HANDS: A Heuristically Arranged Non-Backup In-line Deduplication System

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***Abstract*— Deduplicating in-line data on primary storage is hampered by the *disk bottleneck problem*, an issue which results from the need to keep an index mapping portions of data to hash values in memory in order to detect duplicate data without paying the performance penalty of disk paging. The index size is proportional to the volume of unique data, so placing the entire index into RAM is not cost effective with a deduplication ratio below 45%.**

HANDS reduces the amount of in-memory index storage required by up to 99% while still achieving between 30% and 90% of the deduplication a full memory-resident index provides, making primary deduplication cost effective in workloads with deduplication rates as low as 8%.

HANDS is a framework that dynamically pre-fetches fingerprints from disk into memory cache according to working sets statistically derived from access patterns. We use a simple neighborhood grouping as our statistical technique to demonstrate the effectiveness of our approach. HANDS is modular and requires only spatio-temporal data, making it suitable for a wide range of storage systems without the need to modify host file systems.

I. Introduction

Though the price of storage is falling rapidly, recent data from the IDC indicates that the rate of data growth is outpacing the rate of storage growth [1]. This divide is projected to increase in the near future, even before taking into account the effect of localized natural disasters on the global storage supply, which can price available storage above what many organizations can afford at scale [2]. Analysts believe that over half of the information we currently produce does not have a permanent home [3].

To address a growing need for primary space savings, researchers such as Constantinescu [4], Jones [5], the iDedup team [6], and the DBLK team [7] have proposed deduplicating primary storage in addition to backups and archival systems. At a high level, deduplication compares segments of data against an index to determine if the segment in question is already stored on a system. Unlike backups, primary storage is constantly accessed, so the deduplication system must check segments against the index shortly after the write request. This is known as in-line deduplication.

In-line deduplication is rarely used on primary storage because checking for duplicate blocks has a significant performance impact. Many groups have tried to reduce this impact by moving parts of the index to memory, but the cost of storing the index in memory scales with the amount of unique data in the storage system and quickly becomes economically infeasible. In a system where some of the index must remain on disk, performance is impacted by paging to and from disk: this is known as the *disk bottleneck* [8].

To illustrate the cost of memory, suppose we want to deduplicate incoming writes to a system with 100 TB of unique data and a data segment size of 4 KB, resulting in 2.7 billion segments. At an average of 32 bytes per segment hash, this would result in a massive 800 GB of memory to store the deduplication index. At $100 per terabyte of disk and $10 per gigabyte of DRAM, the $10,000 disk array would require $8,000 of dedicated memory to store the entire deduplication index. This means that if the deduplication rate for the workload is under 45%, which is more than many primary deduplication systems achieve [6], we are actually paying extra to store less data with primary deduplication. To make matters worse, many systems use a data segment size of 1 KB to get more fine-grained de-duplication, increasing the break-even point for deduplication from 45% to an effectively unattainable 76% [4].

To make deduplication on primary storage economically feasible we introduce HANDS: a scalable, in-line, chunk-based deduplication framework for primary storage. HANDS generates correlated groups of segments, or working sets, based on usage patterns and places the corresponding segment hashes, or fingerprints, adjacently in the index cache so the entire group can be accessed atomically when an element is accessed. The method we propose for working set identification relies only on historical segment I/O access data, which is easy to collect and interpret across diverse storage environments including HPC and enterprise. Though we propose a domain agnostic method for determining working sets, our technique does not rely on any particular method of generating groupings.

We tested HANDS on trace data from a large, multi-user enterprise storage system as well as a university research server and found that loading groups of data into the index

cache significantly reduces the number of accesses to the on-disk index cache while realizing most of the data reduction potential.

Our work presents two major contributions. First, we demonstrate a dynamic, scalable method to select a portion of the deduplication index to store in memory, reducing the memory cost for primary deduplication by up to 99%. Second, we provide an experimental evaluation of deduplication with different methods of in-memory index management and memory footprint size, demonstrating the generality and adaptability of our technique. We found that we can reduce the percentage of the index cache that is stored in memory to 1% while still achieving 90% of the optimal space savings for stored data. We also found that only 10% of the total data blocks read by a trace need to be pulled into the memory cache at all to achieve reasonable results.

The rest of this paper is laid out as follows. First, in Section II we discuss primary deduplication and the solutions other researchers have proposed for scalability. In Sections III and IV, we present an overview of our working set calculation methods and system design. Then, in Section V, we present our experimental results and an analysis of our methodology. We conclude with a discussion of how our work could be extended to different workloads and storage systems.

II. Background and Related Work

The goal of any deduplication method is to identify redundancy in storage and eliminate it. Much work has been done in increasing the efficiency of deduplication of data streams, such as for backups. This work generally does not apply to our problem because backup workloads have a known stream ordering and different performance constraints.

In-line data deduplication generally consists of three steps per incoming data segment:

1) Identify whether the segment is a duplicate
2) If the segment is a duplicate, create an index pointer for that write
3) If the segment is new, store the data and add its fingerprint to the deduplication index

The critical step that our work addresses is the need to access and potentially update the index without increasing the perceived I/O write time. Manipulating memory is relatively imperceptible, so we focus our efforts on moving as many of the accesses as possible from disk into memory.

Much of the data in large systems, generated data in particular, has a high duplication rate [4], [9]. Some workloads, such as virtual machines, have obvious massive duplication, and these images do not get cleaned up the way localized storage does [10]. Other workloads, such as scientific computing, have little file level duplication since results are unique, but they have a high level of chunk level deduplication from the results being similar or accretive.

Scalable primary storage has become more of a concern as the concept of "stale data" evolves. While organizations used to be able to identify older data to store on tertiary storage, many modern datasets exhibit an unpredictable long-tail access pattern, creating an archival-type workload where the write-once, read-maybe assumption no longer holds [11].

While some groups have presented solutions for backup and archival workloads, primary deduplication at the peta and exabyte level remains relatively unstudied [8], [12]. The main argument against deduplication on primary storage is the performance impact on the system caused by hash calculation and additional I/O requests [4]. Researchers such as Constantinescu [4] and Storer [13] use deduplication on primary storage in addition to backups and archival systems, but they focus on compression and security, respectively, and do not directly address the disk bottleneck problem. El-Shimi *et al.* show how naturally existing partitions in workloads can be exploited for de-deduplication in enterprise workloads [14]. Our work complements theirs since they have shown that the type of workload patterns we propose occur in a broader range of workloads. Efforts that do address the disk-bottleneck problem have typically been limited to backup systems, though Mandagere *et al.* demonstrate the type of trade-offs that are typically made to limit a deduplication index to available memory, mainly by increasing the chunk size [15]. Srinivasan *et al.* [6] propose to improve primary deduplication performance with iDedup by only duplicating chunks with high spatial locality. They also use temporal locality to restrict their in-memory cache of hashes to LRU. Essentially, they limit the blocks they de-duplicate to blocks that are hot and sequential. While this may be necessary for workloads with extremely high IOPS, we show in this work that it is possible to de-duplicate every block instead of restricting ourselves to blocks which have a high probability of duplication in certain workloads. Our technique is broadly applicable and results in better space savings than iDedup.

The Extreme Binning project tackles the data bottleneck problem by noting that file similarity can be determined by comparing the IDs of a subset of chunks, allowing similar files to be grouped together in backup workloads by subsampling larger pieces of a stream [8]. Our approach aims for the same ends with different means. First, we assume we do not know about existing chunk to file relationships when grouping our data. Our groups are purely based on chunks. This is beneficial because it allows us to proceed with less system knowledge in an environment where many accesses are not sequential. Adding groups to the file similarity metric in Extreme Binning could improve their results on primary workloads. A similar technique used by Lillibridge *et al.* addresses the disk bottleneck problem by breaking up the backup streams into very large chunks and selectively de-duplicating them against similar chunks stored in a sparse index [16]. Though their throughput is very high, they rely on the large similar blocks of data that are common in backup workloads but generally absent in multi-user primary storage.

Grouping in particular has been successfully used by some projects to improve scalability in backup systems. Both Zhu *et al.* [17] and Efstathopoulos and Guo [12] found that pulling in data by group membership had a significant impact on

the memory requirement of the index cache. However, their method of group detection, relying on the spatial locality of the data stream in a backup workload, does not carry over to the random accesses of a primary deduplication workload.

Zhu *et al.* also provide a comprehensive look at data deduplication on backup workloads, and we build on their use of Bloom filters to quickly test whether a write is a duplicate [17]. DEBAR improved the scalability and performance of deduplication for backup systems by aggregating a set of small I/Os into large sequential blocks after passing them through a preliminary filter [18]. Our work captures similar sequentiality through working set identification and thus does not need to rely on the backup stream.

Data grouping has been put forward as a means to improve the efficiency of a variety of applications [19], [20], though the grouping usually relies on domain knowledge. We use a domain agnostic grouping methodology designed for conditions when a minimal amount of trace data is available [21]. There are several extant methods for working set prediction such as C-Miner [22], which uses frequent sequence matching on block I/O data, or grouping using static, pre-labeled groups as Dorimani *et al.* does [23]. There is also a large and varied body of work on file access prediction which could be used in place of working set selection [24], [25], [26].

III. Working Set Identification

Working sets are groups of blocks that are likely to be accessed together. A good working set identification algorithm for HANDS produces groups that are small, making them less likely to churn the cache and more likely to have high predictive value. The algorithm must also avoid overfitting to the training data. Finally, any technique used for grouping has to have low overhead and produce a grouping lookup table with a small memory footprint.

Identifying working sets bears some similarity to cache prefetching algorithms. Instead of trying to predict the next access based on popularity, however, we co-locate elements on disk if they are likely to be accessed together regardless of whether the elements have a high probability of being accessed at all. The important distinction between working set identification and caching is that we are not limited in the size of what we can, essentially, "pre-pre-fetch." By grouping data regardless of how it is accessed, we hope to capture associations caused by the long tail of rare accesses that occur in observable clusters.

A. Selecting a Grouping Technique

Working sets need to reflect the changing workloads of large scale systems without constant maintenance. For example, we cannot rely on semantic qualities of the data such as project membership or filetype, since the definitions of these qualities can shift, requiring regular manual updating to keep the groupings relevant. Instead, we apply a statistical analysis to a training set to establish initial groupings and then alter these groupings based on their observed predictive capacity. Though any predictive grouping technique can be easily dropped in. To demonstrate HANDS, we extend *Neighborhood Partitioning*, a working set classification technique that looks at pairwise comparisons of accesses within a window [21]. We modified neighborhood partitioning to add likelihood values and scalability by combining the results of several overlapping windows to return a resultant grouping.

B. N-Neighborhood Partitioning

Neighborhood Partitioning (NP) is a statistical method to compare data across multiple dimensions with a definable distance metric. Though it is very efficient and has some ability to detect interleaved groupings, it does not scale well. To support arbitrarily large amounts of data, we introduce N-Neighborhood Partitioning (NNP), which merges several NP groupings without the memory overhead of a single large partitioning. By aggregating incoming accesses into regions of fixed size, NNP is highly scalable and able to perform in real time even in systems with high IOPS. The size of regions is determined by the memory capabilities of the system calculating the working sets, though increasing the size of the region quickly meets diminishing returns [21]. The regions in our implementation also overlap by a small number of accesses to account for groups that straddle the arbitrary breakpoints in our region selection. The choice of overlap is based on desired group size and is independent of the data. For each region, the partitioning steps are:

1) Collect data
2) Calculate the pairwise distance matrix
3) Calculate the neighborhood threshold and detect working sets in I/O stream
4) Combine new grouping with any prior groupings

1) Data Collection: NP requires a minimum of two dimensions of data to calculate similarity between accesses. For disk-based storage systems and block devices, this is always possible to collect without impacting system performance because of the ability to directly monitor the storage bus to get block I/O access data [27]. From block I/O traces, we can extract temporal and spatial locality data. Though we use only spatio-temporal locality to maximize the general applicability of our technique, the algorithm is trivially extendible to other dimensions such as source file, LUN, or PID; adding metadata typically leads to tighter groupings [19].

2) Calculating the Distance Matrix: NP depends on a precalculated list of distances between every pair of points, where points each represent single accesses *i.e.*, reads or writes in a block I/O trace, and are of the form $\langle time, offset \rangle$. For n accesses, we represent pairwise distance between every pair of accesses (p_i, p_j), as an $n \times n$ matrix d with $d(p_i, p_i) = 0$. We calculate the distances in this matrix using weighted Euclidean distance, defined as

$$d(p_i, p_j) = d(p_j, p_i) = \sqrt{(t_i - t_j)^2 + oscale \times (o_i - o_j)^2}$$

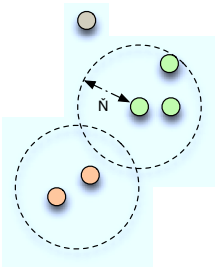


Fig. 2. Each incoming access is compared to the preceding access to determine whether it falls within the neighborhood ($\check{N}$) to be in the same group. If it does not, a new group is formed with the incoming access.

where a point $p_i = (t_i, o_i)$, $t =$ time, $o =$ offset, and $oscale$ is a scaling factor based on the typical relative distance between accesses in space versus time.

We treat the spatial component of our access as a unique identifier for the purpose of classification, which is safe as long as the classifier has a short memory [21]. We were most interested in recurring offset pairs that were accessed in short succession. As a result, we also calculated an $m \times m$ matrix, where m is the number of unique block offsets in our data set. This matrix was calculated by identifying all the differences in timestamps $T = [T_1 = t_{i1} - t_{j1}, T_2 = t_{i1} - t_{j2}, T_3 = t_{i2} - t_{j1}, \ldots]$ between the two offsets o_i and o_j. Weighting timestamps led to overfitting, so we decided to treat the unweighted average of these timestamp distances as the time element in our distance calculation. Thus, the distance between two offsets is:

$$d(o_i, o_j) = \sqrt{\left(\frac{\sum_{i=1}^{|T|} T_i}{|T|}\right)^2 + oscale \times (o_i - o_j)^2}$$

3) Identifying Working Sets: Once the distance matrix is calculated, we calculate a value for the neighborhood threshold, $\check{N}$. In the online case, $\check{N}$ must be selected *a priori* and then re-calculated once enough data has entered the system to smooth out any cyclic spikes. In the absence of extended trace data, we found the recalculating working sets once per day was sufficient. In Section VI we discuss more empirical techniques for determining when to re-calculate groupings. Once the threshold is calculated, the algorithm looks at every access in turn. The first access starts as a member of group g_1. If the next access occurs within $\check{N}$, the next access is placed into group g_1, otherwise, it is placed into a new group g_2, and so on. Figure 2 illustrates a simple case.

4) Combining Neighborhood Partitions: A grouping G_i is a set of groups $g_1, \ldots, g_l$ that were calculated from the i^{th} region of accesses. Unlike NP, NNP is not entirely memoryless; NNP combines groupings from newer data to form an aggregate grouping.

We do this through fuzzy set intersection between groupings and symmetric difference between groups within the groupings. So, for groupings
$G_1, G_2, \ldots G_k$, the total grouping G is :

$$G = (G_i \cap G_j) \cup (G_i \Delta_g G_j) \quad \forall i, j \quad 1 \leq i, j \leq k$$

where the groupwise symmetric difference, Δ_g, is defined as every group that is not in $G_i \cap G_j$ and also shares no members with a group in $G_i \cap G_j$. For example, for two group lists $G_1 = [(x_1, x_4, x_7), (x_1, x_5), (x_8, x_7)]$ and $G_2 = [(x_1, x_3, x_7), (x_1, x_5), (x_2, x_9)]$, the resulting grouping would be $G_1 \cap G_2 = (x_1, x_5) \cup G_1 \, \Delta_g \, G_2 = (x_2, x_9)$, yielding a grouping of $[(x_1, x_5), (x_2, x_9)]$. (x_1, x_4, x_7), (x_1, x_3, x_7), and (x_8, x_7) were excluded because they share some members but not all. We choose this aggregation technique because it has a natural bias against larger groups; this in turn limits the amount of churn in our cache. This group calculation happens in the background during periods of low activity.

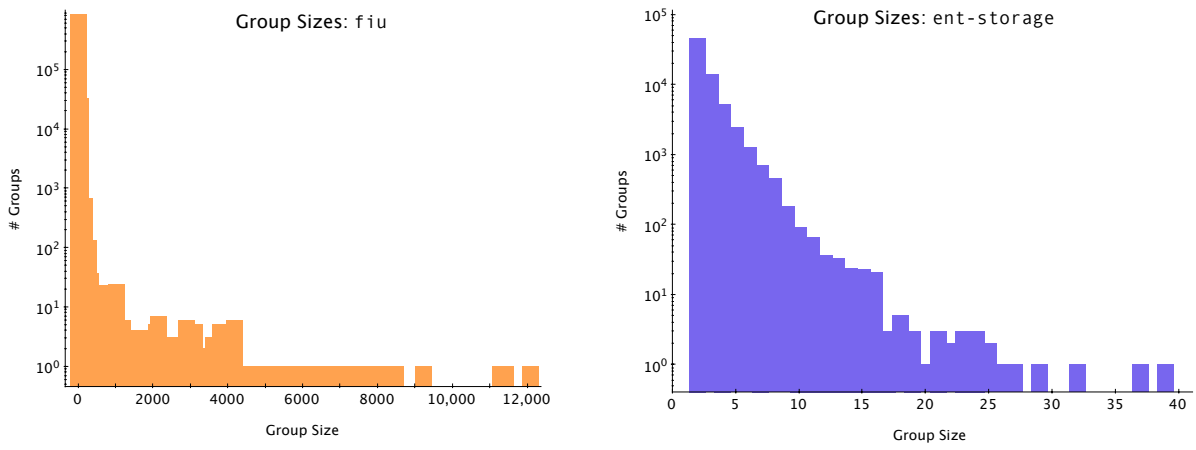
As accesses come in, we need to update groups to reflect a changing reality. We do this by storing a likelihood value for every group. This numerical value starts as the median intergroup distance value and is incremented when the grouping is pulled into cache and successfully predicts a future access. If a requested fingerprint appears in multiple groups, only the group with the highest likelihood is returned. This serves to further augment the bias towards small groupings, which we have found to have a higher average likelihood. This is expected because with fewer group members, there is less chance of a group member being only loosely correlated with the remainder of the group, bringing the entire group likelihood down.

Figure 1 shows that the working set distributions of both of our workloads were heavily biased towards small working sets. Additionally, when calculating likelihood values over working sets, small sets had higher average likelihood. We leverage this distribution property to reduce working set lookup times by arranging our working set data structure as a tiered hashtable (Figure 5). The upper tier maps working set sizes to a group of working sets while the second tier maps fingerprints to the appropriate working set.

NNP is especially well suited to rapidly changing usage patterns because individual regions do not share information until the group combination stage. When an offset occurs again in the trace, it is evaluated again, with no memory of the previous occurrence. Combining the regions into a single grouping helps mitigate the disadvantage of losing the information of repeated correlations between accesses without additional bias. The groups that result from NNP are by design myopic and will ignore long-term trend data, reducing the impact of fingerprints being updated over time.

C. Runtime

Neighborhood partitioning runs in $O(n)$ since it only needs to pass through each neighborhood twice: once to calculate the neighborhood threshold and again to collect the working sets. This makes it an attractive grouping mechanism for workloads with high IOPS (for example, the enterprise system we worked with can support 200,000 IOPS, though we saw far fewer in our trace), where a full $O(n^2)$ comparison is prohibitive. Additionally, we can capture groups in real time and quickly take advantage of correlations. We also can easily influence the average group size by weighting the threshold value. A main concern for us was cache churn, so we heavily biased our grouping parameters towards smaller groups. While larger



(a) `fiu` (b) `ent-storage`

Fig. 1. Group size distributions for neighborhood partitioned data sets. Both data sets have a median group size of about 3; the y axis is on a log scale.

groups improve prediction immediately after groupings are calculated, over time larger groups need more re-calculation to prevent false negatives as the workload shifts. This negates their short term predictive benefit.

D. Validity

96% of group elements shared a process ID with an arbitrarily selected "first" group element in the groupings for the research(`fiu`) dataset. We refer to this number as the *group purity* of this grouping. The high group purity of `fiu` indicates that NNP can catch interleaved groups, which prior work supports [21]. On small subsets of this data, the result is closer to 80%, likely because the groupings do not have enough occurrences to obtain high likelihood. For the enterprise data set we used (`ent-storage`), the equivalent metric showed a group purity of 100%, though the groups were generally so small that this reflects group size more than the strength of the grouping algorithm.

IV. Design

HANDS is a framework for content addressed in-line deduplication that incorporate working sets to manage the memory footprint of the fingerprint cache. These algorithms can be interchanged modularly so, for example, another grouping technique could easily be substituted to tune HANDS for a particular environment. Our high-level framework consists of three elements: the *fingerprint index* mapping fingerprints to chunks, the *index cache*, which is a subset of the fingerprint index that is kept in memory, and the *working set table* that maps fingerprints to working sets of fingerprints.

A. Initialization

The first step towards deduplication is creating the working set table. Our method for compiling this table is covered in Section III, but any grouping mechanism that results in groups that are small and predictive can be substituted. The next step is to allocate the fingerprint index and the index cache. The index cache is fixed size, allocated in memory, and starts out empty. We explored bootstrapping the index cache with the most frequently accessed or highest likelihood working sets from training data, but found that neither improved our results. The working sets are then written serially into the on-disk fingerprint index such that entire working sets can be retrieved without seeking. Since fingerprints can be members of several groups, this could lead to duplication within the on-disk fingerprint index. We accept this because the small amount of extra index cache required is inexpensive compared to the memory savings.

B. Deduplication

Once the indices are established, we can begin deduplicating incoming I/O requests. We expected most of our benefit to come from having the fingerprints for incoming write requests in cache instead of the main fingerprint index on disk. While there is some conceivable benefit to also calculating fingerprints for chunks read, that benefit is highly dependent on the underlying data retrieval mechanisms, and thus we limit the scope of this paper to write requests. We also assume that all the accesses we get are post disk cache.

Figure 4 outlines the interactions of the components of our deduplication system. Our first step on receiving a write request is to calculate a hash value for the write. Any fast, low-collision hash method works equally well; we recommend SHA-1, which for an exabyte scale system has under a 1 in 10 billion chance of hash collision in non-adversarial situations while still having a fast runtime [10], [28].

1) Duplicate Data: After the hash is computed, we compare the hash to the fingerprints in the index cache. If the hash is found in the index cache, the request is identified as a duplicate and the index cache is updated according to the caching algorithm in use. We refer to this as a *cache hit*.

In the case of a *cache miss*, the request is sent to the on-disk fingerprint cache, which is arranged in tiers as shown in Figure 5. There is a Bloom filter across the entire index to quickly detect new data. Each tier represents groups of a given size, and they are searched from smallest to largest

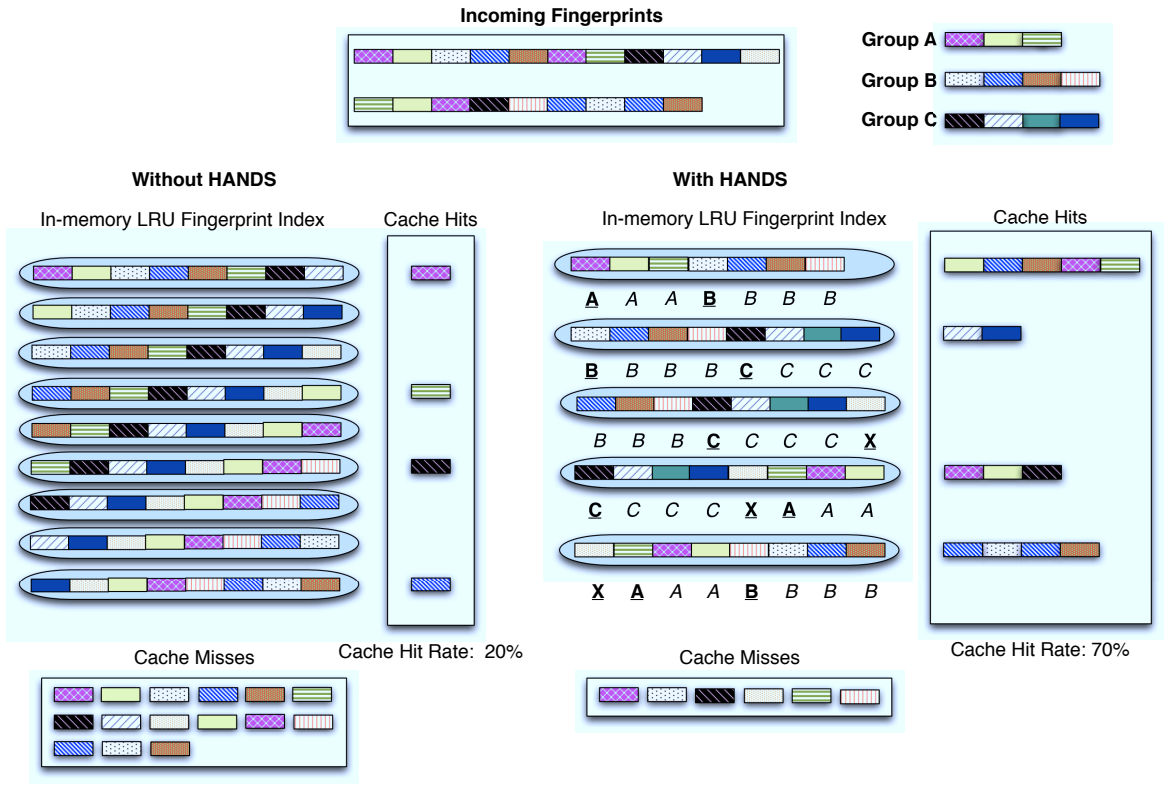


Fig. 3. Illustration of HANDS on a toy example. The patterned rectangles correspond to fingerprints. We see that adding three working sets, or groups, improves the cache hit rate significantly by pre-fetching fingerprints into memory. In the diagram, the letters underneath the fingerprints correspond to group membership where the bolded letter is a group member that required a disk seek (a cache miss) and the italicized letters are group members that were pulled in with a bolded member.

until a group is found. The bias towards small groups here is intentional and designed to limit cache churn.

If the fingerprint is found in the fingerprint index, in addition to serving the content the system also queries the working set table to see if the fingerprint has any known working sets. We accept the first working set match for a hash where the likelihood value is above the mean likelihood minus one standard deviation. Smaller working sets are more likely to have high likelihood, so our tiered working set index (Figure 5) reduces the search time in very large on-disk indices. The working set returned by the working set cache is then copied into the index cache; overflow cache contents are removed based on the caching algorithm replacement policy. While this results in some CPU overhead, we accept this because it is negligible compared to the penalty for the I/O.

2) New Data: If a fingerprint is not in the fingerprint index, the data is written and the hash is stored to the fingerprint index. New writes are not members of any working sets, so they can safely be placed in a temporary area without being accidently pulled into memory as a working set member. When working sets are next computed, the fingerprints will be added to working sets as appropriate. Fingerprints on disk are co-located based on group membership. Since fingerprints can be members of several groups, this could lead to duplication within the on-disk fingerprint index. We accept this because the small amount of extra index cache required is inexpensive compared to the memory savings.

C. Design Considerations

Figure 3 shows how HANDS noticeably improves the cache hit rate. The rectangles represent fingerprints, uniquely identified by color and pattern. There are three groups, identified by the letters underneath the fingerprints. An LRU cache without HANDS (left) catches most quickly repeated fingerprints and must go to disk for everything else. With HANDS (right), the cache predicts future fingerprint accesses and thus achieves considerably better cache hit rate. There is a concern that large working sets could fill the cache quickly, causing a high amount of cache churn that would push out relevant data. With the working set calculation methodology we propose, however, the likelihood of a working set tends to decrease with every additional member. This inherent bias towards smaller working sets led to less cache churn in our experimental results.

Fingerprints and blocks do not share a fixed mapping. In fact, for one of our workloads we found that over 78% of the time, consecutive accesses of the same block had different fingerprints. Thus, we group using block address but need data with actual fingerprints in order to estimate index cache performance. We found experimentally that groups tend to stay the same over time even as the fingerprints associated with blocks change [21]. Therefore, we hypothesize that our block

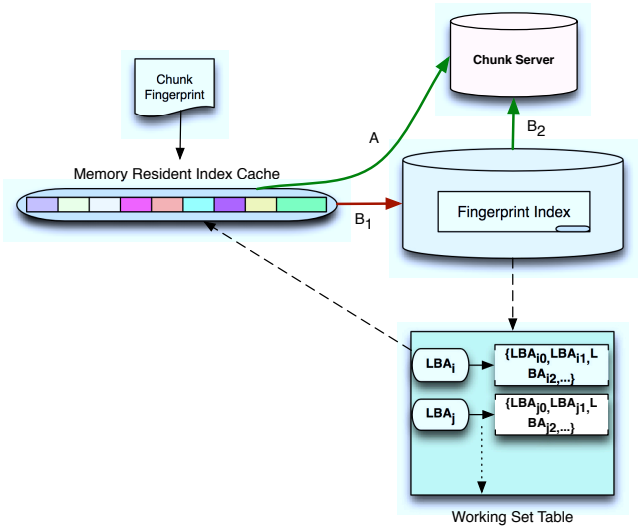


Fig. 4. Deduplication framework. A duplicate chunk is either in the index cache (path A) or must be recovered from disk (path B). When a fingerprint enters path B, the working set for that fingerprint is pulled into the index cache from the fingerprint index, which is laid out in working set order.

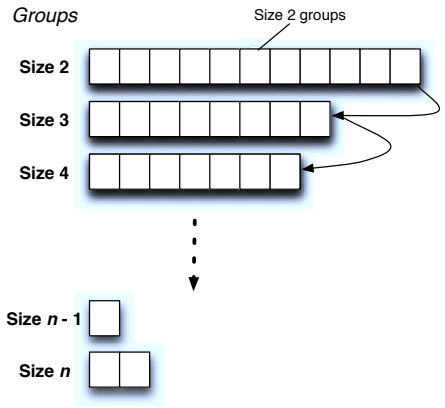


Fig. 5. The fingerprint index is tiered so groups of size $n-1$ are searched before groups of size n

addresses are generally "unique under mutation," meaning that the usage of the data stays similar even as the actual data is modified. We discuss this shift more in Section V-C.

V. Experiments

To test the HANDS design, we simulated a deduplication environment where a portion of the fingerprint index is stored in memory both with and without the addition of working sets. We pass real traces with fingerprint hashes through the simulator to determine the efficacy of the working set based cache.

We measured the effect of working set grouping using three cache replacement algorithms: LRU, naïve LFU (LFU), and working set aware LFU (LFU-ws). Our implementation of LRU is straightforward; the oldest elements are dropped successively until there is enough room for the new element. Elements of the same age (*e.g.*, members of a working set that were pulled in together) are dropped in the order in which they appear on disk, which is preserved in the cache. Naïve LFU is an approximation of LFU that drops the least frequently used elements in the cache and is unaware of out-of-band relationships between data once the data is in the index cache. As a result, after a cache hit only the accessed element has its frequency value updated. When the LFU-ws algorithm records a hit to the index cache, the access frequency for every member of the working set associated with the accessed fingerprint and currently in cache is updated by .5, while the frequency of the accessed fingerprint is updated by 1 as usual. This biases the algorithm towards keeping working sets together in cache and quickly throwing out "singleton" accesses that have no working set and are not rapidly accessed.

A. Data

We tested our design using data sets from two real systems. Our first dataset was collected from an enterprise grade storage server at a major technology company. This storage server has 120 TB of disk along with a 60 GB cache. The traces from this server are labeled `ent-storage`. Sequential accesses are handled by the storage server, so we do not see these in the trace. Our second trace, `fiu`, is from Florida International University and traces local researchers' storage [29]. For both of these traces, we used timestamp and logical block address (LBA) to create working sets. We provide statistics about these two data sets in Table I. For our purposes, the most important difference between these two data sets was average IOPS, meaning that over time it was harder to get predictive groups for `ent-storage` than `fiu`.

B. Results

We present graphs as percent of *ideal cache* versus percent of total fingerprint size. We measure ideal cache as the best a cache could do if it could always recall an element it has seen before, *i.e.*, if the entire fingerprint index were in memory. Total fingerprint size is the sum of all of the unique fingerprints over an entire trace. We realize that this may underestimate the data size a real system needs to handle: all of our data is accessed, which is not true in many systems. However, this is the best representation that was available to us and is useful for our work because we are primarily interested in predicting accesses to elements we have seen before.

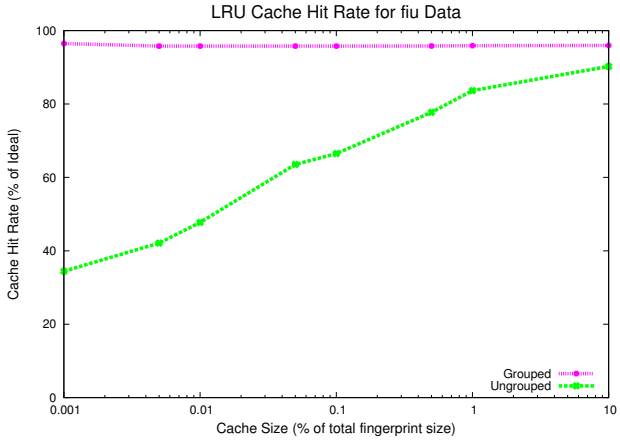
1) LRU: LRU was the best cache replacement strategy for the index cache with working sets. Figure 6(a) shows that the cache hit rate for the `fiu` dataset was almost ideal even with an index cache that was only .01% of the total fingerprint size. In contrast, without working sets `fiu` had an unsurprisingly steady increase in index cache hits as the cache size increased. Adding working sets to LRU in the `fiu` case worked so well because `fiu` almost entirely represents accesses by real people and so has a very high degree of temporal locality. The `fiu` workload also has far lower IOPS, which helps groups remain stable over time.

In the `ent-storage` dataset (Fig. 6(b)), we see a more modest but still clear improvement in cache hit rate for every cache size except about .05% after adding working sets. At

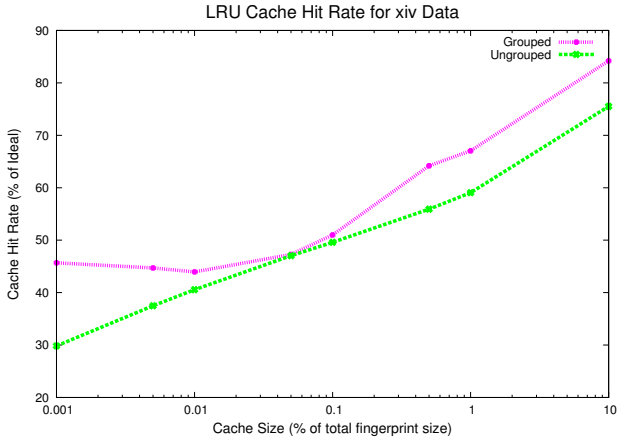
TABLE I

WORKLOAD STATISTICS. WRITES ARE REMOVED FROM ENT-STORAGE TRACE

Trace	avg IOPS	max IOPS	R/W Ratio	# of Accesses	# Unique LBAs	# Groups	Time (h)
`fiu`	37	11897	96/4	17836701	1684407	2062671	503
`ent-storage`	75997	342142	100*	2161328	968620	70759	36

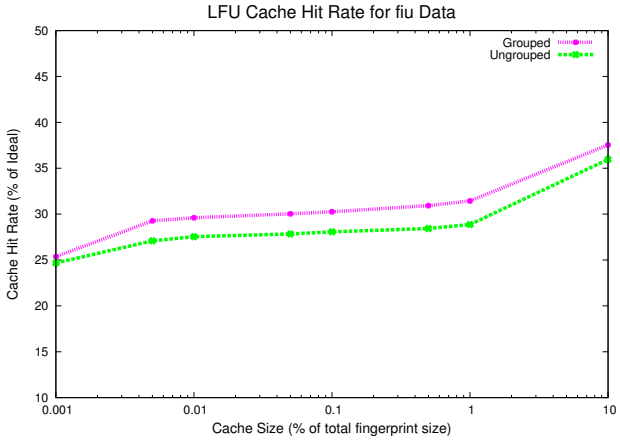


(a) `fiu`: The ideal cache hit rate was 33.94%

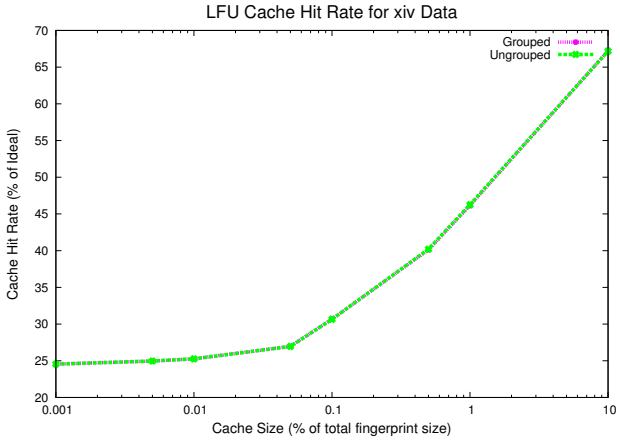


(b) `ent-storage`: The ideal cache hit rate was 35.59%

Fig. 6. LRU Cache hits across cache sizes. Grouped data does consistently at least as well and often significantly better than ungrouped data.



(a) `fiu`: The ideal cache hit rate was 33.94%

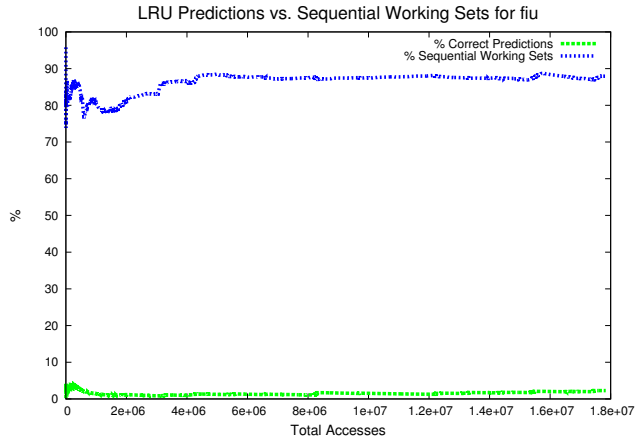


(b) `ent-storage`: The ideal cache hit rate was 35.59%

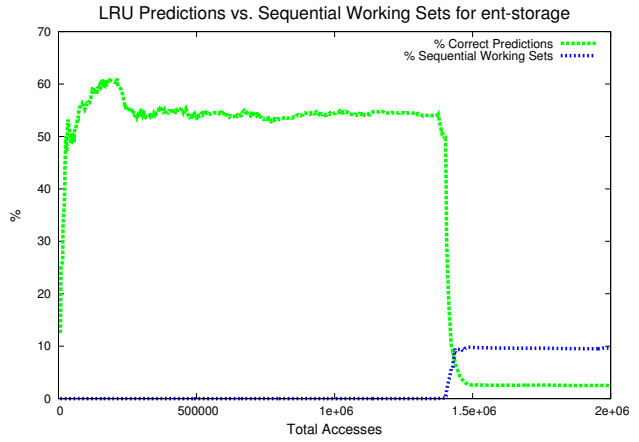
Fig. 7. LFU Cache hits across cache sizes. The `ent-storage` dataset sees no benefit from grouped data while the `fiu` dataset sees a modest benefit from grouping.

.05%, we see the beginnings of cache churn: the phenomenon where the cache is too small to hold all of the elements that are being accessed and so is passing elements in and out. This is due to a large group being pulled into cache and being quickly ejected. Smaller caches reject the group entirely and thus remain unaffected. We can reduce this churn in the future by modifying the LRU to remove entire working sets at a time instead of just elements. We also note that the working set line never dips below the base LRU line, implying that the cache churn is not severe enough to impact performance.

2) LFU: Figure 7 shows that for both the `fiu` and `ent-storage` datasets, there is a substantially smaller improvement in cache hit rate when grouping is added to the LFU caching algorithm as compared to LRU. This is surprising at first glance, but it is logical when the effect that the cache replacement policies have on working sets are taken into account. The benefit of working sets for access prediction comes from a heightened probability of co-access within a working set in a given period of time. LFU evicts working set members almost as soon as they are pulled in, since they are often not used immediately. Indeed, if they were used immediately, they would be trivially easy to find and much less interesting. We attribute the slight success of LFU on the `fiu` dataset to the presence of a large number of sequential working sets. Sequential accesses were automatically filtered out of the `ent-storage` trace before it was given to us, so LFU underperforms. Note that even without sequential accesses the grouped line never falls below the ungrouped line, indicating



(a) `fiu` data set using .01% cache



(b) `ent-storage` data set using .01% cache

Fig. 8. For the `fiu` data set using LRU, predictive power of groups was unrelated to sequentiality. In the `ent-storage` data set using LRU, predictive power of groups fell as sequential groups increased. The percentage of predictive accesses is deceivingly low because it is calculated as a percentage of total accesses, which were an order of magnitude higher for `fiu` than `ent-storage`. The cache size was .01%

that the working sets are not pushing enough other predictive elements out of cache to impact the base performance.

We also ran our simulations with LFU-ws, but saw essentially identical results compared to LFU, and thus do not include those in this paper. The results were likely identical because the bias provided by LFU-ws is not enough to offset the huge disadvantage of having working sets pushed out of cache quickly. We believe it is worth investigating whether there is a balance, but we reserve that for future work.

3) Random Working Sets: We also implemented a random working set generator to compare HANDS against. Our goal was to identify any unforeseen externalities in pulling large chunks of data into the index cache created in our deduplication system. To best mirror our observed working set distributions, we wrote a random generator sampling from a discretized Pareto distribution. The Pareto distribution is sampled from uniform using the formula:

$$X = \frac{x^m}{U^{1/\alpha}}$$

Here, x^m is a parameter indicating the minimum value of X, which for groups is 1, U represents the uniform distribution between $[0, 1]$, and α is a shaping parameter. We set $\alpha = 3$ to replicate our small-group bias. The resulting continuous value is then rounded to obtain an integer group size. This distribution skews towards small values with few outliers and thus is a good fit for our small working sets (Fig. 1).

When we ran this, however, we found that the results were identical to the ungrouped results. We attribute this to the large search space of LBAs combined with the small size of groups resulting in an exceptionally low probability of successful access. Indeed, the `ent-storage` case had 0 predictive fingerprints while the `fiu` random run had under 5%. Thus, we can say with some confidence that the benefit of working sets is more than just pulling extra data into cache; the pre-computed correlation of data in working sets has value.

C. Analysis

Throughout this project, our technique performed as well as or better on the `fiu` dataset compared to the `ent-storage` dataset. We learned that, in the `ent-storage` dataset, sequential accesses are not part of the trace we were given because they are pre-fetched by the storage hardware. Since previous work has shown that sequential working sets are common and strong groupings, we thought that the lack of sequentiality in the `ent-storage` dataset was to blame for its relatively poor showing in both the LRU and LFU cases. However, in Figure 8(b) we see an inverse relationship in the `ent-storage` dataset for the LRU case; there is a strong correlation between groups becoming sequential and groups becoming less predictive. In the parallel figure for the `fiu` dataset (Fig. 8(a)), we see no relationship between the sequentiality and the percentage of predictive accesses. Instead, the difference in the two datasets in the LRU case is likely a consequence of the average IOPS of `ent-storage` being high enough to make groups more transient.

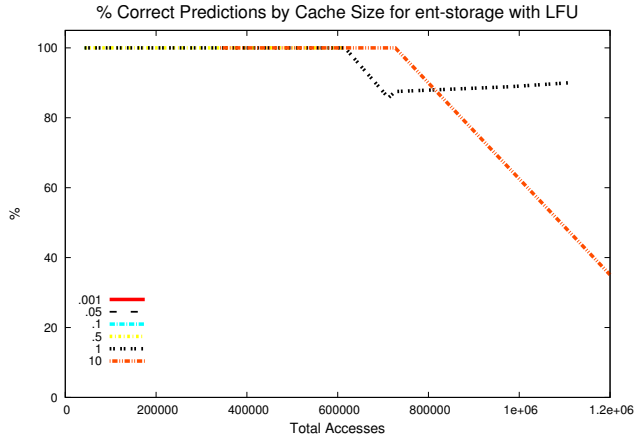
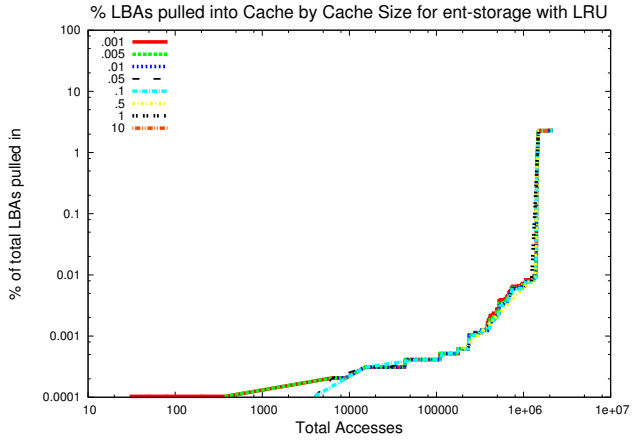
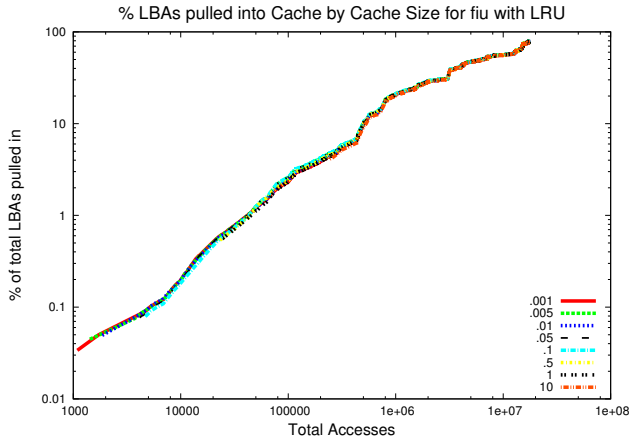


Fig. 9. % of correct predictions by cache size, compared against the total fingerprints pulled into cache and not immediately replaced. We see that the few fingerprints that were pulled in were predictive at small cache sizes, while extra elements were pulled into a larger cache. Cache sizes below 1% had fewer predictions and are thus hidden by the overlap in the graph.

We also verified our theory that the LFU `ent-storage` case suffered from cache churn by tracking correct predictions over time based on cache size. In Figure 9, we see that the few accesses that have a chance to be predictive are correct for small cache sizes before taking a precipitous drop as the cache size grows. This indicates two things: first, that working sets are being evicted early on, leading to an inflated rate of correct predictions, and second, that as the cache grows there are enough legitimate fingerprints being removed from cache that even an improvement in longevity of working set members is not enough to salvage the algorithm. LFU is simply a poor choice for a deduplication index cache with working sets.



(a) % LBAs pulled in for `ent-storage`; there are 968620 unique LBAs



(b) % LBAs pulled in for `fiu`; there are 1684407 unique LBAs

Fig. 10. Each line corresponds to a run with the given cache size. Adding working sets to `ent-storage` with LRU achieves an increased cache hit rate while only pulling in $< 3\%$ of the total LBAs. Conversely, `fiu` with LRU pulls in up to 80%.

Figure 10(a) shows that smaller cache sizes pull in more LBAs early on, but over time the total number of LBAs pulled converges. Even though the average increase in cache hit rate for adding working sets to `ent-storage` for LRU was only about 10%, we accomplish this by only pulling in 3% of the total LBAs. For the `fiu` case, we see that at about one million accesses, where the `ent-storage` trace ends, about 15% of the total LBAs are pulled in regardless of cache size. In contrast to `ent-storage`, by the end of the trace almost 80% of the total dataset LBAs had been pulled in. This high percentage of LBAs in cache is almost certainly why the cache performed so well for the `fiu` with LRU case.

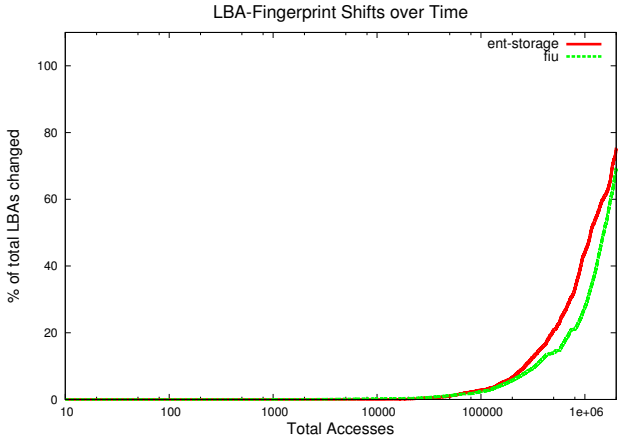
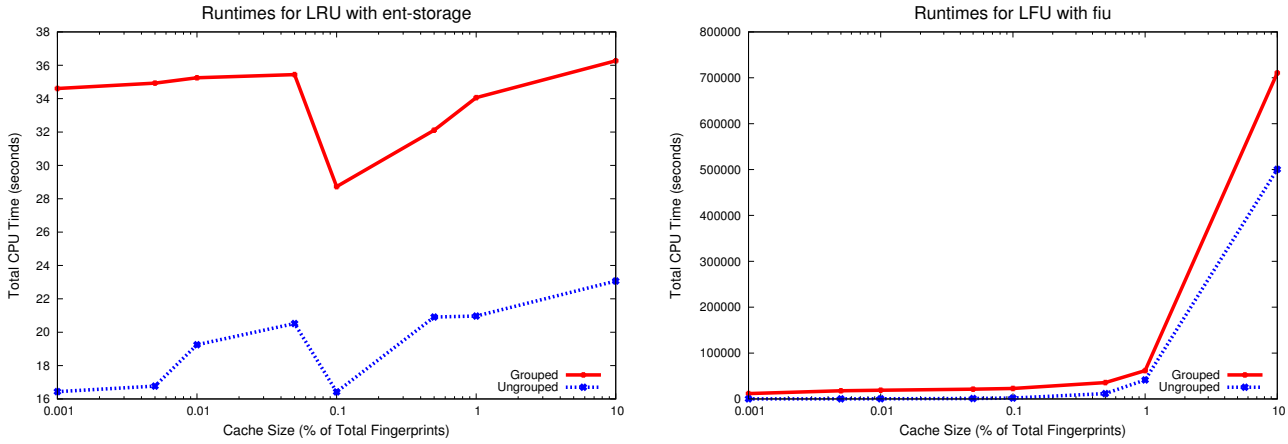


Fig. 11. LBA-fingerprint correlation shifts over time. Though the data sets have very different characteristics, both show a sharp rise in shifts after about 500,000 accesses.

One concern with this method is that the working sets are made without the content data in mind. As we see in Figure 11, the fingerprint-LBA pairing is transient. If this pairing falls away before working sets are re-calculated, the quality of predictions could decline. In this case, however, there were significantly more write accesses than read accesses, and so we have good reason to believe that the different fingerprints on consecutive LBAs thus represent different content with the same access characteristics. In a subset of `fiu` with a slightly higher read ratio of 9.5%, the maximum percent of LBAs changed drop from 78% to 58.5%. Even with our high read ratio, we see that for both the `fiu` and `ent-storage` datasets the correlations between LBAs and fingerprints remain fairly consistent until the system sees about 500,000 accesses. We are interested in acquiring more datasets with fingerprints to determine how this compares to other types of workloads.

Determining when to recalculate the groupings will be essential to future real-time systems. Though we did not recalculate groupings often during the course of our runs because we had relatively little data, we looked for insights to determine when to recalculate our groupings. Figures 8(b) and 8(a) show that the predictive power of our groupings is strongest early on. A real system could have an automatic alert system to track the level of predictive power and re-calculate groups in the background as needed. Alternatively, working groups could be calculated even more frequently to correspond with the need to go to disk to fetch recent LBA-fingerprint pairs. As we see in Figure 11, the LBAs and fingerprints shift at about 500,000 accesses in both traces, though the `fiu` trace stops shifting for a time after. More frequent group calculation is likely to slightly improve cache hit rate numbers as the groups will more closely match the current working environment. However, since groups are based on a somewhat



(a) Times for LRU with `ent-storage`

(b) Times for LFU with `fiu`

Fig. 12. A comparison of runtime vs. cache size for our algorithms. This was run in a prototyping environment; for translation to a real system the key is that the grouped performance closely tracks the ungrouped performance with a fixed overhead.

longer term system view, re-calculation should not provide a large bonus in the absence of a major usage shift.

D. Overhead

While keeping the working set table up to date results in some CPU overhead, we accept this because group calculation will never cause I/O blocking. We also used NNP, an $O(n)$ grouping algorithm that runs in our simulator in under ten minutes. Our implementation was done on a personal desktop using Python for both group calculation and cache simulation. Figure 12 shows the overhead for LRU for `ent-storage` and LFU for `fiu`. These graphs are representative of all of the experiments we did, and show that while the grouped version takes about twice as long, the grouped and ungrouped lines closely track each other. This indicates that overhead is mostly fixed and can be predicted. Though we used the PyPy high-speed Python implementation [30], our code is designed for prototyping. As a result, the runtime numbers we have should only be considered relative to each other.

Finally, it is likely that the systems' own cache policies will also place the data from the active working set into system cache, but that is outside the scope of this paper.

VI. Discussion and Future Work

It is important to note that, contrary to our expectations, adding working sets to the index cache never reduced the cache hit rate. This indicates that there is room for larger working sets to be pulled in before cache churn starts becoming a serious problem. Thus, a workload specific implementation with domain informed grouping will have a greater improvement in cache hits. For example, a system with extra computational power could update working sets continually, resulting in more large working sets and corresponding cache hits. Also, though LFU was ineffective, a variant that is partially working set aware might prove effective for more archival workloads.

We create working sets based on minimal features, namely location and timestamp. We used these to show our method was valuable even in cases where it is not practical to extract rich system traces. Additional features such as request origin or client type could make the working sets more reflective of real workload phenomena. Any method for working set prediction or even file level access prediction can be substituted into our system with little modification, making HANDS a general purpose tool to improve primary deduplication.

Though we showed significant improvement in research and enterprise deduplication, there are particular workloads where we believe HANDS will shine. For example, a collection of virtual machine images would have both higher deduplication ratios and tighter working sets, since they correspond closely to individual systems. Workloads from businesses that operate based on strict timing rules such as banks and trading houses should show a cyclic usage pattern that would be amenable to our deduplication method. In addition to large scale data, our technique could be applied to object stores where any reduction in media cost is amplified because of the relative expense of storage class memory technologies. Our method could also be used to cost-effectively address the growing problem of archival-like storage that does not obey "write-once, read maybe" semantics and instead has transient periods of primary activity. Storing exabytes of data and maintaining a usable primary deduplication index is prohibitive, but storing .1% of the index size in memory should be much more manageable and cost effective for long term storage such as Internet archives and media.

We are seeking new data sets to test our algorithm on, particularly datasets with a high degree of inherent duplication. We then intend to attempt a characterization of workloads based on the most salient features for working set analysis and examine the possibility of automatically tuning working set algorithms based on the workload type.

VII. Conclusion

We have demonstrated the use of a fingerprint cache guided by algorithms to predict and then prefetch accesses to solve the

disk-bottleneck problem in deduplication scalability. HANDS scalably calculates working sets and pulls entire sets of fingerprints into memory when a single fingerprint is accessed, significantly increasing the number of cache hits for the in-memory deduplication index cache. We include a novel tiered working set index for rapid retrieval. We also showed that LRU outperforms LFU for index cache replacement regardless of context awareness, and we hypothesize that a similar pattern will hold for most other workloads.

Our design translates directly into fewer disk accesses for inline deduplication and, from there, better user-facing performance. HANDS is highly modular and adaptable to specific environmental constraints, and thus is an approach that can be deployed in nearly any system to alleviate the disk bottleneck problem. Although neither of our workloads had the requisite 45% deduplication ratio to benefit from traditional primary deduplication, with HANDS both achieve near perfect deduplication using between .01% and 10% of the memory. This reduces the required deduplication ratio to break even on cost to a mere 8% of incoming data if using 4KB blocks. Since such a small percentage of fingerprints need to be kept in cache for good performance, we encourage wider adoption of primary deduplication in industry and even personal servers.

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