Accordion: Better Memory Organization for LSM Key-Value Stores

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ABSTRACT

Log-structured merge (LSM) stores have emerged as the technology of choice for building scalable write-intensive key-value storage systems. An LSM store replaces random I/O with sequential I/O by accumulating large batches of writes in a *memory store* prior to flushing them to log-structured disk storage; the latter is continuously re-organized in the background through a *compaction* process for efficiency of reads. Though inherent to the LSM design, frequent compactions are a major pain point because they slow down data store operations, primarily writes, and also increase disk wear. Another performance bottleneck in today's state-of-the-art LSM stores, in particular ones that use managed languages like Java, is the fragmented memory layout of their dynamic memory store.

In this paper we show that these pain points may be mitigated via better organization of the memory store. We present Accordion – an algorithm that addresses these problems by re-applying the LSM design principles to memory management. Accordion is implemented in the production code of Apache HBase, where it was extensively evaluated. We demonstrate Accordion's double-digit performance gains versus the baseline HBase implementation and discuss some unexpected lessons learned in the process.

PVLDB Reference Format:
Edward Bortnikov, Anastasia Braginsky, Eshcar Hillel, Idit Keidar, and Gali Sheffi. Accordion: Better Memory Organization for LSM Key-Value Stores. *PVLDB*, 11 (12): 1863 - 1875, 2018.
DOI: https://doi.org/10.14778/3229863.3229873

1. INTRODUCTION

1.1 LSM Stores

Persistent NoSQL *key-value stores (KV-stores)* have become extremely popular over the last decade, and the range of applications for which they are used continuously increases. A small sample of recently published use cases includes massive-scale online analytics (Airbnb/ Airstream [2], Yahoo/Flurry [7]), product search and recommendation (Alibaba [13]), graph storage (Facebook/Dragon [5], Pinterest/Zen [19]), and many more.

The leading approach for implementing write-intensive key-value storage is *log-structured merge (LSM)* stores [31]. This technology is ubiquitously used by popular key-value storage platforms [9, 14, 16, 22, 4, 1, 10, 11]. The premise for using LSM stores is the major disk access bottleneck, exhibited even with today's SSD hardware [14, 33, 34].

An LSM store includes a *memory store* in addition to a large *disk store*, which is comprised of a collection of files (see Figure 1). The memory store absorbs writes, and is periodically *flushed* to disk as a new immutable file. This approach improves write throughput by transforming expensive random-access I/O into storage-friendly sequential I/O. Reads search the memory store as well as the disk store.

The number of files in the disk store has adverse impact on read performance. In order to reduce it, the system periodically runs a background *compaction* process, which reads some files from disk and merges them into a single sorted one while removing redundant (overwritten or deleted) entries. We provide further background on LSM stores in Section 2.

1.2 LSM Performance Bottlenecks

The performance of modern LSM stores is highly optimized, and yet as technology scales and real-time performance expectations increase, these systems face more stringent demands. In particular, we identify two principal pain points.

First, LSM stores are extremely sensitive to the rate and extent of compactions. If compactions are infrequent, read performance suffers (because more files need to be searched and caching is less efficient when data is scattered across multiple files). On the other hand, if compactions are too frequent, they jeopardize the performance of both writes and reads by consuming CPU and I/O resources, and by indirectly invalidating cached blocks. In addition to their performance impact, frequent compactions increase the disk write volume, which accelerates device wear-out, especially for SSD hardware [27].

Second, as the amount of memory available in commodity servers rises, LSM stores gravitate towards using larger memory stores. However, state-of-the-art memory stores are

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Proceedings of the VLDB Endowment, Vol. 11, No. 12
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DOI: https://doi.org/10.14778/3229863.3229873

organized as dynamic data structures consisting of many small objects, which becomes inefficient in terms of both cache performance and *garbage collection (GC)* overhead when the memory store size increases. This has been reported to cause significant problems, which developers of managed stores like Cassandra [4] and HBase [1] have had to cope with [12, 3]. Note that the impact of GC pauses is aggravated when timeouts are used to detect faulty storage nodes and initiate fail-over.

Given the important role that compaction plays in LSM stores, it is not surprising that significant efforts have been invested in compaction parameter tuning, scheduling, and so on [6, 18, 17, 32]. However, these approaches only deal with the aftermath of organizing the disk store as a sequence of files created upon memory store overflow events, and do not address memory management. And yet, the amount of data written by memory flushes directly impacts the ensuing flush and compaction toll. Although the increased size of memory stores makes flushes less frequent, today's LSM stores do not physically delete removed or overwritten data from the memory store. Therefore, they do not reduce the amount of data written to disk.

The problem of inefficient memory management in managed LSM stores has received much less attention. The only existing solutions that we are aware of work around the lengthy JVM GC pauses by managing memory allocations on their own, either using pre-allocated object pools and local allocation buffers [3], or by moving the data to off-heap memory [12].

1.3 Accordion

We introduce Accordion, an algorithm for memory store management in LSM stores. Accordion re-applies to the memory store the classic LSM design principles, which were originally used only for the disk store. The main insight is that the memory store can be partitioned into two parts: (1) a small dynamic segment that absorbs writes, and (2) a sequence of static segments created from previous dynamic segments. Static segments are created by *in-memory flushes* occurring at a higher rate than disk flushes. Note that the key disadvantage of LSM stores – namely, the need to search multiple files on read – is not as significant in Accordion because RAM-resident segments can be searched efficiently, possibly in parallel.

Accordion takes advantage of the fact that static segments are immutable, and optimizes their index layout as flat; it can further *serialize* them, i.e., remove a level of indirection. The algorithm also performs *in-memory compactions*, which eliminate redundant data *before* it is written to disk. Accordion's data organization is illustrated in Figure 2; Section 3 fleshes out its details.

The new design has the following benefits:

- *Fewer compactions.* The reduced footprint of immutable indices as well as in-memory compactions delay disk flushes. In turn, this reduces the write volume (and resulting disk wear) by reducing the amount of disk compactions.

- *More keys in RAM.* Similarly, the efficient memory organization allows us to keep more keys in RAM, which can improve read latency, especially when slow HDD disks are used.

- *Less GC overhead.* By dramatically reducing the size of the dynamic segment, Accordion reduces GC overhead, thus improving write throughput and making performance more predictable. The flat organization of the static segments is also readily amenable to off-heap allocation, which further reduces memory consumption by allowing serialization, i.e., eliminating the need to store Java objects for data items.

- *Cache friendliness.* Finally, the flat nature of immutable indices improves locality of reference and hence boosts hardware cache efficiency.

Accordion is implemented in HBase production code. In Section 4 we experiment with the Accordion HBase implementation in a range of scenarios. We study production-size datasets and data layouts, with multiple storage types (SSD and HDD). We focus on high throughput scenarios, where the compaction and GC toll are significant.

Our experiments show that the algorithm's contribution to overall system performance is substantial, especially under a heavy-tailed (Zipf) key access distribution with small objects, as occurs in many production use cases [35]. For example, Accordion improves the system's write throughput by up to 48%, and reduces read tail latency (in HDD settings) by up to 40%. At the same time, it reduces the write volume (excluding the log) by up to 30%. Surprisingly, we see that in many settings, disk I/O is *not* the principal bottleneck. Rather, the memory management overhead is more substantial: the improvements are highly correlated with reduction in GC time.

To summarize, Accordion takes a proactive approach for handling disk compaction even before data hits the disk, and addresses GC toll by directly improving the memory store structure and management. It grows and shrinks a sequence of static memory segments resembling accordion bellows, thus increasing memory utilization and reducing fragmentation, garbage collection costs, and the disk write volume. Our experiments show that it significantly improves end-to-end system performance and reduces disk wear, which led to the recent adoption of this solution in HBase production code; it is generally available starting the HBase 2.0 release. Section 5 discusses related work and Section 6 concludes the paper.

2. BACKGROUND

HBase is a distributed key-value store that is part of the Hadoop open source technology suite. It is implemented in Java. Similarly to other modern KV-stores, HBase follows the design of Google's Bigtable [22]. We sketch out their common design principles and terminology.

Data model KV-stores hold data items referred to as *rows* identified by unique row keys. Each row can consist of multiple *columns* (sometimes called fields) identified by unique column keys. Co-accessed columns (typically used by the same application) can be aggregated into *column families* to optimize access. The data is multi-versioned, i.e., multiple versions of the same row key can exist, each identified by a unique *timestamp*. The smallest unit of data, named *cell*, is defined by a combination of a row key, a column key, and a timestamp.

The basic KV-store API includes *put* (point update of one or more cells, by row key), *get* (point query of one or more or (2) cells reside in a bulk-allocated byte array managed by the *MSLAB* – MemStore Local Allocation Buffer [3] – module. In HBase 2.0, MSLAB is mostly used for off-heap memory allocation. With this approach, the MemStore's memory consists of large blocks, called *chunks*. Each chunk is fixed in size and holds data for multiple cells pertaining to a single MemStore.

3. Accordion

We describe Accordion's architecture and basic operation in Section 3.1. We then discuss in-memory compaction policies in Section 3.2 and implementation details and thread synchronization in Section 3.3. Section 3.4 discusses the index layout in off-heap allocation.

3.1 Overview

Accordion introduces a *compacting* memory store to the LSM store design framework. In contrast to the traditional memory store, which maintains RAM-resident data in a single monolithic data structure, Accordion manages data as a *pipeline* of *segments* ordered by creation time. Each segment contains an index over a collection of data cells. At all times, the most recent segment, called *active*, is mutable; it absorbs put operations. The rest of the segments are immutable. In addition to searching data in the disk store, get and scan operations traverse all memory segments, similarly to a traditional LSM store read from multiple files. Memory segments do not maintain Bloom filters like HFiles do, but they maintain other metadata like key ranges and time ranges to eliminate redundant reads. In addition, it is possible to search in multiple memory segments in parallel.

Figure 2 illustrates the Accordion architecture. It is parameterized by two values:

- A – fraction of the memory store allocated to the active segment; and
- S – upper bound on the number of immutable segments in the pipeline.

As our experiments show (Section 4), the most effective parameter values are quite small, e.g., $0.02 \le A \le 0.05$, and $2 \le S \le 5$.

Once the active segment grows to its size bound (a fraction A of the memory store's size bound), an *in-memory flush* is invoked. The in-memory flush makes the active segment immutable and creates a new active segment to replace it.

In case there is available space in the pipeline (the number of pipeline segments is smaller than S), the replaced active segment is simply *flattened* and added to the pipeline. Flattening a segment involves replacing the dynamic segment index (e.g., skiplist) by a compact ordered array suitable for immutable data, as shown in Figure 3. The indexed data cells are unaffected by the index flattening.

The flat index is more compact than a skiplist, and so reduces the MemStore's memory footprint, which delays disk flushes, positively affecting both read latency (by increasing the MemStore's hit rate) and write volume. It is also cache- and GC-friendly, and supports fast lookup via binary search. In managed environments, it can be allocated in off-heap (unmanaged) memory, which can improve performance predictability as discussed in Section 3.4 below.

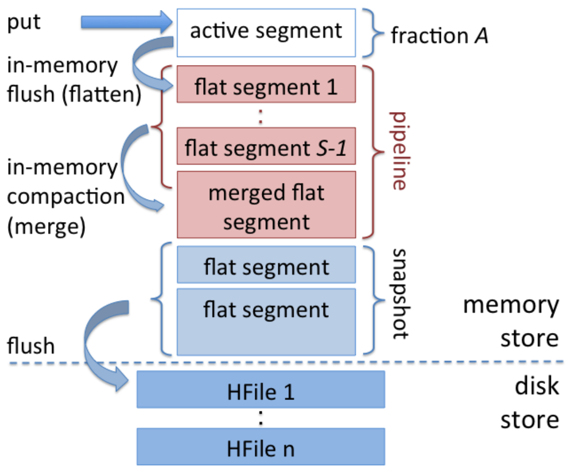


Figure 2: **Accordion's compacting memory store architecture adds a pipeline of flat segments between the active segment and the snapshot. The memory store includes a small dynamic active segment and a pipeline of flat segments. A disk flush creates a snapshot of the pipeline for writing to disk.**

Once the number of immutable segments exceeds S, the segments in the pipeline are processed to reduce their number. At a minimum, an *in-memory merge* replaces the indices of multiple segments by a single index covering data that was indexed by all original segments, as shown in Figure 3c. This is a lightweight process that results in a single segment but does not eliminate redundant data versions. For example, if a cell with the same row key and column key is stored in two different segments in the pipeline (with two different timestamps) then after the merge both cells will appear consecutively in the merged segment.

Optionally, an *in-memory compaction* can further perform *redundant data elimination* by creating a single flat index with no redundancies and disposing redundant data cells, as shown in Figure 3d. In the example above only the more recent cell will appear in the compacted segment. In case the memory store manages its cell data storage internally (via MSLAB), the surviving cells are relocated to a new chunk (to avoid internal chunk fragmentation). Otherwise, the redundant cells are simply de-referenced, allowing the garbage-collector to reclaim them. The choice whether to eliminate redundant data (i.e., perform compaction) or not (perform only merge) is guided by the policies described in Section 3.2 below.

Flushes to disk work the same way as in a standard LSM store: A disk flush first shifts all pipeline segments to the snapshot, which is not part of the pipeline, while the pipeline is emptied so that it may absorb new flat segments. A background flush process merges all snapshot segments while eliminating redundancies, and streams the result to a new file. After the file is written, the snapshot segments are freed.

In case the disk flush process empties the pipeline while an in-memory compaction is attempting to merge some segments, the latter aborts. This behavior is valid since in-memory compactions are an optimization.

as well as by background disk flushes and in-memory compactions. The latter two modify the pipeline by adding, removing, or replacing segments. These modifications happen infrequently.

The pipeline's readers and writers coordinate through a lightweight copy-on-write, as follows. The pipeline object is versioned, and updates increase the version.

Reads access the segments lock-free, through the version obtained at the beginning of the operation. If an in-memory flush is scheduled in the middle of a read, the active segment may migrate into the pipeline. Likewise, if a disk flush is scheduled in the middle of a read, a segment may migrate from the pipeline to the pre-flush snapshot buffer. The correctness of reads is guaranteed by first taking the reference of the active segment then the pipeline segments and finally the snapshot segments. This way, a segment may be encountered twice but no data is lost. The scan algorithm filters out the duplicates.

Each modification takes the following steps: (1) promotes the version number; (2) clones the pipeline, which is a small set of pointers, (3) performs the update on the cloned version, and (4) uses a compare-and-swap (CAS) operation to atomically swap the global reference to the new pipeline clone, provided that its version did not change since (1). Note that cloning is inexpensive – only the segment references are copied since the segments themselves are immutable. For example, in-memory compaction fails if a disk flush concurrently removes some segments from the pipeline.

3.4 Off-Heap Allocation

As explained above, prior to Accordion, HBase allocated its MemStore indicies on-heap, using a standard Java skiplist for the active buffer and the snapshot. Accordion continues to use the same data structure – skiplist – for the active segment, but adopts arrays for the flat segments and snapshot. Each entry in an active or flat segment's index holds a reference to a cell object, which holds a reference to a buffer holding a key-value pair (as pojo or in MSLAB), as illustrated in Figure 4a. HBase MSLAB chunks may be allocated off-heap.

Accordion's *serialized* version takes this approach one step further, and allocates the flat segment index using MSLAB as well as the data. A serialized segment has its index and data allocated via the same MSLAB object, but on different chunks. Each MSLAB may reside either on- or off-heap. The frequent in-memory flushes are less suitable for serialized segments, because upon each in-memory flush the new serialized segment and thus new index chunk is allocated. When the index is not big enough to populate the chunk, the chunk is underutilized.

Serialized segments forgo the intermediate cell objects, and have array entries point directly to the the chunks holding keys and values, as illustrated in Figure 4b. Removing the cell objects yields a substantial space reduction, especially when data items are small, and eliminates the intermediate level of indirection.

Offloading data from the Java heap has been shown to be effective for read traffic [13]. However, it necessitates recreating temporary cell objects to support HBase's internal scan APIs. Nevertheless, such temporary objects consume a small amount of space on-demand, and these objects are deallocated rapidly, making them easier for the GC process to handle.

4. PERFORMANCE STUDY

We fully implemented Accordion in HBase, and it is generally available in HBase 2.0 and up. We now compare Accordion in HBase to the baseline HBase MemStore implementation. Our evaluation explores Accordion's different policies and configuration parameters. We experiment with two types of production machines with directly attached SSD and HDD storage. We exercise the full system with multiple regions, layered over HDFS as in production deployments.

We present the experiment setup in Section 4.1 and the evaluation results in Section 4.2.

4.1 Methodology

Experiment setup Our experiments exploit two clusters with different hardware types. The first consists of five 12-core Intel Xeon 5 machines with 48GB RAM and 3TB SSD storage. The second consists of five 8-core Intel Xeon E5620 servers with 24GB RAM and 1TB HDD storage. Both clusters have a 1Gbps Ethernet interconnect. We refer to these clusters as SSD and HDD, respectively.

In each cluster, we use three nodes for HDFS and HBase instances, which share the hardware. The HDFS data replication ratio is 3x. HBase exploits two machines as region servers, and one as a master server. The workload is driven by the two remaining machines, each running up to 12 client threads.

A region server runs with a 8GB heap, under G1GC memory management. For serialized segment experiments, we use MSLAB memory management. We use the default memory layout, which allocates 40% of the heap (roughly 3GB) to the MemStore area, and 40% more to the read-path block cache. We apply an asynchronous WAL in order to focus on real-time write-intensive workloads (a synchronous WAL implies an order-of-magnitude slower writes). The log aggregation period is one second.

Workloads Data resides in one table, pre-split into fifty regions (i.e., each region server maintains twenty-five regions). The table has a single column family with four columns. We populate cells with 25-byte values, and so each row comprises 100 bytes; this is a typical size in production workloads [35].

We seek to understand Accordion's performance impact in large data stores. We therefore perform 300M–500M writes, generating 30–50GB of data in each experiment. As a result, experiments are fairly long – the duration of a single experiment varies from approximately 1.5 hours to over 12 hours, depending on the setting (workload, algorithm, and hardware type). In addition, given that Accordion mostly impacts the write-path, we focus our study mainly on write-intensive workloads. For completeness, we also experiment with read-dominated workloads, in order to show that reads (gets and scans) benefit from or are indifferent to the change in the write-path.

We use the popular YCSB benchmarking tool [23] to generate put, get, and scan requests. Each put writes a full row (4 cells, 100 bytes). Each get retrieves a single cell, while scans retrieve all four cells of every scanned row. The length of each scan (number of retrieved cells) is chosen uniformly at random in the range 1–100. In order to produce a high load, updates are batched on the client side in 10KB buffers.

In each experiment, all operations draw keys from the

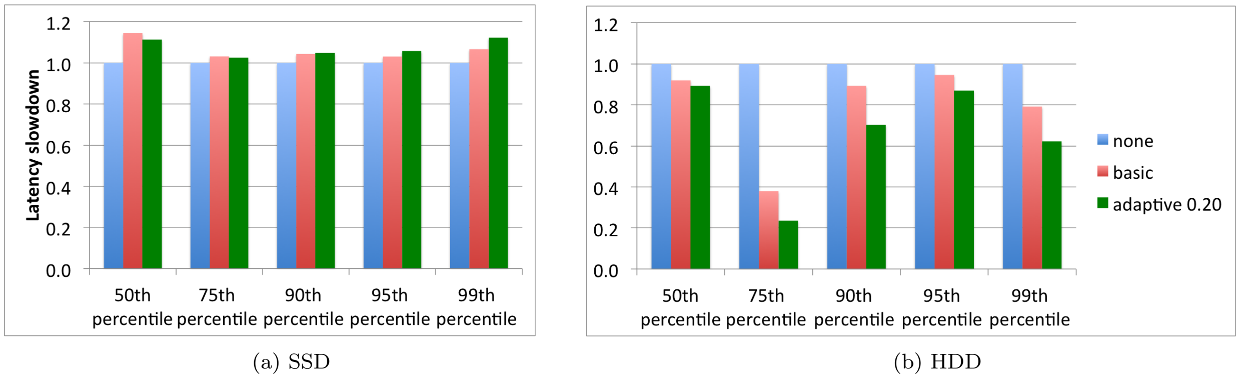


Figure 9: **Read latency speedup (respectively, slowdown) of *Basic* and *Adaptive* versus *NoCompaction*, under high write contention. Latencies are broken down by percentile. In HDD systems, *Adaptive* delivers up to 40% tail latency reduction.**

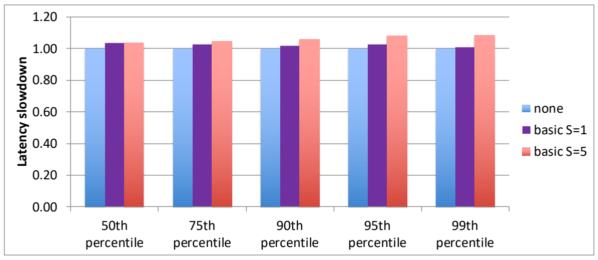


Figure 10: **Latency speedup for scans of *Basic*.**

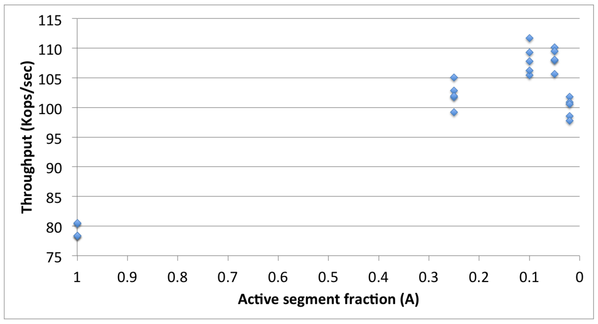


Figure 11: **Tuning of the active segment memory fraction, A, for the *Basic* policy, with $S = 2$, Zipf distribution on SSD. Five experiments are conducted for each A. The write throughput is higher for small values of A.**

baseline by 20%. We also discovered that the write volume for *Eager* is roughly the same in these two settings, whereas *Basic*'s write volume increases with A; (these results are not shown). Since *Adaptive* is always superior to *Eager*, we excluded *Eager* from the experiments reported above.

5. RELATED WORK

The basis for LSM data structures is the *logarithmic method* [21]. It was initially proposed as a way to efficiently transform static search structures into dynamic ones. A *binomial list* structure stored a sequence of sorted arrays, called *runs* each of size of power of two. Inserting an element triggers a cascaded series of merge-sorting of adjacent runs. Searching an element is done by applying a binary search on the runs starting with the smallest run until the element is found. AlphaSort [30] further optimizes a sort algorithm by taking advantage of the entire memory hierarchy (from registers to disk); each run fits into the size of one level in the hierarchy.

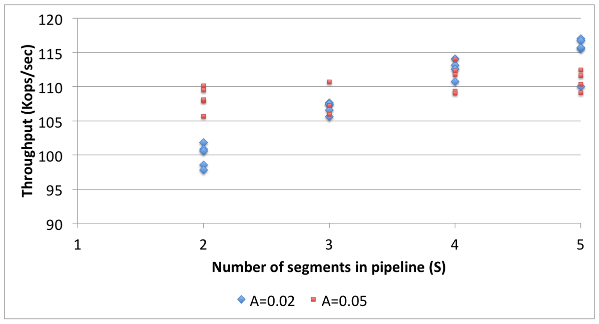
These methods inspired the original work on *LSM-trees* [31] and its variant for multi-versioned data stores [29].

Because compaction frequency and efficiency has a significant impact on LSM store performance and disk wear, many previous works have focused on tuning compaction parameters and scheduling [6, 14, 17, 18, 32] or reducing their cost via more efficient on-disk organization [28]. However, these works focus on *disk compactions*, which deal with data *after* it has been flushed to disk. We are not aware of any previous work that added *in-memory* compactions to LSM stores.

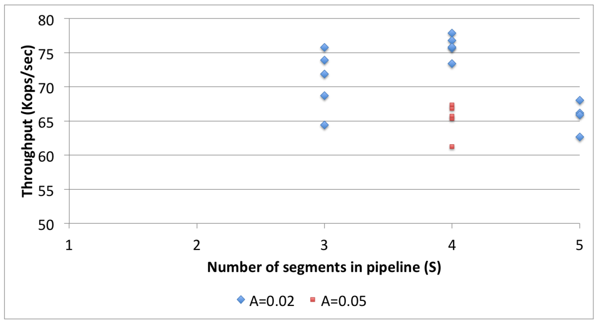
Some previous works have focused on other in-memory optimizations. cLSM [25] focused on scaling LSM stores on multi-core hardware by adding lightweight synchronization to LevelDB. Accordion, on the other hand, is based on HBase, which already uses a concurrent in-memory skiplist; improving concurrency in the line of cLSM is orthogonal to our contribution.

Facebook's RocksDB [14] is the state-of-the-art implementation of a key-value store. All writes to RocksDB are first inserted into an in-memory active segment (called memtable). Once the active segment is full, a new one is created and the old one becomes immutable. At any point in time there is exactly one active segment and zero or more immutable segments [15]. Unlike Accordion immutable segments take the same form of mutable segments. Namely, there is no effort done to flatten the layout of the indices of immutable segments or to eliminate redundant data versions in any way while it is in-memory.

Similarly to Accordion, the authors of FloDB [20] also observed that using large skiplists is detrimental to LSM store performance, and so FloDB also partitions the memory component. However, rather than using a small skiplist and large flat segments as Accordion does, FloDB uses a small hash table and a large skiplist. Put operations inserting data to the small hash table are much faster than insertions to the large skiplist, and the latter are batched and inserted via multi-put operations that amortize the cost of the slow skiplist access. Unlike Accordion, FloDB does not reduce the memory footprint by either flattening or compaction.



(a) SSD



(b) HDD

Figure 12: **Tuning the pipeline size bound, S, for the *Basic* policy. Five experiments are conducted for each S.**

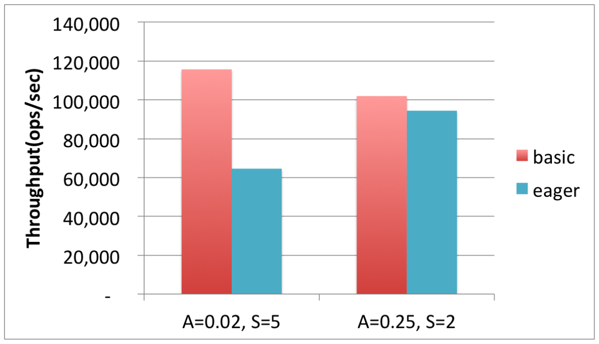


Figure 13: **Throughput (op/sec): *Eager* versus *Basic* in different settings.**

LSM-trie [35] is motivated by the prevalence of small objects in industrial NoSQL workloads. Like us, they observed that skiplists induce high overhead when used to manage many small objects. They suggest to replace the LSM store architecture with an LSM trie, which is based on hashing instead of ordering and thus eliminates the memory for indexing. This data structure is much faster, but only for small values, and, more importantly, does not support range queries.

6. DISCUSSION

While disk compactions in LSM stores have gotten a lot of attention, their in-memory organization was, by and large, ignored. In this work, we showed that applying the LSM principles also to RAM can significantly improve performance and reduce disk wear. We presented Accordion, a new memory organization for LSM stores, which employs *in-memory* flushes and compaction to reduce the LSM store's memory footprint and improve the efficiency of memory management and access. We integrated Accordion in Apache HBase following extensive testing. It is available in HBase 2.0 and up.

In this paper, we evaluated Accordion with different storage technologies (HDD and SSD) and various compaction policies, leading to some interesting insights and surprises:

Flattening and active component size We showed that flattening the in-memory index reduces the memory management overhead as well as the frequency of disk writes, thus improving performance and also reducing disk wear-out. Originally, we expected an active segment (skiplist) comprising 10–20% of the memory store to be effective, and anticipated that smaller active components would result in excessive flush and compaction overhead. Surprisingly, we found that performance is improved by using a much smaller active component, taking up only 2% of the memory store. This is due in part to the fact that our workload is comprised of small objects – which are common in production workloads [35] – where the indexing overhead is substantial.

Impact of memory management on write throughput We showed that the write volume can be further reduced, particularly in production-like self-similar key access distributions, by merging memory-resident data, namely, eliminating redundant objects. We expected this reduction in write volume to also improve performance. Surprisingly, we found that disk I/O was not a principal bottleneck, even on HDD. In fact, write throughput is strongly correlated with GC time, regardless of the write volume.

Cost of redundant data elimination We expected redundant data elimination to favorably affect performance, since it frees up memory and reduces the write volume. This has led us to develop *Eager*, an aggressive policy that frequently performs in-memory data merges. Surprisingly, this proved detrimental for performance. The cost of the *Eager* policy was exacerbated by the fact that we benefitted from a significantly smaller active component than originally expected (as noted above), where it literally could not keep up with the in-memory flush rate. This led us to develop a new policy, *Adaptive*, which heuristically decides when to perform data merges based on an estimate of the expected yield. While *Adaptive* does not improve performance compared to the *Basic* policy, which merges only indices and not data, it does reduce the write volume, which is particularly important for longevity of SSD drives.

Deployment recommendations Following the set of experiments we ran, we can glean some recommendations for selecting policies and parameter values. The recommended compaction policy is *Adaptive*, which offers the best performance vs disk-wear tradeoff. When running without MSLAB (i.e., with a flat index), an active segment size of $A = 0.02$ offered the best performance in all settings we experimented with, though bigger values of A might be most appropriate in settings with big values (and hence lower meta-data-to-data ratios). When using MSLAB allocation, it is wasteful to use such a small active segment, because an entire chunk is allocated to it, and so we recommend using $A = 0.1$. Assuming the workload is skewed (as production workloads usually are), we recommend using a fairly aggressive compaction threshold $R = 0.2$. If the workload is more uniformly distributed or if write throughput is more crucial than write amplification, then one can increase the value R up to 0.5 or even higher to match the throughput of *Basic*. The pipeline size S induces a tradeoff between read and write performance. If the workload is write-intensive then we recommend using $S = 5$, and if the workload is read-oriented $S = 2$ is better. We note that most of the recommendations here are set as default values in the coming HBase 2.0 release.

Acknowledgments

We are thankful to the members of the HBase community for many helpful discussions during the development of the Accordion project. In particular, we would like to thank Michael Stack, Ramakrishna Vasudevan, Anoop Sam John, Duo Zhang, Chia-Ping Tsai, and Ted Yu.

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