Accelerating LSM-Tree with the Dentry Management of File System

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Abstract

The log-structured merge tree (LSM-tree) gains wide popularity in building key-value (KV) stores. It employs logs to back up arriving KV pairs and maintains a few on-disk levels with exponentially increasing capacity limits, resembling a tiered tree-like structure. A level comprises SST files, each of which holds a sequence of sorted KV pairs. From time to time, LSM-tree redeploys KV pairs from a full level to the lower level by compaction, which merge-sorts and moves KV pairs among SST files, thereby incurring substantial disk I/Os.

In this paper, we revisit the design of LSM-tree and find that organizing multiple KV pairs in an SST file entails the heavyweight redeployment of actual KV pairs in a compaction. Accordingly we revolutionize the organization of KV pairs by transforming an SST file of KV pairs to an SST directory, in which each KV pair makes into an independent KV file with the key and value as filename and main file contents, respectively. Moving KV pairs in a compaction converts to transferring directory entries (dentries), which causes concretely fewer disk I/Os. This is the essence of our design named DeLSM. We build a prototype of DeLSM on LevelDB and evaluation results show that it significantly outperforms the state-of-the-art LSM-tree variants in different dimensions.

1 Introduction

The log-structured merge tree (LSM-tree) plays an important role in building key-value (KV) stores to service omnipresent workloads, such as web indexing, social networking, and e-commerce [1–7]. LSM-tree is a tiered tree-like structure composed of multiple levels in memory and on disk. It employs in-memory memtables to absorb arriving KV pairs after appending them to an on-disk log for crash consistency. A shortage of memtable space triggers a minor compaction that dumps a full memtable into a sorted string table (SST) file to be placed at the top level (L₀) on disk. Each on-disk level has a fixed capacity limit and Lₙ is typically 10× smaller than Lₙ+1 (n ≥ 0). When Lₙ becomes full, LSM-tree initiates a major compaction which merge-sorts KV pairs from selected SST files residing in Lₙ and Lₙ+1. It then orderly moves and packs involved KV pairs into new Lₙ+1 SST files.

A major compaction results in substantial disk I/Os and impairs performance due to redeploying KV pairs among SST files. Worse, it may stall LSM-tree from serving foreground requests. Moreover, a KV pair would be factually written again whenever it is involved in a further compaction, causing severe write amplification. Researchers have looked into how to reduce the performance penalty of LSM-tree [6,8–24]. Some of them focused on emerging storage devices [6,7,9,15,18,21], while others sought the aid from specific hardware [19,20]. In this paper, however, we envisage a solution to revolutionize LSM-tree, which shall be 1) simplistic but efficient, and 2) generic and software-only, for the ease of development and portability.

With this intention, we have studied LevelDB, one typical LSM-tree-based KV store, with emphasis on its data structures and compaction procedure. Through the intensive study, we have obtained several key observations.

• An SST file indexes multiple KV pairs stored in it, which shares similarities with a directory of file system indexing files with directory entries (dentries). Although users put individual KV pairs in the foreground, LevelDB treats an SST file as the unit for processing in the background.
• SST files are the core of compaction. A compaction is a series of unpacking, sorting, and redeploying KV pairs with a few SST files through disk reads and writes.
• An SST file remains immutable (read-only) in its lifetime, i.e., since its creation until it is compacted. In fact, once put into LevelDB, a KV pair stays unchanged unless it subsequently encounters a future deletion.
• LevelDB relies on the underlying file system to manage SST files. To get a KV pair, LevelDB waits for file system to fetch the dentry of corresponding SST file and then searches in the file. In each compaction, file system adds dentries for LevelDB to index new SST files. Such is much more lightweight than moving KV pairs within these files.
Inspired by these observations, we consider reorganizing KV pairs for LSM-tree by leveraging the fundamental idiosyncrasies of file system, i.e., the directory-files structure. In a nutshell, we transform an SST file to an SST directory and make each KV pair into an individual KV file. A compaction converts to a succession of efficient directory operations between SST directories. This is the essence of our design, namely DeLSM (directory-based LSM-tree). The main ideas of DeLSM are summarized as follows.

- **DeLSM processes a KV pair as the integral unit in a compaction.** In a minor compaction dumping a memtable, it creates a KV file for each KV pair, with the key and value being the filename and main file content, respectively. DeLSM retains the mechanism of logging and memtables like standard LSM-trees but schedules a minor compaction to be performed in the background once a memtable becomes immutable.

- **DeLSM manages a level directory to hold SST directories of each level.** A major compaction between L_n and L_{n+1} (n ≥ 0) directories is a succession of linking and unlinking KV files (directory) over existing and new SST directories, thereby incurring drastically fewer disk I/Os compared to conventional redeployment of actual KV pairs.

- **DeLSM basically serves a search request with the underlying file system traversing directories to locate a key or key range (point or range search).** For optimization, it employs a local meta file with SST-level Bloom filter in each SST directory and global structures that keep key ranges of all valid SST directories.

The avoidance of moving KV pairs for compactions enables DeLSM’s high efficacy. DeLSM also embraces high portability as a software-only solution with neither hardware tailoring or customization nor any onerous change of file system. We have implemented a prototype for it with LevelDB and Ext4. Evaluation results show that DeLSM boosts the performance of LevelDB up to 18.9× and 2.8×, respectively, for write and read requests. It also significantly outperforms LSM-tree variants including WiscKey [9], PebblesDB [13], LDS [16], and Bolt [22] in different dimensions.

The remainder of this paper is organized as follows. In Section 2 we briefly introduce LSM-tree with LevelDB. In Section 3 we analyze observations obtained in the aforementioned study. We detail the design and implementation of DeLSM in Section 4. We describe the evaluation of DeLSM in Section 5. In Section 6, we discuss relevant LSM-tree variants. We conclude the paper in Section 7.

2 Background

2.1 LSM-tree

LevelDB [2] is a typical KV store based on LSM-tree. Without loss of generality, we take LevelDB to illustrate the structure of LSM-tree and how it serves write and read requests.

Figure 1 sketches the architecture of LevelDB. It leverages on-disk logs for crash consistency and maintains memtables in memory and multiple levels on disk. Each level is a sorted run of many KV pairs stored in SST files. The capacity limit of a level is at least ten times larger than the level immediately above it, thereby resembling a hierarchical tree-like structure.

**Write request and compaction** On a write request (e.g., Put), LevelDB appends the KV pair to the log (① in Figure 1). After that, LevelDB inserts it into the mutable memtable (②). These are two main steps happening in the foreground of LevelDB. A full memtable is made immutable and a new mutable one is created for incoming KV pairs (②).

When the space of mutable memtable is insufficient, LevelDB triggers a minor compaction (③). It creates an SST file at L_0 and dumps KV pairs of the immutable memtable to the file. Since L_0 SST files are directly converted from memtables that have been receiving KV pairs from users, key ranges may overlap between them. When the size of all L_0 SST files reaches L_0’s capacity limit, LevelDB merges KV pairs from L_0 and selected L_1 SST files into new L_1 SST files that rule out overlapping key ranges. This process is called major compaction (④) that can occur between any L_n and L_{n+1} (n ≥ 0), as every level has a capacity limit. Compactions badly impair performance due to sorting, moving, and persisting KV pairs on-disk files. Worse, if the mutable memtable is full but a minor compaction is still ongoing, LevelDB will stall serving requests in the foreground until the compaction is completed.

**Read request** Upon a Get request to read a KV pair (point search), LevelDB successively searches mutable memtable, immutable memtable, L_0, L_1, and so on, since a newer version for the key exists in a higher level. As to a range search that demands a number of KV pairs, e.g., keys starting with ‘a’, the organization of contiguously sorted keys in the memtables and SST files is supportive. Yet keys in a range may reside in multiple SST files, possibly across several levels [25].

**Log** LevelDB dedicates a log file to a memtable. It appends a KV pair with operation (e.g., Put) to the tail of log file before an insertion with the mutable memtable. LevelDB discards a log file after compacting its corresponding memtable.
as the latter has been transformed into an $L_0$ SST file.

**SST** Figure 2 shows the format of an SST file. It begins with multiple data blocks comprised of sorted KV pairs. Next there are meta blocks used to index KV pairs in data blocks. A meta block mainly contains a sequence of block-level Bloom Filters that can help LevelDB quickly determine if a key is in the SST file or not. The subsequent metaindex and index blocks record in-file offsets that track meta and data blocks, respectively. The last footer field holds in-file offsets to the metaindex and index blocks. Figure 2 summarizes the functions of these fields. An SST file at any level is immutable (read-only), and remains alive until it is compacted into the next level. LevelDB also employs a global manifest file to track valid SST files with their respective key ranges.

### 2.2 Directory Management of File System

LevelDB defines rules to name its SST, log, and manifest files. It puts them in directories and relies on the underlying file system to manage them. File system makes each directory into a specific file comprised of directory entries (dentries). A dentry records the mapping from a filename to the file’s inode number, with which the file’s contents can be retrieved.

Using dentries to organize directory and files is one of the fundamental idiosyncrasies of file system. A directory of dentries and all files in it are all permanently stored on disk and file system must efficiently index them. For example, Ext4 employs a hash tree (HTree) to do so. It hashes each filename and uses the hash value as a key to build a B-tree over a directory’s dentries. Given a filename, Ext4 loads the HTree into memory and searches it to locate the file by calling ext4_lookup. To fetch multiple files with a pattern, e.g., any file with a name starting with ‘a’, Ext4 calls ext4 readdir that 1) builds an in-memory red-black tree (RB-tree) with dentries loaded from the HTree, and 2) traverses the RB-tree to filter out files that match the pattern. Obviously, to get one or a few files in a large number of dentries is not efficient for either B-tree or RB-tree. The operating system hence employs a global dentry cache (dcache) to buffer dentries that are recently and frequently used. Note that LevelDB also maintains a table cache in which the file descriptors of SST files are buffered for quick reference [2, 22].

### 3 Motivation

By running LevelDB on top of Ext4, we have conducted a study, especially on the similarity and interaction between them. All the disk I/Os that LevelDB incurs for heavyweight compactions are performed by Ext4. Our aim with the study is to find a way that makes the most of file system to minimize disk I/Os for LSM-tree.

**Ø1. LevelDB receives individual KV pairs issued by users in the foreground but packs them into a large SST file as the unit for subsequent processing in the background.**

KV pairs are individually put by users. To take advantage of sequential writes of storage devices, LevelDB appends them to a log in the foreground. However, LevelDB bundles multiple KV pairs into an on-disk SST file that is used as the unit for background processing. An SST file is generally configured to have a large size, e.g., 4MB. Assuming that a KV pair takes 512B on average, about 8,000 KV pairs stay in one SST file. It is non-trivial to frequently merge-sort and redistribute so many KV pairs from multiple SST files during a compaction.

**Ø2. The way LevelDB organizes and indexes KV pairs in one SST file shares similarities with file system’s dentry management strategy.**

To trace and index data is a fundamental functionality for any application- or system-level data management system. LevelDB encapsulates metadata in an SST file to index stored KV pairs, while Ext4 employs an HTree with dentries to index SST files in accordance with their filenames. To move or read a KV pair needs to go through both levels of indexes.

**Ø3. A compaction that moves KV pairs between SST files is severely inefficient compared to file system moving files (dentries) between directories.**

In a compaction, LevelDB redeploys KV pairs from existing SST files into newly-created ones, resulting in substantial disk read and write I/Os. Comparatively, when Ext4 moves files between directories, it just moves dentries, which causes insignificant I/Os as the size of a dentry is generally small.

**Ø4. Most on-disk KV pairs stay alive and unchanged for a long time but they would migrate from one SST file to the next one due to compactions.**

The life of an SST file ceases once KV pairs it holds have been compacted. A KV pair yet remains alive and unchanged on disk since dumped into $L_0$, unless it encounters a deletion propagated from upper levels. Whereas, considering the compaction algorithm of LevelDB, a KV pair does not stay at a specific on-disk location but is repeatedly transferred by Ext4.
from one SST file to the other one at the lower level once a further compaction happens to it.

In light of foregoing observations, we conclude that 1) to reorganize an individual KV pair as the independent unit for processing aligns with the nature of KV store and promises flexibility, and 2) the similarity between an SST file with KV pairs and a directory with dentries implies a potential collaboration of file system and LSM-tree to revolutionize the latter’s organization of KV pairs and in turn gain higher performance with fewer disk I/Os.

4 Design of DeLSM

As the conventional organization of KV pairs causes heavy-weight compactions, we propose DeLSM that leverages file system, particularly the directory-files structure, to reorganize KV pairs for LSM-tree. Figure 3 shows the architecture of DeLSM. Firstly, DeLSM reformats an SST file into an SST directory, in which each KV pair exists as an independent KV file with a dentry (Section 4.1). Secondly, during a compaction, DeLSM moves dentries for KV files instead of redeploying actual KV pairs between SST directories, thereby concretely improving the efficiency of compactions (Section 4.2). Thirdly, besides utilizing file system’s native dentry management for searches, DeLSM employs a meta file with an SST-level Bloom filter in each SST directory (Section 4.3). DeLSM also guarantees the crash consistency of stored KV pairs (Section 4.4). Last but not the least, DeLSM is effectively implementable with a generic file system (Section 4.5).

4.1 KV File and SST Directory

DeLSM reorganizes a KV pair as an individual KV file. It appoints the key and value as the filename and main file content, respectively, since the two can be viewed as byte-arrays (strings). In each KV file, there is a header that contains the operation code for the KV pair, e.g., ‘0’ for Put and ‘1’ for Delete, and a globally monotonic increasing sequence number. DeLSM groups multiple KV files in an SST directory, the name of which follows LevelDB’s naming rule for SST files. Consequently, DeLSM delegates file system to manage KV files through dentries in an SST directory, which obviates the metadata LevelDB puts down in each SST file (cf. Figure 2). DeLSM adds a supplemental meta file in an SST directory for faster lookup (cf. Section 4.3). In addition, DeLSM makes a level directory for each level, i.e., $L_n$ directory ($n \geq 0$), in which it accommodates all SST directories belonging to $L_n$. An SST directory corresponds to a memtable. In the foreground, before inserting KV pairs into the mutable memtable, DeLSM still uses a log to absorb them, as logging generates sequential writes favored by storage devices. When the mutable memtable is full, DeLSM marks it to be immutable and creates a new mutable one. In the meantime, DeLSM starts a minor compaction in the background and transforms each KV pair in the immutable memtable to be a KV file. This can be done through a background thread (cf. Section 4.5).

As shown in the top-right of Figure 3, like LevelDB, DeLSM maintains a global manifest file that backs an in-memory structure known as the version to track all valid SST directories. In brief, the version 1) monitors the increase of sequence number, 2) regulates the naming of logs and SST directories, 3) records the addition and removal of SST directories for a compaction, and so on.

4.2 Lightweight Compaction

KV files remain in SST directories until selected for a major compaction, in which DeLSM moves their dentries rather than themselves. As a result, DeLSM redefines the capacity limit of a level as the number of dentries for KV files, instead of the size of KV pairs. The capacity limit of a level is still ten times that of the upper one for DeLSM.

When $L_n$ ($n \geq 0$) reaches its capacity limit, DeLSM initiates a major compaction (④ in Figure 3). In existing $L_n$ and $L_{n+1}$ SST directories, DeLSM finds out appropriate keys by iterating over dentries and inserts them into a newly-created $L_{n+1}$ SST directory. When the new $L_{n+1}$ SST directory becomes full, DeLSM creates the next one and continues moving dentries until all involved keys are compacted. Then it removes dentries of compacted SST directories from $L_n$ and $L_{n+1}$. At the end of a compaction, DeLSM records the change of SST directories in the in-memory version and manifest file. The key ranges of newly-generated SST directories are also added to the version for ease of searches (cf. Section 4.3). As DeLSM’s major compaction is mainly composed of finding and redeploying dentries rather than moving KV pairs, it is more lightweight and efficient with much fewer disk I/Os.

A deletion or overwrite of a KV pair is also conducted in the process of compaction. When DeLSM encounters two files with the same filename, it handles them regarding their operation codes and sequence numbers. The KV file with a greater sequence number decides the KV pair’s fate. For
Figure 4: A Compaction of DeLSM

example, given one KV file with a deletion code and a greater sequence number, DeLSM shall remove the other one.

Figure 4 illustrates an example of compacting two SST directories ($SST^{(L_0)}_2$ and $SST^{(L_1)}_1$) into $L_1$. Before the compaction, each SST directory contains keys in different ranges. The compaction creates new $L_1$ directories ($SST^{(L_1)}_2$ and $SST^{(L_1)}_3$), and redeploys dentries into them. As a compaction of DeLSM is mainly a series of directory operations, a comparison between dentries before and after the compaction in Figure 4 indicates that KV files and their inode numbers remain the same as DeLSM incurs no change to them.

4.3 Point Search and Range Search

On a point search for a key, DeLSM first checks memtables, which hold the latest updates to KV pairs. A miss leads DeLSM to $L_0$. $L_0$ SST directories contain overlapping key ranges. DeLSM asks the version for all $L_0$ SST directories that the target key falls in. In a candidate SST directory, DeLSM needs file system to find if the key (filename) exists among dentries. A match returns the target value, i.e., file content pointed by the dentry’s inode. Otherwise, DeLSM does with the next candidate. If the key is not found in $L_0$, DeLSM goes down to $L_1$ that is with non-overlapping key ranges and searches in one candidate SST directory. It continues until the key is found or traverses all levels without a hit. Given a range search to get, say, keys starting with ‘a’. DeLSM still goes through memtables and on-disk levels. It obtains SST directories with appropriate key ranges from the version and traverse dentries for KV files accordingly.

Relying on file system to search keys through dentries is sound but not very efficient. Take Ext4 for instance. To get one KV file for point search, Ext4 needs to first load on-disk nodes of an HTree (B-tree) into memory. Regarding $L_0$ SST directories with overlapping key ranges, searching the key in non-target SST directories incurs substantial disk I/Os. To reduce such performance penalties, DeLSM encapsulates a meta file in each SST directory. It makes and puts an SST-level Bloom filter for all keys in the meta file when the SST directory is being built during a compaction. Consequently, if a key is not hit in the Bloom filter, DeLSM no longer scans dentries of an SST directory. Note that DeLSM’s SST-level Bloom filter differs from the block-level Bloom filters used by LevelDB which stores KV pairs contiguously in disk blocks of an SST file [2, 13]. Also, in contrast to LSM-trees that hold numerous metadata in an SST file for indexing (cf. Figure 2), DeLSM only keeps one Bloom filter, since file system helps to index KV pairs for DeLSM. This both gains space efficiency and simplifies management.

Besides the meta file, DeLSM also maintains a block cache and a table to buffer frequently used KV pairs and file descriptors of KV files [2, 4, 11, 26], respectively. These caches further accelerate search operations for DeLSM. In the future, we would explore how to jointly manage and utilize DeLSM’s user-space caches with kernel-space buffers, such as the page cache, dentry cache and ino
cache.

4.4 Crash Consistency of DeLSM

Conventional LSM-trees log KV pairs before putting them in memtables. For KV pairs involved in a minor or major compaction, LSM-trees sync new SST files by fdatasync or fsync before removing obsolete logs or compacted SST files. Comparatively, DeLSM also utilizes logging to guarantee the consistency of arriving KV pairs to be put in memtables. The minor compaction is the only occasion on which DeLSM generates KV files from an immutable memtable. DeLSM does not sync KV files though, as syncing multiple small files is costly. Instead, DeLSM syncs a full log file when a memtable is made immutable. Next DeLSM transiently retains the synced log file until an approximate duration, say, 60 to 120 seconds, elapses after the generation of KV files, in order to secure the consistency and durability of generated KV files. This duration gives file systems like Ext4 sufficient time to commit data and metadata of KV files into disk [27, 28].

On the other hand, like LevelDB and other LSM-tree variants, DeLSM leverages the manifest file for recovery. Either a major or minor compaction of DeLSM involves the addition and/or removal of SST directories. DeLSM composes, appends, and syncs a record of the changes of SST directories to the manifest file. As a result, the manifest file contains all traceable changes over time.

A record synced to the manifest file marks the end of a compaction and enables the recoverability of DeLSM. In case of a crash, DeLSM loads and checks the manifest file to rebuild the in-memory version that tracks valid SST directories. Upon a corrupted record of adding and removing SST directories, DeLSM does with relevant directories and makes a new proper record. No corrupted record does not rule out inconsistency as the crash might have happened before writing the record or during a compaction. DeLSM scans the manifest file, log files, and directories across all levels. Each KV pair is stored along with a monotonic increasing sequence number in a log or an SST directory while the manifest file has the
Table 1: Underlying Supports of File System for DeLSM

| DeLSM functions       | File system’s supports with system calls                                                                 |
|-----------------------|-----------------------------------------------------------------------------------------------------------|
| Put a KV pair (file)  | open to create the KV file, and write to store the value into the file                                    |
| Delete a KV pair (file)| remove to remove a file or directory                                                                        |
| Remove an SST directory| mkdir to create a new SST directory                                                                       |
| Create a directory    | mkdir to create new SST directories, link to redeploy the dentries by hard links, and remove to remove existing SST directories |
| Major Compaction      | lseek to find a dentry in SST directory                                                                   |
| Search                | readdir to check dentries in SST directory                                                                 |

The supports of file system As shown in Table 1, all the supports demanded by DeLSM from file system can be satisfied by standard POSIX-compliant system calls. Putting a new KV pair is creating a file with the key as filename via open and writing down the value via write. Deleting an on-disk KV pair is removing the KV file and dentry via remove. For compactions, DeLSM mainly makes use of mkdir to create directories and link to redeploy dentries. There are two types of links, i.e., hard or symbolic link. The hard link factually refers to the inode of a file. After creating new SST directories, DeLSM sets hard links to KV files to be moved. At last, DeLSM removes compacted dentries, files, and SST directories by successively calling remove. To sum up, the implementation of DeLSM is viable with a generic file system.

Compactions Considering the speed mismatch between putting KV pairs into memtable in the foreground and generating a KV file in the background, DeLSM transiently keeps multiple immutable memtables to be compacted, instead of stalling to wait for the completion of a minor compaction. It employs a background thread to handle those memtables. On the other hand, DeLSM triggers a major compaction if the number of KV files (dentries) at a level reaches a limit that is configurable. For example, we set the limit for L₀ as 10,000 after empirical tests with our machine.

The limits of filename Using the key as filename entails three issues. One is the maximum length of a filename. Most file systems allow up to 255 bytes for a filename. With regard to state-of-the-art studies, keys are generally in dozens of bytes. Therefore, the limit of 255 bytes is not a thwarting concern. Moreover, such a length limit is adjustable by slightly changing the implementation of file system.

The second issue is that, despite supporting tens of thousands of diverse characters from various human languages, a filename fundamentally denies a handful of characters. For example, Linux forbids the forward slash (‘/’) in a filename.

When DeLSM receives a key with such illegal characters, a straightforward solution is to return the key back with a revision suggestion. This is empirically feasible and used in our implementation. In practice, many online service providers, like Google and Microsoft, define respective rules to refuse a few characters in their account names, such as forward slash (‘/’) and asterisk (“*”).

Thirdly, file system does not allow files with the same filename to exist in one directory. However, standard LSM-trees provide a snapshot feature that retains all variants of a KV pair with sequence numbers no smaller than the sequence number at which the snapshot option has been switched on. To support snapshots, DeLSM puts values with the same key into one KV file according to the ascending order of their sequence numbers. Hence there are no KV files with the same filename in an SST directory. If a user aims to access a key’s value for a specific snapshot saved at some sequence number, DeLSM retrieves from the KV file variants with sequence numbers no smaller than the snapshot’s.

The next concern is that DeLSM operates more files and dentries through system calls than standard LSM-trees and also transfigures many sequential I/Os to be random ones. The overhead of file system calls and their impact in the context of LSM-trees have been investigated [16, 32–35]. There is a trade-off between moving actual KV pairs and handling more system calls with random I/Os. Our evaluation in Section 5 confirms that, due to the overwhelming disk I/Os caused by conventional compactions, DeLSM’s reorganization of KV pairs in the way of directory-files is worthwhile and efficient.

5 Evaluation

We evaluate DeLSM against state-of-the-art LSM-tree variants with micro-benchmarks for preliminary tests. We mainly aim to answer the following questions.

- Does DeLSM’s avoidance of moving actual KV pairs yield high write performance?
- How significant is the drop of I/O amplification caused by DeLSM?
- How is the read performance of DeLSM?
5.1 Evaluation Setup

Platform We have run all experiments on a server with 1) 64-core Intel Xeon Gold 5218 CPU, 2) 192GB memory, 3) 1TB SSD, and 4) Ubuntu 20.04.2 with Linux 5.11.0 and GCC/G++ 9.3.0. In particular, the underlying file system is Ext4 mounted in the default ‘data=ordered’ mode.

Competitors Besides the original LevelDB, we considered state-of-the-art LSM-tree variants including WiscKey [9], LDS [16], PebblesDB [13], and BoLT [22]. The latter two have official source codes1,2 while we implemented the former two and our DeLSM atop LevelDB in accordance with their respective designs. These LSM variants were selected for comparison because they represent different approaches of reducing performance penalties for LSM-tree.

WiscKey was developed for SSD. It employs a value log to store each actual KV pair. In the memtable and SST files, WiscKey keeps a KV pair’s offset in the value log. As a result, like DeLSM, WiscKey does not move actual KV pairs. However, WiscKey has to manually index KV pairs in the value log. Worse, WiscKey must manage the log space by itself. Given a workload with many deletions, its garbage collection significantly impairs performance. DeLSM, on the other hand, delegates such space management to the file system.

LDS took an opposite direction to DeLSM by bypassing file system and mapping LSM-tree’s data directly to a block storage device. Although LDS avoids file-level operations and attempts to preserve sequential writes for disk drives, its compactions still move actual KV pairs across storage space.

PebblesDB was inspired by the skip-list data structure. It places ‘guards’ at each level to partition the key range of the level into disjoint segments. Such guards help PebblesDB avoid rewriting the same KV pairs at a level, but it still writes them once into the level during a compaction. BoLT is also a contrast to DeLSM as BoLT creates a single compaction file for each compaction in order to reduce the calls of syncs. BoLT uses logical SST indexes to track KV pairs in the compaction file. In a compaction, BoLT physically moves KV pairs between levels and generates logical indexes though.

5.2 Microbenchmarks

5.2.1 Sequential and Random Writes without Deletions

We used the default db_bench as the microbenchmark with 16B keys and a variety of value sizes, i.e., 16B, 64B, 256B, 512B, 1KB, and 4KB. We chose these value sizes because studies had revealed that small values are prevalent and even dominant in today’s typical real-world workloads [8, 29]. We collected the average execution time (microsecond/operation) by running fillseq (sequential writes), fillrandom (random writes), readseq (sequential reads), and readrandom (random reads) of db_bench with 10 million KV pairs. Fillseq (resp. readseq) sequentially puts (resp. searches) KV pairs in ascending order of keys while fillrandom (resp. readrandom) puts (resp. searches) KV pairs in a random order.

Figure 5a and Figure 5b capture the results of write performances of six LSM-tree variants, from which we can obtain several observations. Firstly, we have built DeLSM on top of LevelDB, and DeLSM significantly boosts the write performance of LevelDB, by up to 18.9× with fillrandom and 4KB values. DeLSM differs from LevelDB mainly in 1) the reorganization of KV pairs in the fashion of directory-files and 2) the retention of multiple immutable memtable for minor compactions. The reorganization with SST directories and KV files enables DeLSM to avoid moving KV pairs in the background for major compactions, thereby incurring much fewer disk I/Os compared to LevelDB. Maintaining multiple memtables yet helps to avoid stalling in the foreground like LevelDB to wait for an ongoing minor compaction. Consequently, DeLSM manages to yield much higher performance.

Secondly, DeLSM also dramatically outperforms other LSM-tree variants except WiscKey with much less execution time in writing KV pairs, especially with fillrandom (cf. Figure 5b). Take fillrandom and 4KB value size for illustration again. The average write time of BoLT, LDS, and PebblesDB is 14.5×, 13.0× and 6.3× that of DeLSM, respectively. In spite of reducing I/O amplifications in different approaches, these three LevelDB-like LSM-tree variants still have to physically move KV pairs between levels by their very designs. Therefore, their write performances are lower than that of DeLSM which only moves dentries in major compactions.

The third observation is on the comparison between DeLSM and WiscKey, which indicates that DeLSM is evidently inferior to WiscKey, particularly with larger values. For example, with fillrandom and 4KB values, DeLSM is 52.0% slower than WiscKey. WiscKey appends all arriving KV pairs to a value log with disk-favored sequential writes and like DeLSM, WiscKey only redeploy the key and offset to the KV in the value log, rather than actual KV pairs in a major compaction. WiscKey also does not dump KV pairs through minor compactions. Although DeLSM uses a log to efficiently absorb arriving KV pairs like WiscKey, it generates individual KV files in minor compactions over time, which is likely to entail random writes as well as inode and dentry operations [16]. Worse, DeLSM needs more time to make a KV with larger value into a KV file. As a result, DeLSM cannot compete against WiscKey on workloads that are fully composed of write requests.

5.2.2 Random Writes with Deletions

In contrast to DeLSM that relies on file system for space management, WiscKey contains a module of garbage collection to reclaim the space of value log occupied by obsolete data. In the process of garbage collection, WiscKey scans the value

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1BoLT: https://github.com/DICL/BoLT
2PebblesDB: https://github.com/utsaslab/pebblesdb
log and separates valid KV pairs from deleted ones by moving the former to the tail of value log. However, db_bench’s fillseq and fillrandom do not issue any deletion request. Therefore, the garbage collection of WiscKey was never triggered in the standard tests with db_bench. For a fair comparison, we enhanced db_bench with two more workloads that are both with three stages. One is write-delete-write that first randomly writes 1 million KV pairs, each of which is with 16B key and 512B values, then deletes a part of them, and puts 1 million new KV pairs at last. The other one is write-delete-read with the third stage changed to read out all 1 million KV pairs put at the first stage after partial deletions. We varied the percentage of KV pairs deleted at the second stage to be 10%, 30%, 50%, 70%, and 90%. As Figure 5b has presented results with random writes. Figure 6a shows the average execution time for deletions and the second batch of random writes. A deletion is lightweight compared to writing a KV pair with 512B value. However, WiscKey has demanded much longer time than others. For example, with 30% and 70% deletions, the average deletion time of WiscKey is 3.2× and 2.9× that of DeLSM, because WiscKey frequently executed garbage collections to move valid KV pairs and reclaim space. In the subsequent writing of new KV pairs after 30% and 70% deletions, the average write time of WiscKey is 1.5× and 2.7× that of DeLSM, respectively. During the third stage, WiscKey was still doing garbage collections. With more KV pairs deleted in the second stage (30% to 70%), it should encounter more obsolete data and perform more extra I/Os for garbage collection. This explains why WiscKey is interestingly slower than DeLSM in the latter two stages of deleting and writing KV pairs and the performance gap between them becomes wider with more KV pairs deleted.

In addition, for DeLSM, deletions need file system to do with dentries and inodes. Such cost, albeit being little, impairs performance, especially considering LevelDB-like LSM-tree variants only put a key with a deletion tag. Such is the reason why the average deletion time of DeLSM is longer than some LSM-tree variants.

5.2.3 Write Amplifications

The primary target of DeLSM is to reduce performance penalties caused by write amplifications. To make a quantitative analysis of the aforementioned write performances, we have collected the actual write I/Os through iotop\(^3\) when running write-delete-workloads. Table 2 captures the amplification factors of actual data size committed to disk against data size that users issued with six LSM-tree variants. Firstly, the results of writing 10 million KV pairs, deleting half of them, and then writing new 10 million KV pairs align with the observations of write performances we have discussed in Section 5.2.1 and Section 5.2.2. For example, with 4KB values written in the first stage, DeLSM writes 2.4× data to disk, including log entries, data and metadata (inodes and dentries) for KV files, and manifest records. However, compared to other LSM-tree variants except WiscKey, such an amplification factor is much lower as they caused 12.3× to 18.7× write I/Os, particularly due to redeploying KV pairs in compactions. These numbers endorse why DeLSM is superior in write performances and in turn justify the soundness of DeLSM that leverages file system’s directory management to

\(^3\)https://www.man7.org/linux/man-pages/man8/iotop.8.html
avoid moves of KV pairs. In the meantime, WiscKey incurred 1.5× write I/Os in putting down 10 million KV pairs with 4KB values, 37.5% fewer than that of DeLSM. This margin and the speed mismatch between WiscKey’s sequential writes and DeLSM’s random writes justify their performance gap (52.0%) reported in Section 5.2.1.

When handling deletions and subsequent write requests, however, the module of garbage collection would badly move valid KV pairs for WiscKey, which amplified the write I/Os by as much as 1,471.6× and 42.3×, respectively, with 4KB values. These two are much higher than those factors of other LSM-tree variants. Nonetheless, because WiscKey manages the space of value log by itself, the functionality of space recycling and defragmentation is essential but costly. Comparatively, DeLSM embraces higher flexibility and efficacy as it delegates the underlying file system to manage the space allocation and deallocation for SST directories and KV files.

To summarize the tests for write performance, like all scientific designs, DeLSM is greatly effectual for some workloads but not very well for some others. It drastically outperforms LevelDB-like LSM-tree variants that move actual KV pairs for compactions with much fewer disk I/Os. As to DeLSM and WiscKey that also does not move actual KV pairs, they both exhibit respective strengths and weaknesses in serving different workloads while DeLSM is more flexible without application-level space management.

### 5.2.4 Read Performance

Figure 5c and Figure 5d show the read performances of six LSM-tree variants with readseq (sequential reads) and readrandom (random reads), respectively. Note that the Y axes of these three diagrams are not in logarithmic scale. From them we can observe that 1) for sequential reads that resemble range queries, DeLSM achieves comparable or even faster performance compared to other LSM-tree variants, especially with smaller values, and 2) for random reads that emulate point searches, DeLSM is generally faster than the most of other LSM-tree variants. With sequential reads, DeLSM is inferior as its values are stored in separate files and cannot efficiently generates sequential accesses onto disk drive. As to random reads, however, the meta file and the dentry management of file system enable DeLSM to quickly locate a KV file. For instance, with readrandom and 1KB values, the performance of DeLSM is 2.8× that of LevelDB.

### 6 Related Works

Researchers have considered how to reduce I/O amplifications caused by compactions within LSM-trees [8–15, 18–21, 23, 24, 36]. However, their designs mainly followed the conventional way of grouping multiple KV pairs in one integral SST file. Shetty et al. [37] proposed VT-Tree that attempts to reduce disk reads and writes by merging sorted segments of non-overlapping levels in the tree. Similarly, Wu et al. [8] proposed LST-trie that uses a trie (prefix tree) to organize KV pairs in an LSM-tree and compact SST files without overlapping keys. Both of them still move excessive KV pairs in a compaction. Balmau et al. [10] and Huang et al. [23] considered how to separate hot and cold data so as to reduce frequently moving KV pairs caused by hot ones in a compaction. The aforementioned PebblesDB [13] fragments an SST file into fine-grained pieces and appends such pieces to the next level during a compaction. In spite of writing KV pairs to a level only once, the move of KV pairs is inevitable. DeLSM, nonetheless, redeployed dentrys pointing to KV pairs (files) in compactions, thereby gaining high efficiency. Also, DeLSM does not employ complex structures to index or separate data, but relies on the underlying file system.

DeLSM can also be viewed as an approach that leverages file system to accelerate LSM-trees, which is a stark contrast to research works that use databases, especially LSM-trees, to augment and accelerate local or distributed file systems [14, 37–44]. For example, Shetty et al. [37] utilized the aforesaid VT-Tree to build KVFS that translates an access request to one or more KV operations for VT-Tree to process. Ren, Gibson, and their collaborators successively developed TableFS, IndexFS, and SlimDB that make use of LSM-tree and compact SST files without overlapping keys. Both of them still move excessive KV pairs in a compaction. Balmau et al. [10] and Huang et al. [23] considered how to separate hot and cold data so as to reduce frequently moving KV pairs caused by hot ones in a compaction. The aforementioned PebblesDB [13] fragments an SST file into fine-grained pieces and appends such pieces to the next level during a compaction. In spite of writing KV pairs to a level only once, the move of KV pairs is inevitable. DeLSM, nonetheless, redeployed dentrys pointing to KV pairs (files) in compactions, thereby gaining high efficiency. Also, DeLSM does not employ complex structures to index or separate data, but relies on the underlying file system.

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DeLSM is a generic, software-only solution while there are LSM-tree variants that have either taken into account the characteristics of storage devices or made use of specific hardware supports [6, 9, 15, 16, 18–20, 45, 46]. The emergence of SSDs

| LSM-trees | 16B Key, 512B Value | Overall | 16B Key, 4KB Value | Overall |
|-----------|-------------------|---------|-------------------|---------|
| LevelDB   | 11.8× 8.1× 12.6× 12.1× 15.8× 20.1× 17.0× 16.5× |         |                   |         |
| BoLT      | 12.6× 10.6× 13.7× 13.1× 16.3× 50.6× 17.6× 17.0× |         |                   |         |
| WiscKey   | 1.2× 185.6× 35.9× 210.0× 1.5× 1471.6× 42.3× 24.7× |         |                   |         |
| LDS       | 12.7× 11.5× 13.0× 12.8× 18.7× 68.1× 20.0× 19.5× |         |                   |         |
| PebblesDB | 8.0× 8.8× 7.9× 8.0× 12.3× 52.5× 12.0× 12.3× |         |                   |         |
| DeLSM     | 2.5× 18.5× 2.9× 3.0× 2.4× 20.0× 2.6× 2.5× |         |                   |         |

Table 2: The Write Amplifications of LSM-tree Variants with Write (10 million)–Delete (50%)–Write (10 million) Workloads
motivated the designs of SSD-conscious LSM-trees, such as WiscKey [9], FlashKV [15], and LDC [18]. Using KV-store in turn to redesign SSDs was also exploited [47–50]. Meanwhile, Yao et al. [12,21] developed LSM-trees for the Shingled Magnetic Recording (SMR) disk drives while Kannan et al. [6], Kaiyrakhmet et al. [51], and Yao et al. [46] devised LSM-tree variants with byte-addressable non-volatile memories (NVM). Reducing the CPU overheads for LSM-tree [45] and transfiguring LSM-tree into in-memory database [17] were considered as well. Recent studies [19,20] sought aid from FPGA for hardware supports to accelerate compactions. Comparatively, the idea of DeLSM is more portable and applicable.

7 Conclusion

We revisit LSM-tree and attempt to reduce performance penalties caused by major compactions through making a KV pair into an individual KV file, no longer a component of one large SST file. As a result, we transform a compaction of physically moving actual KV pairs into a series of lightweight dentry operations that link and unlink KV files. This is the essence of DeLSM proposed in this paper. Preliminary experiments confirm that a prototype of DeLSM significantly outperforms LevelDB, one that the prototype has been built on, by up to 18.9 × and 2.8 × on write and read performances, respectively. DeLSM also shows superior performance compared against state-of-the-art LSM-tree variants in different dimensions. Currently we are working on the optimization of DeLSM and conducting furthermore tests.

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