes mainly propose to leverage rewriting-based solutions to rewrite the duplicate fragmented chunks to mitigate the decrease of the restore performance, which is actually a trade-off between deduplication ratio and restore performance.

In the primary storage deduplication, iDedup [18] deduplicates a sequence of chunks whose physical addresses are also sequential exceeding a minimum length threshold. POD [35] identifies capacity-insensitive and performance-sensitive small duplicate writes and files to further improve

restore performance. Unlike them, SMR aims to improve restore performance in deduplication-based backup storage systems.

Nam et al. [15], [16] selectively deduplicate chunks with the proposed quantitative metric called chunk fragmentation level (CFL) for backup workloads. This scheme becomes inefficient to deduplicate chunks that are not included in the sequence like former backups. The backup and restore units in SMR are segments. Due to overlooking the order of chunks in a segment, the chunks which are not in the sequence like former backups can still be deduplicated.

Context-Based Rewriting(CBR) [36] rewrites fragmented chunks by judging the degree of the difference between stream and disk contexts. It limits the entire amount of deduplication loss to a small value, which overlooks the unbounded fragmentation and decreases restore speeds. Capping [11] selectively deduplicates chunks referring to top T containers ordered by the number of referenced chunks in containers, and rewrites the remaining duplicate chunks to improve restore speed. NED [12] selectively rewrites fragmented chunks if the reference ratio of the referred storage is lower than a threshold. In fact, CBR, Capping and NED determine the fragmented chunks in the write buffer using their fragmentation metric. CBR aims to guarantee the deduplication ratio to exceed a limit with the cost of deduplicating some fragmented chunks. SMR mainly aims to gain better restore performance. Capping and NED share the similar design goal with SMR, but they overlook the redundancy among containers. Hence, redundant chunks in different containers are all counted in the utilization for each container. But one chunk can deduplicate and restore all chunks with identical contexts, and other redundant chunk copies are unreferenced. SMR considers the redundancy among containers and eliminates redundant copies counted in the utilization for containers. As shown in Section 5.3, compared with Capping and NED, SMR achieves better restore performance and higher deduplication ratio. Moreover, HAR [9] classifies fragmentation into two categories: sparse and out-of-order containers. It exploits historical information of backup versions to identify sparse containers and rewrites chunks in sparse containers to improve data locality. In fact, HAR is orthogonal with SMR. HAR rewrites the chunks in the sparse containers which can offer less referenced chunks for multiple consecutive backups. SMR rewrites chunks in each backup phase mainly to ensure high restore performance for the current backup. Chunks which are not rewritten in HAR are further examined by SMR.

7 Conclusion

The fragmentation problem significantly decreases the restore performance in chunk-based deduplication systems. We observe that existing rewriting schemes addressing the fragmentation problem often result in significant redundancy among containers, decreasing the deduplication ratio and causing redundant chunks to be read from disks to restore the backup, which wastes limited disk bandwidth and decrease the restore performance. The main challenge to alleviate the fragmentation is how to select suitable referenced containers to perform deduplication during the backup. In order to address this problem, this paper proposes a submodular maximization rewriting scheme (SMR). SMR formulates this challenge as an optimal container selection problem, which is addressed by building a submodular maximization model. The salient feature of SMR is to reduce the number of redundant and unreferenced chunks in selected containers, alleviating the waste of disk accesses caused by unreferenced and redundant chunks to improve the restore performance. Moreover, we observe that the differences among versions are accumulated, which increase the number of fragmented chunks and decrease the restore performance. We propose a grouped deduplication scheme to synergize SMR by reducing the fragmented chunks, which further improves the restore performance. Our experimental results based on three real-world datasets demonstrate SMR outperforms the state-of-the-art work in terms of both restore performance and deduplication ratio. Moreover, compared with SMR, GSMR can achieve higher restore performance without significant decrease of deduplication ratio.

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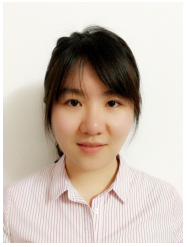

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