LSM-based Storage Techniques: A Survey

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Abstract In recent years, Log-Structured Merge-trees (LSM-trees) have been widely adopted for use in the storage layer of modern NoSQL systems. Because of this, there have been a large number of research efforts, from both the database community and the systems community, that try to improve various aspects of LSM-trees. In this paper, we provide a survey of recent LSM efforts so that readers can learn the state of the art in LSM-based storage techniques. We provide a general taxonomy to classify the literature of LSM improvements, survey the efforts in detail, and discuss their strengths and trade-offs. We further survey several representative LSM-based open-source NoSQL systems and we discuss some potential future research directions resulting from the survey.

Keywords LSM · NoSQL · Storage Management · Indexing

1 Introduction

The Log-Structured Merge-tree (LSM-tree) has been widely adopted in the storage layers of modern NoSQL systems, including BigTable [19], Dynamo [24], HBase [3], Cassandra [1], LevelDB [4], RocksDB [6], and AsterixDB [10]. Different from traditional index structures that apply in-place updates, the LSM-tree first buffers all writes in memory and subsequently flushes and merges them using sequential I/Os. This design brings a number of advantages, including superior write performance, high space utilization, tunability, and simplification of concurrency control and recovery. For example, its high space utilization, due to the fact that on-disk data can be stored fully compacted, was the main motivation for Facebook to widely adopt LSM-based storage [25]. LSM-based storage engines have greatly improved SSD utilization, thus lowering the storage cost, compared to traditional B-tree-based storage engines where leaf pages are typically just 2/3 full on average [74].

A key advantage of the LSM-tree is that it is a highly tunable structure. Its inherent merge operations continuously reorganize data to improve storage and query efficiency, with theoretical bounds on write performance, query performance, and space utilization. This versatility enables the LSM-tree to serve a large variety of workloads. As reported by Facebook [25], RocksDB, an LSM-based key-value store engine, has been used for real-time data processing [21], graph processing [2], stream processing [21], and OLTP workloads [5].

Due to the popularity of LSM-trees among today’s data stores, a large number of proposed LSM improvements have come from the research community; these have come from both the database and operating systems communities. In this paper, we survey these recent LSM improvements, ranging from key-value store settings with a single LSM-tree to more general database settings with secondary indexes. This paper aims to serve as a guide to the state of the art in LSM-based storage techniques for researchers, practitioners, and users. We first provide a general taxonomy to classify the existing LSM improvements based on the specific aspects that they attempt to optimize. We then present the various improvements in detail and discuss their strengths and trade-offs. To reflect how LSM-trees are being used in real systems, we further survey five representative LSM-based NoSQL open-source systems, including LevelDB [4], RocksDB [6], HBase [3], Cassandra [1], and AsterixDB [9]. Finally, we also identify several interesting future research
directions through categorizing and reviewing the existing LSM improvements.

The reminder of this paper is organized as follows. Section 2 briefly reviews the history of LSM-trees and presents the basics of today’s LSM-tree implementations. Section 3 presents a taxonomy of the proposed LSM improvements and surveys the existing work using that framework. Section 4 surveys some representative LSM-based NoSQL systems, focusing on their storage layers. Section 5 reflects on the results of this survey, identifying several outages and opportunities for future work on LSM-based storage systems. Finally, Section 6 concludes the paper.

2 LSM Basics

In this section, we present the background of LSM-trees. We first briefly review the history of work on LSM-trees. We then discuss in detail the basic structure of LSM-trees as used in today’s storage systems. We also provide an analysis of the cost complexity of writes, queries, and space utilization of LSM-trees.

2.1 History of LSM-trees

In general, a database storage engine can choose one of two strategies to handle updates, that is, in-place updates and out-of-place updates. An in-place update structure, such as a B∗-tree, directly overwrites old records to store new updates. For example in Figure 1a, to update the value associated with key k1 from v1 to v4, the index entry (k1, v1) is directly modified to apply this update. These structures are often read-optimized since only the most recent version of each record is stored. However, this design sacrifices write performance, as updates incur random I/Os. Moreover, disk pages can be fragmented by updates and deletes, reducing the storage system’s space utilization.

In contrast, an out-of-place update structure, such as an LSM-tree, always stores updates into new locations instead of overwriting old records. For example in Figure 1b, the update (k1, v4) is stored into a new structure instead of updating the old entry (k1, v1) directly. This design improves write performance since it can exploit sequential I/Os to handle writes. It can also simplify the recovery process by not overwriting old data. However, the major problem of this design is that read performance is sacrificed since a record may be stored in any of multiple locations. Furthermore, these structures generally require a separate data reorganization process to improve storage and query efficiency continuously.

The idea of sequential, out-of-place updates is not new; it has been successfully applied to database systems since the 1970s. Differential files [60], presented in 1976, were an early example of an out-of-place update structure. In this design, all updates are first applied to a differential file, which is merged with the main file periodically. Later, in the 1980s, the Postgres project [62] pioneered the idea of log-structured database storage. Postgres appended all writes into a sequential log, enabling fast recovery and “time-travel” queries. It used a background process called the vacuum cleaner to continuously garbage-collect obsolete records from the log. Similar ideas have been adopted by the file system community to fully utilize disk write bandwidth, such as in the Log-Structured File System (LFS) [57].

Prior to the LSM-tree, the approaches to log-structured storage suffered from several key problems. First and foremost, storing data into append-only logs leads to low query performance, as related records are scattered across the log. Another problem is low space utilization due to obsolete records that have not yet been removed. Even though various data reorganized processes were designed, there was no principled cost model to analyze the trade-offs among the write cost, read cost, and space utilization, which made early log-structured storage hard to tune; the data reorganization processes could easily become a serious performance bottleneck [59].

The LSM-tree [50], proposed in 1996, addressed these problems by designing a merge process which is integrated into the structure itself, providing high write performance with bounded query performance and space utilization. The original LSM-tree design contains a sequence of components C0, C1,  · · · , Ck, as shown in Figure 2. Each component is structured as a B∗-tree. C0 resides in memory and serves incoming writes, while all remaining components C1,  · · · , Ck reside on disk. When Ck is full, a rolling merge process is triggered to merge a range of leaf pages from Ck into Ck+1.

![Fig. 2: Original LSM-tree Design](image-url)
This design is often referred to as the leveling merge policy\textsuperscript{1,2,3} today. However, as we shall see later, the originally proposed rolling merge process is not used by today's LSM implementations because of its implementation complexity. The original LSM paper showed that under a stable workload, where the number of levels remains static, write performance is optimized when the size ratios $T_i = \frac{|C_{i+1}|}{|C_i|}$ between all adjacent components are the same. This principle has impacted all subsequent LSM implementations and the proposed improvements.

In parallel to the LSM-tree, Jagadish et al.\textsuperscript{4} proposed a similar structure with the stepped-merge policy to achieve even better write performance than the original LSM-tree design. This policy organizes the LSM components into levels, and when level $L$ is full with $T$ components, these $T$ components are merged together into a new component at level $L + 1$. This design becomes the tiering merge policy\textsuperscript{2,3} used in today's LSM implementations.

### 2.2 Today's LSM-trees

#### 2.2.1 Basic Structure

Today's LSM implementations still use the same design of first buffering writes in memory to eliminate random I/Os. All incoming writings are appended into a memory component. An insert or update operation simply adds a new entry, while a delete operation adds an anti-matter entry indicating that a key has been deleted. Different from the original LSM-tree design\textsuperscript{50}, however, today's LSM implementations exploit the immutability of disk component\textsuperscript{4} to simplify concurrency control and recovery. Multiple disk components are merged\textsuperscript{2} together into a new one without modifying existing components.

Internally, an LSM component can actually be any index structure. Today's LSM-based key-value stores typically organize their memory component using a concurrent data structure such as a skip-list or a B$^+$-tree, while they organize their disk components using B$^+$-trees or sorted-string tables (SSTables). An SSTable contains a list of data blocks and an index block; a data block stores key-value pairs ordered by keys, and an index block stores key ranges of all data blocks.

A query over an LSM-tree has to search multiple components to perform reconciliation, that is, to find the latest version of each key. A point lookup query, which fetches the value for a specific key, can simply search all components one by one, from newest to oldest, and stop immediately after the first match is found. A range query can search all components at the same time, feeding the search results into a priority queue to perform reconciliation.

As disk components accumulate over time, LSM query performance tends to degrade since more components must be examined. To address this, disk components are gradually merged to reduce the total number of components. Two types of merge policies are typically used in practice\textsuperscript{22,23}. As shown in Figure\textsuperscript{3}, both policies organize disk components into logical levels and are controlled by a size ratio $T$. In the leveling merge policy (Figure\textsuperscript{3a}), each level only maintains one component, but the component at level $L$ is $T$ times larger than the component at level $L - 1$. As a result, the component at level $L$ will be merged multiple times with incoming components at level $L - 1$ until it fills up, and it will then be merged into level $L + 1$. For example in the figure, the component at level 0 is merged with the component at level 1, which will result in a bigger component at level 1. In contrast, the tiering merge policy (Figure\textsuperscript{3b}) maintains up to $T$ components per level. When level $L$ is full, its $T$ components are merged together into a new component at level $L + 1$. In the figure, the two components at level 0 are merged together to form a new component at level 1. It should be noted that if level $L$ is already the configured maximum level, then the resulting component remains at level $L$. In practice, for a stable workload where the volume of inserts equals the volume of deletes, the total number of levels remains static\textsuperscript{21}. In general, the leveling merge policy optimizes for query performance since there are fewer components to search in the LSM-tree. The tiering merge policy is more write optimized since it reduces the merge frequency. We will discuss the performance of these two merge policies further in Section\textsuperscript{2.3}.

#### 2.2.2 Some Well-Known Optimizations

There are two well-known optimizations that are used by most LSM implementations today.

**Bloom Filter.** A Bloom filter\textsuperscript{16} is a space-efficient probabilistic data structure designed to aid in answering membership queries. It supports two operations, that is, inserting a key and testing the membership of a given key. To insert a key, it applies multiple hash functions to map the key into multiple locations in a bit vector and sets the bits at these locations to 1. To check the existence of a given key, the key again is hashed to multiple locations. If all of the bits are 1, then the Bloom filter reports that the key probably exists. By design, the Bloom filter can report false positives but not false negatives.

\textsuperscript{1} Also referred to as runs in the literature.

\textsuperscript{2} Also referred to as compaction in the literature.

\textsuperscript{3} Even for an append-mostly workload, the total number of levels will grow extremely slowly since the maximum number of entries that an LSM-tree can store increases exponentially with a factor of $T$ as the number of levels increases.
Bloom filters can be built on top of LSM disk components to greatly improve point lookup performance. To search a disk component, a point lookup query can first check its Bloom filter and then proceed to search its B^+ -tree only if its associated the Bloom filter reports a positive answer. Alternatively, a Bloom filter can be built for each leaf page of a disk component. In this design, a point lookup query can first search the non-leaf pages of a B^+ -tree to locate the leaf page, where the non-leaf pages are assumed to be small enough to be cached, and then check the associated Bloom filter before fetching the leaf page to reduce disk I/Os. Note that the false positives reported by a Bloom filter do not impact the correctness of a query, but a query may waste some I/O searching for non-existent keys. The false positive rate of a Bloom filter can be computed as \(1 - e^{-kn/m}\), where \(k\) is the number of hash functions, \(n\) is the number of keys, and \(m\) is the total number of bits [16]. Furthermore, the optimal number of hash functions that minimizes the false positive rate is \(k = \frac{n}{\ln 2}\). In practice, most systems typically use 10 bits/key as a default configuration, which gives a 1% false positive rate. Since Bloom filters are very small and can often be cached in memory, the number of disk I/Os for point lookups is greatly reduced by their use.

**Partitioning.** Another commonly adopted optimization is to range-partition LSM disk components into multiple (usually fixed-size) small components. This optimization has several advantages. First, partitioning breaks a large component merge operation into multiple smaller ones, bounding the processing time of each merge operation as well as the temporary disk space needed to store new components. Moreover, partitioning can optimize for workloads with sequentially created keys or skewed updates by only merging components with overlapping key ranges. For sequentially created keys, essentially no merge is performed since there are no components with overlapping key ranges. For skewed updates, the merge frequency of the components with cold update ranges can be greatly reduced. It should be noted that the original LSM-tree [50] automatically takes advantage of partitioning because of its rolling merges. However, due to the implementation complexity of its rolling merges, today’s LSM implementations typically opt for actual physical partitioning rather than rolling merges.

An early proposal that applied partitioning to LSM-trees is the partitioned exponential file (PE-file) [55]. A PE-file contains multiple partitions, where each partition can be logically viewed as a separate LSM-tree. A partition can be further split into two partitions when it becomes too large. This design enforced strict key range boundaries among partitions, which reduced the flexibility of scheduling merges.

We now discuss the partitioning optimizations used in today’s LSM implementations. To minimize the potential confusion caused by different terminologies, throughout the rest of the paper we will use the term component to denote an unpartitioned LSM component and the term SSTable to denote a partition of a partitioned LSM component. Based on this terminology, a component can be range-partitioned into many SSTables. Note that the partitioning idea is orthogonal to merge policies; both leveling and tiering (as well as other emerging merge policies) can be adapted to incorporate partitioning. However, to the best of our knowledge, only the partitioned leveling policy has actually been implemented by industrial LSM-based storage systems, such as LevelDB [4] and RocksDB [6]. Some recent papers [12, 47, 55, 73, 76] have proposed various forms of a partitioned tiering merge policy to achieve better write performance.

In the partitioned leveling merge policy, pioneered by LevelDB [4], the disk component at each level is range-partitioned into multiple fixed-size SSTables, as shown in Figure [4]. Each SSTable is further labeled with its key range in the figure. Note that the disk components at level 0 are not partitioned since they are directly flushed from memory. This design can also help the system to absorb write bursts.
since it can tolerate multiple unpartitioned components at level 0. To merge an SSTable from level \( L \) into level \( L + 1 \), all of its overlapping SSTables at level \( L + 1 \) are selected, and these SSTables are merged with it to produce new SSTables still at level \( L + 1 \). For example in the figure, the SSTable labeled 0-30 at level 1 is merged with SSTables labeled 0-15 and 16-32 at level 2. This merge operation produces new SSTables labeled 0-10, 11-19, and 20-32 at level 2, and the old SSTables will then be garbage-collected. Different policies can be used to select which SSTable to merge next at each level. For example, LevelDB uses a round-robin policy (to minimize the total write cost).

The partitioning optimization can be applied to the tiering merge policy as well. However, one major issue in doing so is that each level can then contain multiple SSTables with overlapping key ranges that must be ordered properly based on their recency to ensure correctness. Two possible schemes can be used to organize the SSTables at each level, namely vertical grouping and horizontal grouping. In both schemes, SSTables at each level are organized into groups. The vertical grouping scheme groups SSTables with overlapping key ranges together so that the groups have disjoint key ranges. Thus, it can be viewed as an extension of the partitioned leveling merge policy to support tiering. Under the horizontal grouping scheme, each logical disk component, which is range-partitioned into a set of SSTables, serves as a group directly. This allows a disk component to be formed incrementally based on the unit of SSTables. We will discuss these two schemes in detail below.

An example of the vertical grouping scheme is shown in Figure 5a. In this scheme, SSTables with overlapping key ranges are grouped together so that the groups have disjoint key ranges. During a merge operation, all of the SSTables in a group are merged together to produce the resulting SSTables based on the key ranges of the overlapping groups at the next level, which are then added to these overlapping groups. For example in the figure, SSTables labeled 0-30 and 0-31 at level 1 are merged together to produce SSTables labeled 0-12 and 17-31, which are then added to the overlapping groups at level 2. Note the difference between the SSTables before and after this merge operation. Before the merge operation, SSTables labeled 0-30 and 0-31 have overlapping key ranges and both must be examined together by a query. However, after the merge operation, SSTables labeled 0-12 and 17-31 have disjoint key ranges and only one of them needs to be examined. It should also be noted that under this scheme SSTables are no longer strictly fixed-size since they are produced based on the key ranges of the overlapping groups at the next level instead of based on their sizes.

Figure 5b shows an example of the horizontal grouping scheme. In this scheme, each component, which is range-partitioned into a set of fixed-size SSTables, serves as a logical group directly. Each level \( L \) further maintains an active group, which is also the first group, to receive new SSTables merged from the previous level. This active group can be viewed as a partial component being formed by merging the components at level \( L-1 \) in the unpartitioned case. A merge operation selects the SSTables with overlapping key ranges from all of the groups at a level, and the resulting SSTables are added to the active group at the next level. For example in the figure, SSTables labeled 35-70 and 35-65 at level 1 are merged together, and the resulting SSTables labeled 35-52 and 53-70 are added to the first group at level 2. However, although SSTables are fixed-size under the horizontal grouping scheme, it is still possible that one SSTable from a group may overlap a large number of SSTables in the remaining groups, causing potentially unbounded processing time for merges.

| Level | SSTable | Merging SSTable | New SSTable | SSTable Group |
|-------|---------|----------------|-------------|--------------|
| 0     | 0-100   | 0-100          |             |              |
| 1     | 0-20    | 0-20           | 0-20        |              |
| 2     | 0-10    | 0-10           | 0-10        |              |
| 0     | 16-32   | 16-32          | 16-32       |              |
| 1     | 34-72   | 34-72          | 34-72       |              |
| 2     | 100-200 | 100-200        | 100-200     |              |
| 1     | 74-100  | 74-100         | 74-100      |              |
| 0     | 75-95   | 75-95          | 75-95       |              |
| 1     | 95-75   | 95-75          | 95-75       |              |
| 2     | 100-95  | 100-95         | 100-95      |              |

Fig. 5: Partitioned Tiering Merge Policy
2.2.3 Concurrency Control and Recovery

We now briefly discuss the concurrency control and recovery techniques used by today’s LSM implementations. The immutability of LSM disk components greatly simplifies the concurrency control and recovery of LSM-trees. For concurrency control, an LSM-tree needs to handle concurrent reads and writes and to take care of concurrent flush and merge operations. Ensuring correctness for concurrent reads and writes is a general requirement for access methods in a database system. Depending on the transactional isolation requirement, today’s LSM implementations either use a locking scheme [9] or a multi-version scheme [1,3,6]. A multi-version scheme works well with LSM since LSM itself can store multiple versions of a key, which are naturally garbage-collected during merges. Concurrent flush and merge operations, however, are unique to LSM. These operations modify the metadata of an LSM-tree, e.g., the list of active components. Thus, accesses to the component metadata must be properly synchronized. To prevent a component in use from being deleted, each LSM component can maintain a reference counter. Before accessing the components of an LSM-tree, a query can first obtain a snapshot of active components and increment their in-use counters.

Since all writes are appended first into memory, write-ahead logging (WAL) can be performed to ensure their durability. To simplify the recovery process, existing systems typically employ a no-steal buffer management policy. That is, a memory component can only be flushed when all active write transactions have terminated. During recovery for an LSM-tree, the transaction log is replayed to redo all successful transactions, but no undo is needed due to the no-steal policy. Meanwhile, the list of active disk components must also be recovered in the event of a crash. For unpartitioned LSM-trees, this can be accomplished by adding a pair of timestamps to each disk component that indicate the range of timestamps of the stored entries. This timestamp can be simply generated using local wall-clock time or a monotonic sequence number. To reconstruct the component list, the recovery process can simply find all components with disjoint timestamps. In the event that multiple components have overlapping timestamps, the component with the largest timestamp range is chosen and the rest can simply be deleted since they have been merged to form the selected component. For partitioned LSM-trees, this timestamp-based approach does not work anymore since each component is further range-partitioned. To address this, a typical approach, used in LevelDB [4] and RocksDB [6], is to maintain a separate metadata log to store all changes to the structural metadata, such as adding or deleting SSTables. The state of the LSM-tree structure can then be reconstructed by replaying the metadata log during recovery.

2.3 Cost Analysis

To help understand the performance trade-offs of an LSM-tree, we can turn to the cost analysis of writes, point lookup queries, range queries, and space amplification presented in [22,23]. The cost of writes and queries can be measured by counting the number of disk I/Os per operation. The analysis shown here will consider an unpartitioned LSM-tree and thus represents a worst-case cost.

Let the size ratio of a given LSM-tree be $T$, and suppose the LSM-tree contains $L$ levels. In practice, for a stable LSM-tree where the volume of inserts equals the volume of deletes (updates), $L$ remains static. Let $B$ denote the page size, that is, the number of entries that each data page can store, and let $P$ denote the number of pages of a memory component. As a result, a memory component will contain at most $B \cdot P$ entries, and level $i$ will contain at most $T^{i-1} \cdot B \cdot P$ entries. Given $N$ total entries, the largest level contains approximately $N \cdot \frac{T^{L-1}}{T} \cdot P$ entries since it is $T$ times larger than the previous level. Thus, the total number of levels for $N$ entries can be approximated as $L = \left\lceil \frac{\log_T N}{\log_T T} \right\rceil$. The write cost, which is also referred to as write amplification in the literature, measures the amortized I/O cost of inserting an entry into an LSM-tree. It should be noted that this cost measures the overall I/O cost for this entry to be merged into the largest level since inserting an entry into memory does not incur any disk I/O. For leveling, a component at each level will be merged $T - 1$ times until it fills up and is pushed to the next level. When the $i^{th}$ ($1 \leq i \leq T$) component arrives at level $L$, it will be merged with the existing component at level $L$, which contains the entries that arrived with the previous $i - 1$ components. As a result, each entry will be merged (written) on average $T/2$ times at level $L$. For tiering, on the other hand, multiple components at each level are merged only once and are pushed to the next level directly. Since each disk page contains $B$ entries, the write cost for each entry will be $O(T \cdot \frac{L}{B})$ for leveling and $O(\frac{L}{P})$ for tiering.

The I/O cost of a query depends on the number of components in an LSM-tree. Without Bloom filters, the I/O cost for a point lookup will be $O(L)$ for leveling and $O(T \cdot L)$ for tiering. However, Bloom filters can greatly improve the point lookup cost. For a zero-result point lookup, i.e., a search for a non-existent key, all disk I/Os are caused by Bloom filter false positives. Suppose all Bloom filters have $M$ bits in total and have the same false positive rate across all levels. With $N$ total keys, each Bloom filter has a false positive rate of $O(e^{-\frac{N}{M}})$ [16]. Thus, the I/O cost of a zero-result point lookup will be $O(L \cdot e^{-\frac{N}{M}})$ for leveling and $O(T \cdot L \cdot e^{-\frac{N}{M}})$ for tiering. To search for an existing unique key, at least one I/O must be performed to fetch the entry. Given that in practice the Bloom filter false positive rate is much smaller than
1, the successful point lookup I/O cost for both leveling and tiering will be $O(1)$.

For a range query, the cost analysis depends on the query selectivity. Let $s$ be the number of unique keys accessed by a range query. A range query can be considered to be long if $\frac{s}{T} > 2\cdot L$, otherwise it is short \cite{22,23}. A key distinction is that the I/O cost of a long range query will be dominated by the largest level since the largest level contains most of the data. In contrast, the I/O cost of a short range query will derive equally from all levels since the query must issue one I/O to each disk component (in the absence of partitioning). Thus, the I/O cost of a long range query will be $O(\frac{s}{T})$ for leveling and $O(T \cdot \frac{s}{T})$ for tiering. For a short range query, the I/O cost will be $O(1)$ for leveling and $O(T)$ for tiering.

Finally, let us examine the space amplification of an LSM-tree, which is defined as the overall number of entries divided by the number of unique entries. It can be computed as $\frac{N}{unq}$, where $N$ is total the number of entries in the LSM-tree and $unq$ is the number of unique entries. For leveling, the worst case occurs when all of the data at the first $L - 1$ levels, which contain approximately $\frac{1}{T}$ of the total data, are updates to the entries at the largest level. Thus, the worst case space amplification for leveling is $O(\frac{L}{T})$. For tiering, the worst case happens when all of the components at the largest level contain exactly the same set of keys. As a result, the worst case space amplification for tiering will be $O(T)$. In practice, the space amplification is an important factor to consider when deploying storage systems \cite{25}, as it directly impacts the storage cost for a given workload.

The cost complexity of LSM is summarized in Table \ref{tab:cost_complexity}. Note how the size ratio $T$ impacts the performance of leveling and tiering differently. In general, leveling is optimized for query performance and space utilization by maintaining one component per level. However, components must be merged more frequently, which will incur a higher write cost by a factor of $T$. In contrast, tiering is optimized for write performance by maintaining up to $T$ components at each level. This, however, will decrease query performance and space utilization by a factor of $T$. As one can see, the LSM-tree is highly tunable structure. For example, by changing the merge policy from leveling to tiering, one can greatly improve write performance with only a small negative impact on point lookup queries due to the Bloom filters. However, range queries and space utilization will be significantly impacted. As we proceed to examine the recent literature on LSM improvements, we will see that each makes certain performance trade-offs. It will be important for the reader to keep in mind the cost complexity described here to better understand the trade-offs being made by the various proposed improvements.

| Merge Policy | Write (Zero-Result/ Non-Zero-Result) | Point Lookup (Zero-Result/ Non-Zero-Result) | Short Range Query | Long Range Query | Space Amplification |
|--------------|-------------------------------------|---------------------------------------------|-------------------|------------------|---------------------|
| Leveling     | $O(T \cdot \frac{1}{T})$          | $O(L \cdot \frac{1}{T}) / O(1)$           | $O(L)$            | $O(T)$           | $O(T)$              |
| Tiering      | $O(\frac{1}{T})$                 | $O(T \cdot L \cdot \frac{1}{T}) / O(1)$   | $O(T \cdot L)$   | $O(T \cdot \frac{1}{T})$ | $O(T)$              |

Table 1: Summary of Cost Complexity of LSM

\[4\] The original analysis presented in \cite{22,23} defines the space amplification to be the overall number of obsolete entries divided by the number of unique entries. We slightly modified the definition to ensure that the space amplification is no less than 1.

\section{3 LSM Improvements}

In this section we present a taxonomy of LSM structural and algorithmic improvements for use in classifying the existing LSM research efforts. We then provide an in-depth survey of the LSM improvement literature that follows the structure of the proposed taxonomy.

### 3.1 A Taxonomy of LSM Improvements

Our taxonomy of various LSM improvements is shown in Figure \ref{fig:taxonomy}. Based on this taxonomy, we can classify the existing LSM improvements in the literature based on the aspects that they attempt to optimize. Here we briefly explain the major categories in our taxonomy.

**Write Amplification.** Even though LSM-trees provide much better write throughput than in-place update structures such as B$^+$.trees, the leveling merge policy adopted by modern key-value stores, such as LevelDB \cite{4} and RocksDB \cite{6}, still incurs relatively high write amplification. This not only decreases write performance, but also reduces the lifespan of SSDs. A large body of research has been conducted to reduce the write amplification of LSM-trees.

**Merge Operations.** Merge operations are critical to the performance of LSM-trees and must therefore be carefully implemented and tuned. Moreover, merge operations can have negative impacts on the system, including buffer cache misses after merges and write stalls during large merges. Several improvements have been proposed to optimize merge operations to address these problems.

**Hardware.** In the recent years, new hardware platforms have presented new opportunities for database systems to achieve better performance. In order to fully exploit the new features provided by new hardware platforms, the basic LSM
implementation should be adapted accordingly. A significant body of research has been devoted to improving LSM-trees on new hardware platforms including large memory, SSD/NVM, multi-core, and direct I/O.

**Special Workloads.** In addition to new hardware, some proposed LSM improvements target special workloads to achieve better performance in those use cases. These special workloads include temporal data, semi-sorted data, small data, and append-most data.

**Auto-Tuning.** The LSM-tree is a highly tunable structure, but it can be generally hard to tune. Auto-tuning techniques, which automatically adopt optimal parameters for a given workload, are a promising approach to alleviate the tuning burden for the end-user. Several auto-tuning techniques have been proposed to tune LSM-trees. Some of the proposed techniques co-tune all parameters of an LSM-tree to achieve maximum performance, while others focus on one specific aspect, such as merge policies, Bloom filters, or data placement.

**Secondary Indexing.** A given LSM-tree only provides a simple key-value interface. To support the efficient processing of queries on non-key attributes, secondary indexes must be maintained. One issue in this area is how to maintain a set of related secondary indexes efficiently with small overhead on write performance. Various LSM-based secondary indexing structures and techniques have been designed and evaluated as well.

Given this taxonomy, Table 2 classifies the LSM improvement literature in terms of each improvement’s primary and secondary concerns. With this taxonomy in hand, we can now proceed to examine each of the improvements in more depth.

### 3.2 Reducing Write Amplification

In this section, we review the improvements in the literature that aim to reduce the write amplification of LSM-trees. Most of these improvements are based on tiering since it has much better write performance than leveling. Other proposed improvements have developed new techniques to perform merge skipping or to exploit data skews.

#### 3.2.1 Tiering

One way to optimize write amplification is to employ the tiering merge policy, since it has much lower write amplification than leveling. The improvements in this category can all be viewed as some variants of the partitioned tiering design with vertical or horizontal grouping discussed in Sections 2.2.2 and 2.2.3. Here we will mainly focus on the modifications made by these improvements.

The WriteBuffer (WB) Tree [12] can be viewed as a variant of the partitioned tiering design with vertical grouping. It has made the following modifications. First, it relies on hash-partitioning to achieve workload balance so that each SSTable group roughly stores the same amount of data. Furthermore, it organizes SSTable groups into a B+-tree-like structure to enable self-balancing to minimize the total number of levels. Specifically, each SSTable group is treated like a node in a B+-tree. When a non-leaf node becomes full with T SSTables, these T SSTables are merged together to form new SSTables that are added into its child nodes. When a leaf node becomes full with T SSTables, it is split into two leaf nodes by merging all of its SSTables into two leaf nodes with smaller key ranges so that each new node receives about T/2 SSTables.

The light-weight compaction tree (LWC-tree) [75, 76] adopts a similar partitioned tiering design with vertical grouping. It further presents a method to achieve workload balance of SSTable groups. Recall that under the vertical grouping scheme SSTables are no longer strictly fixed-size since they are produced based on the key ranges of the overlapping groups at the next level instead of based on their sizes. In the LWC-tree, if a group contains too many entries, it will shrink the key range of this group after the group has been merged (now temporarily empty) and will widen the key ranges of its sibling groups accordingly.

PebblesDB [55] also adopts a partitioned tiering design with vertical grouping. The major difference is that it determines the key ranges of SSTable groups using the idea of guards as inspired by the skip-list [53]. Guards, which are the key ranges of SSTable groups, are selected probabilistically based on inserted keys to achieve workload balance. Once a guard is selected, it is applied lazily during the next
merge. PebblesDB further performs parallel seeks of SSTables to improve range query performance.

dCompaction [51] introduces the concept of virtual SSTables and virtual merges to reduce the merge frequency. A virtual merge operation produces a virtual SSTable that simply points to the input SSTables without performing actual merges. However, since a virtual SSTable points to multiple SSTables with overlapping ranges, query performance will degrade. To address this, dCompaction introduces a threshold based on the number of real SSTables to trigger actual merges. It also lets queries trigger actual merges if a virtual SSTable pointing to too many SSTable is encountered.

| Publication          | Write Amplification | Merge Operations | Hardware | Special Workloads | Auto Tuning | Secondary Indexing |
|----------------------|---------------------|------------------|----------|------------------|-------------|-------------------|
| WB-tree [12]         | ▲                   |                  |          |                  |             |                   |
| LWC-tree [76,75]     | ▲                   | △                |          |                  |             |                   |
| PebblesDB [55]       | ▲                   | △                |          |                  |             |                   |
| dCompaction [51]     | ▲                   | △                |          |                  |             |                   |
| Zhang et al. [79]    | ▲                   | △                |          |                  |             |                   |
| SifrDB [47]          | ▲                   | △                | △        |                  |             |                   |
| Skip-Tree [78]       | ▲                   | △                | △        |                  |             |                   |
| TRIAD [14]           | ▲                   |                  |          |                  |             |                   |
| VT-Tree [61]         | ▲                   |                  |          |                  |             |                   |
| Zhang et al. [81]    | ▲                   | △                | △        |                  |             |                   |
| Ahmad et al. [8]     | ▲                   | △                | △        |                  |             |                   |
| LSbM-tree [63,60]    | ▲                   | △                | △        |                  |             |                   |
| bLSM [53]            | ▲                   | △                | △        |                  |             |                   |
| FloDB [13]           | ▲                   | △                | △        |                  |             |                   |
| Accordion [12]       | ▲                   | △                | △        |                  |             |                   |
| FD-Tree [51]         | ▲                   | △                | △        |                  |             |                   |
| FD+Tree [68]         | ▲                   | △                | △        |                  |             |                   |
| WiscKey [43]         | ▲                   | △                | △        |                  |             |                   |
| HashKV [18]          | ▲                   | △                | △        |                  |             |                   |
| LOCS [71]            | ▲                   | △                | △        |                  |             |                   |
| Kreon [52]           | ▲                   | △                | △        |                  |             |                   |
| NovelSM [56]         | ▲                   | △                | △        |                  |             |                   |
| cLSM [51]            | ▲                   | △                | △        |                  |             |                   |
| LDS [46]             | ▲                   | △                | △        |                  |             |                   |
| NoFTL-KV [70]        | ▲                   | △                | △        |                  |             |                   |
| LHAM [49]            | ▲                   | △                | △        |                  |             |                   |
| LSM-trie [73]        | ▲                   | △                | △        |                  |             |                   |
| SlimDB [59]          | ▲                   | △                | △        |                  |             |                   |
| Mathieu et al. [56]  | ▲                   | △                | △        |                  |             |                   |
| Lim et al. [42]      | ▲                   | △                | △        |                  |             |                   |
| Monkey [23]          | ▲                   | △                | △        |                  |             |                   |
| Dostoevsky [22]      | ▲                   | △                | △        |                  |             |                   |
| Thonangi and Yang [67]| ▲                   | △                | △        |                  |             |                   |
| ElasticBF [80]       | ▲                   | △                | △        |                  |             |                   |
| Mutant [77]          | ▲                   | △                | △        |                  |             |                   |
| LSII [72]            | ▲                   | △                | △        |                  |             |                   |
| Kim et al. [39]      | ▲                   | △                | △        |                  |             |                   |
| LSM Filter [11]      | ▲                   | △                | △        |                  |             |                   |
| Qader et al. [54]    | ▲                   | △                | △        |                  |             |                   |
| Diff-Index [63]      | ▲                   | △                | △        |                  |             |                   |
| DELI [64]            | ▲                   | △                | △        |                  |             |                   |
| Luo and Carey [43]   | ▲                   | △                | △        |                  |             |                   |
| Ildar et al. [7]     | ▲                   | △                | △        |                  |             |                   |
| Joseph et al. [26]   | ▲                   | △                | △        |                  |             |                   |
| Zhu et al. [82]      | ▲                   | △                | △        |                  |             |                   |
| Duan et al. [27]     | ▲                   | △                | △        |                  |             |                   |
during query processing. In general, dCompaction delays a merge operation until multiple SSTables can be merged together, and thus it can also be viewed as a variant of the tiering merge policy.

The partitioned tiering merge design with horizontal grouping has been adopted by Zhang et al. [79] and SifrDB [47]. SifrDB further proposes an early-cleaning technique to reduce space utilization during merges. During a merge operation, SifrDB incrementally activates newly produced SSTables and deactivates the old SSTables. After a page in an input SSTable has been deactivated and is no longer used by any queries, the page is reclaimed immediately to reduce the space usage. SifrDB also exploits I/O parallelism to speedup query performance by searching multiple SSTables in parallel.

All of the improvements in this category, as well as some improvements in the later sections, have claimed that they can greatly improve the write performance of LSM-trees, but their performance evaluations often failed to consider the tunability of LSM-trees. These improvements have mainly been evaluated against a default (untuned) configuration of LevelDB or RocksDB, which use the leveling merge policy with size ratio 10. It is not clear how these improvements would compare against a well-tuned LSM-tree. To address this, one possible solution would be to tune RocksDB to achieve a similar write throughput to the proposed improvements by changing the size ratio or by adopting the tiering merge policy and then evaluating how these improvements can improve query performance and space amplification. Moreover, these improvements have primarily focused on query performance; but space amplification has often been neglected. It would be an interesting experimental study to fully evaluate these improvements against a well-tuned baseline LSM-tree implementation to evaluate their actual usefulness. We also hope that this situation can be avoided in future LSM research by considering the tunability of LSM-trees.

3.2.2 Merge Skipping

The skip-tree [78] proposes a merge skipping idea to reduce the write cost of the leveling merge policy. The observation is that each entry must be merged from level 0 down to the largest level. If some entries can be directly pushed to a higher level by skipping some level-by-level merges, then the total write cost will be reduced. As shown Figure 7 during a merge at level $L$, the skip-tree directly pushes some keys to a mutable buffer at level $L + K$ so that some level-by-level merges can be skipped. Meanwhile, the skipped entries in the mutable buffer will be merged with the SSTables at level $L + K$ during subsequent merges. To ensure correctness, a key from level $L$ can be pushed to level $L + K$ only if this key does not appear in any of the intermediate levels $L + 1, \ldots, L + K - 1$. This condition can be tested efficiently by checking the Bloom filters of the intermediate levels. The skip-tree further performs write-ahead logging to ensure durability of the entries stored in the mutable buffer.

3.2.3 Exploiting Data Skew

TRIAD [14] reduces write amplification for skewed update workloads where certain hot keys are updated frequently. The basic idea is to separate hot keys from cold keys in the memory component so that only cold keys are flushed to disk. As a result, when hot keys are updated, old versions can be discarded directly without writing them to disk. Even though hot keys are not flushed to disk, they are periodically copied to a new transaction log so that the old transaction log can be reclaimed. TRIAD also reduces write amplification by delaying merges at level 0 until level 0 contains multiple SSTables. Finally, it presents an optimization that avoids creating new disk components after flushes. Instead, the transaction log itself is used as a disk component and an index structure is built on top of it to improve lookup performance. However, range query performance will still be negatively impacted since entries are not sorted in the log.

3.3 Optimizing Merge Operations

Next we review some existing work that improves the implementation of merge operations, including improving merge
performance, minimizing buffer cache misses, and eliminating write stalls.

### 3.3.1 Improving Merge Performance

The VT-tree \[61\] presents a stitching operation to improve the performance of merge operations. The basic idea is that when merging multiple SSTables, if the key range of a page from one SSTable does not overlap the key range of any pages from other SSTables, then this page can be simply pointed to by the resulting SSTable without reading and copying it again. Note that stitching can cause fragmentations since pages are no longer continuously stored, which will incur random I/Os for scans. To address this, the VT-tree introduces a stitching threshold \(K\) so that a stitching operation is triggered only when there are at least \(K\) continuous pages from an input SSTable. Moreover, since the keys in stitched pages are not scanned during a merge operation, the Bloom filter cannot be used since building a Bloom filter requires accessing all of the keys. To address this issue, the VT-tree uses quotient filters \[15\] since multiple quotient filters can be combined directly without accessing the original keys.

Zhang et al. \[81\] proposed a pipelined merge implementation to better utilize CPU and I/O parallelisms to improve merge performance. The key observation is that a merge operation contains multiple phases, including the read phase, merge sort phase, and write phase. The read phase reads pages from input SSTables, which will then be merged to produce new pages during the merge sort phase. Finally, the new pages will be written to disk during the write phase. Thus, the read phase and write phase are I/O heavy and the merge sort phase is CPU heavy. To better utilize CPU and I/O parallelisms, the proposed approach pipelined the execution of these three phases, as illustrated by Figure 8. In this example, after the first input page has been read, this approach continues reading the second input page using disk and the first page can be merge sorted using CPU.

### 3.3.2 Reducing Buffer Cache Misses

Merge operations can interfere with the caching behavior of a system. After a new component is enabled, queries may experience a large number of buffer cache misses since the new component has not been cached yet. A simple write-through cache maintenance policy cannot solve this problem. If all of the pages of the new component are cached during a merge operation, a lot of other working pages may be evicted, which will again cause buffer cache misses.

Ahmad et al. \[8\] conducted an experimental study of the impact of merge operations on system performance. They found that merge operations consume a large number of CPU and I/O resources and impose a high overhead on query response times. To address this, this work proposed to offload large merges to remote servers to minimize their impact. After a merge operation is completed, a smart cache warmup algorithm is used to fetch the new component incrementally to minimize buffer cache misses. The idea is to switch to the new component incrementally, chunk by chunk, to smoothly redirect incoming queries from the old components to the new component. As a result, the burst of buffer cache misses is decomposed into a large number of smaller ones, minimizing the negative impact of component switching on query performance.

The Log-Structured buffered Merge tree (LSbM-tree) \[65\] \[66\] proposes an alternative approach to alleviate buffer cache misses after merge operations for the leveling merge policy. As illustrated by Figure 9 after an SSTable at level \(L\) is merged into level \(L + 1\), the old SSTable at level \(L\) is appended to a buffer associated with level \(L + 1\) instead of being deleted immediately. Note that there is no need to add old SSTables at level \(L + 1\) into the buffer, as the SSTables at \(L + 1\) all come from level \(L\) and the entries of these old SSTable will have already been added to the buffer before. The buffered SSTables are searched by queries as well to minimize buffer cache misses. These buffered SSTables are deleted gradually based on their access frequency. This approach does not incur any extra disk I/O during a merge operation since it only delays the deletion of the old SSTables. However, it can introduce extra overhead for queries accessing cold data that are not cached, especially for range queries since they cannot benefit from Bloom filters.
3.3.3 Minimizing Write Stalls

Although the LSM-tree offers a much higher write throughput compared to traditional B\(^+\)-trees, it often exhibits write stalls and unpredictable write latencies since heavy operations such as flushes and merges run in the background. bLSM [58] proposes a spring-and-gear merge scheduler to minimize write stalls for the unpartitioned leveling merge policy. Its basic idea is to tolerate an extra component at each level so that merges at different levels can proceed in parallel. Furthermore, the merge scheduler controls the progress of merge operations to ensure that level \(L\) produces a new component to level \(L+1\) only after the previous merge operation at level \(L+1\) has completed. This eventually cascades to limit the maximum write speed at the memory component and eliminates write stalls. However, bLSM itself has several limitations. First, bLSM was designed for the unpartitioned leveling merge policy. Furthermore, it only bounds the maximum write latency of LSM-trees; the overall write rate can still exhibit large variances since the time to complete a flush or merge operation may vary over time.

3.4 Hardware Opportunities

We now review the LSM improvements proposed for new hardware, including large memory, SSD/NVM, multi-core, and direct I/O. A general paradigm of these improvements is to modify the basic design of LSM-trees to fully exploit the unique features provided by the target hardware platform to achieve better performance.

3.4.1 Large Memory

It is beneficial for LSM-trees to have large memory components to reduce the total number of levels, as this will improve both write performance and query performance. However, managing large memory components brings several new challenges. If a memory component is implemented directly using VM-managed data structures, large memory can result in a large number of objects that led to significant GC overheads. In contrast, if a memory component is implemented using off-heap structures such as a concurrent B\(^+\)-tree, large memory can cause a higher search cost (due to tree height) and cause more CPU cache misses for writes, as a write must first locate its position in the structure.

FloDB [13] presents a two-layer design to manage large LSM memory components. In this design, the top level is a small concurrent hash table to support fast writes and the bottom level is a large skip-list to support range queries efficiently. When the hash table is full, its entries are efficiently migrated into the skip-list using a batched algorithm. By limiting random writes to a small memory area, this design significantly improves the in-memory write throughput. However, one problem is to support range queries since range queries are not supported by hash tables. To address this, FloDB requires that a range query must wait for the hash table to be drained so that the skip-list alone can be searched to answer the query.

Accordion [17] further presents a multi-layer approach to manage large LSM memory components, as shown in Figure 10. In this design, there is a small mutable memory component in the top level to process writes. When the mutable memory component is full, instead of being flushed to disk, it is simply flushed into a (more compact) immutable memory component via an in-memory flush operation. Similarly, immutable memory components can be merged via in-memory merge operations to improve query performance and reclaim space occupied by obsolete entries. Note that in-memory flush and merge operations do not involve any disk I/O, which reduces the overall disk I/O cost by leveraging large memory.

3.4.2 SSD/NVM

Different from traditional hard disks that only support efficient sequential I/Os, new storage devices such as solid-state drives (SSDs) and non-volatile memories (NVMs) support efficient random I/Os as well. NVMs further provide efficient byte-addressable random accesses with persistence guarantees.

The FD-tree [41] uses a similar design to LSM-trees to reduce random writes on SSDs. One major difference is that the FD-tree exploits fractional cascading [20] to improve query performance instead of Bloom filters. For the component at each level, the FD-tree additionally stores fence pointers that point to each page at the next level. For example in Figure 11, the pages at level 2 are pointed by fence pointers with keys 1, 27, 51, 81 at level 1. After performing a binary search at level 0, a query can follow these fence pointers to traverse all of the levels. However, this design introduces additional complexity to merges. When the component at level \(L\) is merged into level \(L+1\), all of the previous levels 0 to \(L-1\) must be merged as well to rebuild the fence pointers. Moreover, a query still needs to perform...
disk I/Os when searching for non-existent keys, which can be mostly avoided by using Bloom filters. For these reasons, modern LSM implementations tend to prefer Bloom filters rather than fractional cascading.

The FD+tree [48] improves the merge process of the FD-tree [41]. In the FD-tree, when a merge happens from level 0 to level L, new components at levels 0 to L must be created, which will temporarily double the disk space. To address this, during a merge operation, the FD+tree incrementally activates the new components and reclaims pages from the old components that are not used by any queries.

WiscKey [43] implements an old idea of separating values from keys [62] to reduce the write amplification of LSM-trees. In WiscKey, as shown in Figure 12, key-value pairs are stored in an append-only log and the LSM-tree simply serves as a primary index that maps each key to its location in the log. While this can greatly reduce the write cost by only merging keys, range query performance will be significantly impacted because values are not sorted anymore. Moreover, the value log must be garbage-collected efficiently to reclaim the storage space. In WiscKey, garbage-collection is performed in three steps. First, WiscKey scans the log tail and validates each entry by performing point lookups against the LSM-tree to find out whether the location of each key has changed or not. Second, valid entries, whose locations have not changed, are then appended to the log and their locations are updated in the LSM-tree as well. Finally, the log tail is truncated to reclaim the storage space. However, this garbage-collection process has been shown to be a new performance bottleneck [13] due to its expensive random point lookups.

HashKV [18] improves the garbage-collection process of WiscKey [43] by eliminating point lookups to the LSM-tree. Its basic idea is to hash-partition into multiple partitions the value log based on keys and each partition is garbage-collected independently. Specifically, to garbage-collect a partition, HashKV performs a group by operation on the keys to find the latest value for each key. Valid key-value pairs are added to a new log and their locations are then updated in the LSM-tree. To further optimize the garbage-collection process, HashKV stores cold entries separately so that they can be garbage-collected less frequently.

LOCS [71] is an LSM implementation on open-channel SSDs. Open-channel SSDs expose internal I/O parallelisms via an interface called channels, where each channel functions independently as a logical disk device. This allows applications to flexibly schedule disk writes to leverage the available I/O parallelism, but disk reads must be served by the same channel where their data is stored. To exploit this feature, LOCS dispatches disk writes due to LSM flushes and merges to all channels using a least-weighted-queue-length policy to balance the total amount of work allocated to each channel. To further improve the I/O parallelism for partitioned LSM-trees, LOCS places SSTables from different levels with similar key ranges into different channels so that these SSTables can be read in parallel.

Kreon [52] aims at reducing the CPU overhead and write amplification of LSM-trees on SSDs at the cost of I/O randomness. To reduce write amplification, Kreon applies the idea of key-value separation as in WiscKey [43]. To improve range query performance, Kreon reorganizes data during query processing by storing the scanned key-value pairs together in a new place. Kreon further exploits memory-mapped I/Os to reduce CPU overhead by avoiding unnecessary data copying. It implements a customized memory-mapped I/O manager in the Linux kernel to control cache replacement and to enable blind writes on unused pages.

NovelSM [35] is an LSM implementation on NVMs. NovelSM adds an NVM-based memory component to serve writes when the DRAM memory component is full so that writes can still proceed without being stalled. It further optimizes write performance of the NVM memory component by skipping logging since NVM itself provides persistence. Finally, it exploits I/O parallelism to search multiple levels concurrently to reduce lookup latency.

3.4.3 Multi-Core

cLSM [31] optimizes for multi-core machines and presents new concurrency control algorithms for various LSM operations. It organizes LSM components into a concurrent linked list to minimize blocking caused by synchronization. Flush and merge operations are carefully designed so that...
they only result in atomic modifications to the linked list that will never block queries. When a memory component becomes full, a new memory component is allocated while the old one will be flushed. To avoid writers inserting into the old memory component, a writer acquires a shared lock before modifications and the flush thread acquires an exclusive lock before flushes. cLSM also supports snapshot scans via multi-versioning and atomic read-modify-write operations using an optimistic concurrency control approach that exploits the fact that all writes, and thus all conflicts, involve the memory component.

3.4.4 Direct I/O

The LSM-tree-based Direct Storage system (LDS) \cite{46} is a direct I/O sub-system exploiting the sequential and aggregated I/O patterns exhibited by LSM operations to improve I/O performance. The on-disk layout of LDS contains three parts: chunks, a version log, and a backup log. Chunks store the disk components of the LSM-tree. The version log stores the metadata changes of the LSM-tree after each flush and merge. For example, a version log record can record the obsolete chunks and new chunks resulting from a merge. The version log is regularly checkpointed to aggregate all changes so that the log can be truncated. Finally, the backup log provides durability for in-memory writes by write-ahead logging.

NoFTL-KV \cite{70} proposes to extract the flash translation layer (FTL) from the storage device into the key-value store to gain direct control over the storage device. Traditionally, the FTL translates the logical block address to the physical block address to implement wear leveling, which improves the lifespan of SSDs by distributing writes evenly to all blocks. NoFTL-KV argues for a number of advantages of extracting FTL, such as pushing tasks down to the storage device, performing more efficient data placement to exploit I/O parallelism, and integrating the garbage-collection process of the storage device with the merge process of LSM-trees to reduce write amplification.

3.5 Handling Special Workloads

We now review some existing LSM improvements that target certain special workloads to achieve better performance, including temporal data, small data, semi-sorted data, and append-mostly data.

The log-structured history access method (LHAM) \cite{49} improves the original LSM-tree to more efficiently support temporal workloads. The key improvement made by LHAM is to attach a range of timestamps to each component to facilitate the processing of temporal queries by pruning irrelevant components. It further guarantees that the timestamp ranges of LSM components are disjoint from one another.

This is accomplished by modifying the rolling merge process to always merge the records with the oldest timestamps from a component \( C_i \) into \( C_{i+1} \).

LSM-trie \cite{73} is an LSM-based hash index for managing a large number of small key-value pairs for fast point lookups. It proposes a number of optimizations to reduce the metadata overhead. LSM-trie adopts a partitioned tiering design to reduce write amplification. Instead of storing the key ranges of each SSTable directly, LSM-trie organizes SSTables using the prefix of their hash values to reduce the metadata overhead, as shown in Figure 13. To further reduce the metadata overhead of each SSTable, LSM-trie eliminates the index page but instead assigns key-value pairs into fixed-size buckets based on their hash values. Overflow key-value pairs are assigned to underflow buckets and this information is recorded in a migration metadata table. LSM-trie also builds a Bloom filter for each bucket. Since there are multiple SSTables in each group at a level, LSM-trie further clusters all Bloom filters of the same logical bucket of these SSTables together so that they can be fetched using a single I/O by a point lookup query.

SlimDB \cite{56} targets semi-sorted data in which each key contains a prefix \( x \) and a suffix \( y \). It supports normal point lookups, given both the prefix and the suffix, as well as retrieving all the key-values pairs sharing the same prefix key \( x \). To reduce write amplification, SlimDB adopts a hybrid structure with tiering on the lower levels and leveling on the higher levels. SlimDB further uses multi-level cuckoo filters \cite{29} to improve point lookup performance for levels that use the tiering merge policy. At each level, a multi-level cuckoo filter maps each key to the ID of the SSTable where the latest version of the key is stored so that only one filter check is needed by a point lookup. To reduce the metadata overhead of SSTables, SlimDB uses a multi-level index structure as follows: It first maps each prefix key into a list of pages that contain this prefix key so that the key-value pairs can be retrieved efficiently given a prefix key. It then stores the range of suffix keys for each page to efficiently support point lookup queries based on both prefix keys and suffix keys.

Mathieu et al. \cite{45} proposed two new merge policies optimized for append-mostly workloads with bounded number
of components. One problem of both leveling and tiering is that the number of levels depends on the total number of entries. Thus, with an append-mostly workload where the amount of data keeps increasing, the total number of levels will be unbounded in order to achieve the write cost described in Section 2.3. To address this, this work studied the theoretical lower bound of the write cost of an online merge policy for an append-mostly workload given at most K components. It further proposed two merge policies MinLatency and Binomial to achieve this lower bound.

3.6 Auto-Tuning

The LSM-tree is highly tunable, but it can be generally very hard to tune. We now review some research efforts to develop auto-tuning techniques for the LSM-tree to reduce the tuning burden for the end-user. Some techniques perform co-tuning of all parameters to find an optimal design, while others focus on some specific aspect such as merge policies, Bloom filters, or data placement.

3.6.1 Parameter Tuning

Lim et al. [42] presented an analytical model that incorporates the key distribution to improve the cost estimation of LSM-tree operations and further used this model to tune the parameters of LSM-trees. The key insight is that the conventional worst-case analysis (Section 2.3) fails to take the key distribution into consideration. If a key is found to be deleted or updated during an early merge, it will not participate in future merges and thus its overall write cost will be reduced. The proposed model assumes a priori knowledge of the key distribution using a probability mass function $f_x(k)$ that measures the probability that a specific key $k$ is written by a write request. Given $p$ total write requests, the number of unique keys is estimated using its expectation as follows

$$Unique(p) = N - \sum_{k \in K} (1 - f_x(k))^p$$

where $N$ is the total number of unique keys and $K$ is the total key space. Based on this formula, the total write cost for $p$ writes can be computed by summing up the cost of all flushes and merges, except that duplicates keys, if any, are excluded from future merges. Finally, the cost model is used to find the optimal system parameters by minimizing the total write cost.

Monkey [23] co-tunes the merge policy, size ratio, memory component size, and Bloom filter size to find an optimal LSM-tree design for a given workload maximizing the overall throughput for a workload that contain both reads and writes. The first contribution of Monkey is to show that the usual Bloom filter memory allocation scheme, which allocates the same number of bits per key for all Bloom filters, results in sub-optimal performance. The intuition is that the $T$ components at the last level, which contain most of the data, consume most of the Bloom filter memory but their Bloom filters can only save at most $T$ disk I/Os for a point lookup. To minimize the overall false positive rates across all of the Bloom filters, Monkey analytically shows that more bits should be allocated to the components at the lower levels so that the Bloom filter false positive rates will be exponentially increasing. Under this scheme, the I/O cost of zero-result point lookup queries will be dominated by the last level, and the new I/O cost becomes $O(e^{-\frac{M}{T}})$ for leveling and $O(T \cdot e^{-\frac{M}{T}})$ for tiering. Monkey then finds an optimal LSM-tree design by maximizing the overall system throughput using a cost model similar to the one in Section 2.3.

3.6.2 Tuning Merge Policies

Dostoevsky [22] shows that the existing merge policies, that is, tiering and leveling, are sub-optimal for certain workloads. The intuition is that for leveling, the cost of zero-result point lookups, long range queries, and space amplification are dominated by the largest level, but the write cost derives equally from all of the levels. To address this, Dostoevsky introduces a lazy-leveling merge policy that performs tiering at the lower levels but leveling at the largest level. Lazy-leveling has much better write cost than leveling, but has similar point lookup cost, long range query cost, and space amplification to leveling. It only has a worse short range query cost than leveling since the number of components is increased. Dostoevsky also proposes a hybrid policy that has at most Z components in the largest level and at most K components at each of the smaller levels, where Z and K are tunable. It then finds an optimal LSM-tree design for a given workload using a similar method as Monkey [23]. It is worth noting that the performance evaluation of Dostoevsky [22] is very thorough; it was performed against well-tuned LSM-trees to show that Dostoevsky strictly dominates the existing LSM-tree designs under certain workloads.

Thonangi and Yang [67] formally studied the impact of partitioning on the write cost of LSM-trees. This work first proposed a ChooseBest policy that always selects an SSTable with the fewest overlapping SSTables at the next level to merge to bound the worst case merge cost. While ChooseBest outperforms the unpartitioned merge policy in terms of the overall write cost, there are certain periods when the unpartitioned merge policy has a lower write cost since the current level becomes empty after a full merge, which reduces the future merge cost. To exploit this advantage of full merges, this work further proposed a mixed merge policy that selectively performs full merges or partitioned merges based on the relative size between adjacent levels and that dynamically learns these size thresholds to minimize the overall write cost for a given workload.
All of the existing LSM implementations, including Monkey \cite{23}, adopt a static scheme to manage Bloom filter memory allocation. That is, once the Bloom filter is created for a component, its false positive rate remains unchanged. Instead, ElasticBF \cite{80} dynamically adjusts the Bloom filter false positive rates based on the data hotness and access frequency to optimize read performance. Given a budget of $k$ Bloom filter bits per key, ElasticBF constructs multiple smaller Bloom filters with $k_1, \ldots, k_n$ bits so that $k_1 + \cdots + k_n = k$. When all of these Bloom filters are used together, they provide the same false positive rate to the original monolithic Bloom filter. ElasticBF then dynamically activates and deactivates these Bloom filters based on the access frequency to minimize the total amount of extra I/O. Their experiments reveal that ElasticBF is most effective when the overall Bloom filter memory is very limited, such as only 4 bits per key on average. In this case, the disk I/Os caused by the Bloom filter false positives will be dominant. When memory is relatively large and can accommodate more bits per key, such as 10, the benefit of ElasticBF becomes very limited since the number of disk I/Os caused by false positives is much smaller than the number of actual disk I/Os to locate the keys.

### 3.6.4 Optimizing Data Placement

Mutant \cite{27} optimizes the data placement of the LSM-tree on cloud storage. Cloud vendors often provide a variety of storage options with different performance characteristics and monetary costs. Given a monetary budget, it can be important to place SSTables on different storage devices properly to maximize system performance. Mutant solves this problem by monitoring the access frequency of each SSTable and finding a subset of SSTables to be placed in fast storage so that the total number of accesses to fast storage is maximized while the number of selected SSTables is bounded. This optimization problem is equivalent to a 0/1 knapsack problem, which is N/P hard, and can be approximated using a greedy algorithm.

### 3.7 Secondary Indexing

So far, we have discussed LSM improvements in a key-value store setting that only contains a single LSM-tree to store key-value pairs. Now we discuss LSM-based secondary indexing techniques to support efficient query processing, including index structures, index maintenance, statistics collection, and distributed indexing.

Before we present these research efforts in detail, we first discuss some basic concepts for LSM-based secondary indexing techniques. In general, an LSM-based storage system will contain a primary index with multiple secondary indexes. The primary index stores the record values indexed by the primary keys. Each secondary index stores the corresponding primary keys for each secondary key using either a composite key approach or a key list approach. In the composite key approach, the index key of a secondary index is the composition of the secondary key and the primary key. In the key list approach, a secondary index associates a list of primary keys with each secondary key. Either way, to process a query using a secondary index, the secondary index is first searched to return a list of matching primary keys, and those are then used to fetch the records from the primary index as necessary. An example of LSM-based secondary indexing is shown in Figure 14. The example User dataset has three fields, namely Id, Name, and Age, where Id is the primary key. The primary index stores full records indexed by Id, while the two secondary indexes store secondary keys, i.e., Name and Age, and their corresponding Ids.

### 3.7.1 Index Structures

The Log-Structured Inverted Index (LSII) \cite{72} is an index structure designed for exact real-time search on microblogs. A query $q$ searches for the top $K$ microblogs with the highest scores, which are computed as the weighted sum of significance, freshness, and relevance. To support efficient query processing, each keyword in a disk component stores three inverted lists of primary keys in descending order of significance, freshness, and frequency, respectively. Storing three inverted lists enables queries to be processed efficiently via the threshold algorithm \cite{29}, which stops query evaluation once the upper bound of the scores of the unseen microblogs is lower than the current top $K$ answers. However, only one inverted list is stored in the memory component since documents in the memory component often have high freshness and most of them will be accessed by queries. Moreover, storing multiple inverted lists will significantly increase the memory component’s write cost.

Kim et al. \cite{39} conducted an experimental study of LSM-based spatial indexes for geo-tagged point data, including
LSM versions of the R-tree [32], Dynamic Hilbert B+-tree (DHB-tree) [40], Dynamic Hilbert Value B+-tree (DHVB-tree) [40], Static Hilbert B+-tree (SHB-tree) [50], and Spatial Inverted File (SIF) [37]. An R-tree is a balanced search tree that stores multi-dimensional spatial data using their minimum bounding rectangles. DHB-trees and DHVB-trees store spatial points directly into B+-trees using spatial curves. SHB-trees and SIFs exploit a grid-based approach by statically decomposing a two-dimensional space into a multi-level grid hierarchy. For each spatial object, the IDs of its overlapping cells are stored. The difference between these two structures is that an SHB-tree stores pairs of cell IDs overlapping cells are stored. The key conclusion was that there is no clear winner among these index structures, but the LSM-based R-tree performs reasonably well for both ingestion and query workloads without requiring too much tuning. Moreover, for non-index-only queries, the final primary key lookup step is generally dominant since it often requires a separate disk I/O for each primary key. This further diminished the differences between these spatial indexing methods.

LSM filters [11] augment each component of the primary and secondary indexes with a filter to enable data pruning based on a filter during query processing. A filter stores the minimum and maximum values of the filter key for the entries in a component. Thus, a component can be pruned by a query if the search condition is disjoint with the minimum and maximum values of its filter. Though a filter can be built on arbitrary fields, it is really only effective for time-correlated fields since components are naturally partitioned based on time and are likely to have disjoint filter ranges. Note that some special care is needed to maintain filters when a key is updated or deleted. In this case, the filter of the memory component must be maintained based on both the old record and the new record so that future queries will not miss new updates. Consider the example in Figure 15 which depicts a filtered primary LSM-tree. After updates the new record (k1, v4, T4), the filter of the memory component becomes [T1, T4] so that future queries will properly see that the old record (k1, v1, T1) in the disk component has been deleted. Otherwise, if the filter of the memory component were only maintained based on the new value T4, which becomes [T3, T4], a query with search condition T ≤ T2 would erroneously prune the memory component and thus see the deleted record (k1, v1, T1).

Qadar et al. [54] conducted an experimental study of LSM-based secondary indexing techniques including filters and secondary indexes. For filters, they evaluated component-level range filters and Bloom filters on secondary keys. For secondary indexes, they evaluated two secondary indexing schemes based on composite keys and key lists. Depending on how the secondary index is maintained, the key list scheme can be further classified as being either eager or lazy. The eager key list scheme always reads the previous list to create a new list with the new entry added and inserts the new list into the memory component. The lazy key list scheme simply maintains multiple partial lists at each component. The experimental results suggest that the eager inverted list scheme incurs a large overhead on data ingestion because of the point lookups and high write amplification. When the query selectivity becomes larger, that is, when the result set contains more entries, the performance difference between the lazy key list scheme and the composite key scheme diminishes, as the final point lookup step becomes dominant. Finally, filters were found to be very effective with small storage overhead for time-correlated workloads. However, the study did not consider cleaning up secondary indexes in the case of updates, which means that secondary indexes could return obsolete primary keys.

### 3.7.2 Index Maintenance

A key challenge of maintaining LSM-based secondary indexes is handling updates. For a primary LSM-tree, an update can blindly add the new entry (with the identical key) into the memory component so that the old entry is automatically deleted. However, this mechanism does not work for a secondary index since a secondary key value can change during an update. Extra work must be performed to clean up obsolete entries from secondary indexes during updates.

Diff-Index [63] presents four index update schemes for LSM-based secondary indexes, namely sync-full, sync-insert, async-simple, and async-session. During an update, two steps must be performed to update a secondary index, namely inserting the new entry and cleaning up the old entry. Inserting the new entry is very efficient for LSM-trees, but cleaning up the old entry is generally expensive since it requires a point lookup to fetch the old record. Sync-full performs these two steps synchronously during ingestion time. It optimizes for query performance since secondary indexes are always up-to-date, but incurs a high overhead during data ingestion because of the point lookups. Sync-insert only inserts new data into secondary indexes, leaving obsolete entries to be cleaned up lazily by queries. Async-simple per-
forms index maintenance asynchronously but guarantees its eventual execution by deferring updates in an asynchronous update queue. Finally, async-session enhances async-simple with session consistency by storing new updates temporarily in a local cache in the client-side. These four index update schemes are summarized in Table 3.

Deferred Lightweight Indexing (DELI) [64] similarly defers the maintenance of LSM-based secondary indexes to avoid the high point lookup cost during data ingestion. The obsolete entries in DELI’s secondary indexes are cleaned up when primary index components are merged. Specifically, when multiple records with the identical keys are encountered while merging primary index components, the obsolete records are used to produce anti-matter entries to clean up the secondary indexes. Meanwhile, since secondary indexes are not always up-to-date, queries must always validate search results by fetching records from the primary index. As a result, DELI cannot support index-only queries since point lookups must be performed for validation.

Luo and Carey [44] presents two strategies for maintaining LSM-based secondary indexes and filters. The key insight is to maintain and exploit a primary key index, which only stores primary keys, to reduce disk I/Os. A validation strategy is proposed to maintain secondary indexes lazily in the background, eliminating the point lookup overhead. Queries must validate the search results from a secondary index for correctness either by fetching records directly from the primary index or by searching the primary key index to ensure that the returned primary keys still have the latest timestamps. Secondary indexes are cleaned up efficiently in the background using the primary key index to avoid accessing full records; the basic idea for cleanup is to search the primary key index to validate whether each secondary index entry still has the latest timestamp, as in query validation. A mutable-bitmap strategy is introduced to efficiently maintain a primary index with filters. It attaches a mutable bitmap to each disk component so that the old records can be directly marked as deleted, thereby avoiding the need to maintain filters based on the old records.

### Table 3: Summary of Index Update Schemes Supported by Diff-Index [63]

| Scheme          | Insert New Entry | Delete Old Entry |
|-----------------|------------------|------------------|
| sync-full       | Sync             | Sync             |
| sync-insert     | Sync             | Lazy (Query)     |
| async-simple    | Lazy             | Lazy (Queued)    |
| async-session   | Lazy             | Lazy (Session Consistency) |

3.7.3 Statistics Collection

Absalyamov et al. [21] proposed a lightweight statistics collection framework for LSM-based systems. The basic idea is to integrate the task of statistics collection into the LSM flush and merge operations to minimize the maintenance overhead. During flush and merge operations, statistical synopses, such as histograms and wavelets, are created on-the-fly and are sent back to the system catalog. Due to the multi-component nature of LSM-trees, the system catalog stores multiple statistics for a dataset. To reduce the overhead during query optimization, mergeable statistics, such as equi-width histograms, are merged beforehand. For statistics that are not mergeable, multiple synopses are kept to improve the accuracy of cardinality estimation.

3.7.4 Distributed Indexing

Joseph et al. [26] described two implementations of distributed secondary indexes on top of HBase [3], namely global secondary indexes and local secondary indexes, based on the two common approaches to indexing data in a parallel database. A global secondary index is implemented as a separate table that stores secondary keys plus their corresponding primary keys, and it is maintained using co-processors provided by HBase (similar to database triggers). This approach is easy to implement, but incurs a higher communication cost during data ingestion since a secondary index partition may be stored at a separate node from the primary index partition. A local secondary index avoids the communication cost during data ingestion by co-locating each secondary index partition together with the corresponding primary index partition. However, the downside for HBase is that this approach must be implemented from scratch. Moreover, all partitions of a local secondary index must be searched, even for highly selective queries, since the local secondary index is partitioned by primary keys.

Zhu [82] introduced an efficient approach for loading global secondary indexes using three steps: First, the primary index at each partition is scanned and sorted to create a local secondary index. Meanwhile, the statistics of the secondary key are collected to facilitate the next step. Second, based on the collected statistics from the first stage, the index entries of the secondary index will be range-partitioned and these partitions will be assigned to physical nodes. Finally, based on the assigned secondary key range, each node fetches secondary keys and their primary keys from all other nodes, which can be done efficiently by scanning the local secondary index built in the first stage.

Duan et al. [27] proposed a lazy maintenance approach for materialized views on distributed LSM-trees. The basic idea is to append new updates into a delta list of the materialized view to reduce the overhead during data ingestion. The
changes in the delta list are then applied to the materialized view lazily, during query processing.

4 Representative LSM-based Systems

After discussing the LSM improvements in detail, we now survey five representative LSM-based open-source NoSQL systems, including LevelDB [4], RocksDB [6], Cassandra [1], HBase [3], and AsterixDB [9]. We will focus on their LSM-based storage layers.

4.1 LevelDB

LevelDB [4] is an LSM-based key-value store that was open-sourced by Google in 2011. It supports a simple key-value interface including puts, gets, and scans. LevelDB is not a full-fledged data management system, but rather an embedded storage engine to power higher-level applications. The major contribution of LevelDB was that it pioneered the design and implementation of the partitioned leveling merge policy, which was described in Section 2.2.1. This design has impacted many subsequent LSM improvements and implementations, as we have seen in this survey. Since we have already described the partitioned leveling merge policy in Section 2.2.1, we omit further discussions here.

4.2 RocksDB

RocksDB [6] was initially a fork of LevelDB created by Facebook in 2012. Since then, RocksDB has added a large number of new features. Due to its high performance and flexibility, RocksDB has successfully been used in various systems [25] both inside and outside of Facebook. According to Facebook, a major motivation of for their adoption of LSM-based storage was its high space utilization [25]. With the default size ratio of 10, RocksDB’s leveling implementation has about 90% percent of the total data at the largest level, ensuring that at most 10% of the total storage space can be wasted for storing obsolete entries. As mentioned earlier, this outperforms traditional B-tree-based storage engines, where pages are typically 2/3 full on average due to fragmentation [74]. Here we discuss various improvements made by RocksDB, including its improvements to merge policies, merge operations, and new functionality.

RocksDB’s LSM implementation remains based on the partitioned leveling design, but with some improvements. Since SSTables at level 0 are not partitioned, merging an SSTable from level 0 to level 1 generally causes rewrites of all SSTables at level 1, which often makes level 0 the performance bottleneck. To partially address this problem, RocksDB optionally merges SSTables at level 0 using the tiering merge policy. This elastic design allows RocksDB to better absorb write bursts without degrading query performance too much. RocksDB further supports a dynamic level size scheme to bound the space amplification. The issue is that the ideal leveling space amplification $O(\frac{T}{T-1})$ is achieved only when the last level reaches the maximum size, which may not always happen in practice. To address this, RocksDB dynamically adjusts the maximum capacities of all of the lower levels depending on the current size of the last level, ensuring that the space amplification is always $O(\frac{T}{T-1})$. In addition to a round-robin policy to select the SSTables to be merged, which is used in LevelDB, RocksDB supports two additional policies - namely cold-first and delete-first. The cold-first policy selects cold SSTables to merge to optimize for skewed workloads. It ensures that hot SSTables that are updated frequently will remain in the lower levels to reduce their total write cost. The delete-first policy selects SSTables with a large number of anti-matter entries to quickly reclaim the disk space occupied by the deleted entries. Finally, RocksDB supports an API called the merge filter[6] that allows users to provide custom logic to garbage-collect obsolete entries during merges efficiently. During a merge, RocksDB invokes the user-provided merge filter with each key-value pair and only adds those key-value pairs that are not filtered to the resulting SSTables.

Besides the partitioned leveling merge policy, RocksDB supports other merge policies such as tiering and FIFO. In RocksDB, as well as other systems, the actual tiering merge policy slightly differs from the one described in this paper (and else where in the research community). RocksDB’s tiering merge policy is controlled by two parameters, namely, the number of components to merge (K) and the size ratio (T). It works by examining components from oldest to newest, and for each component $C_i$, it checks whether the total size of the K-1 younger components $C_{i-1}, C_{i-2}, ..., C_{i-K}$ is larger than T times the size of $C_i$. If so, the policy merges all of these components together; otherwise, it proceeds to check the next younger component. In the FIFO merge policy, components are essentially not merged at all, but old components will be deleted based on the specified lifetime. In should be noted that in these two alternative merge policies, the disk components are not partitioned.

In LSM-based storage, merge operations typically consume a lot of CPU and disk resources that can negatively impact query performance. Moreover, the timing of merges is generally unpredictable, as it directly depends on the write rate. To alleviate this issue, RocksDB supports rate limiting to control the disk write speed of merge operations based on the leaky bucket mechanism [69]. The basic idea is to maintain a “bucket” that stores a number of tokens controlled by
a token refill speed. All flush and merge operations must request a certain number of tokens before performing each write. Thus, the disk write speed of flush and merge operations will be bounded by the specified token refill speed.

Finally, RocksDB supports a new operation called read-modify-write. In practice, many applications typically update existing values by reading them first instead of updating old values blindly. To support this operation efficiently, RocksDB allows users to write delta records directly into memory, thereby avoiding reading the original record. Delta records are then combined with base records during query processing and merges based on the user-provided combination logic. If applicable, RocksDB further combines multiple delta records together during merges to improve subsequent query performance.

4.3 HBase

Apache HBase [3] is a distributed data storage system in the Hadoop ecosystem; it is modeled after Google’s Bigtable [19]. HBase is based on a master-slave architecture. It partitions (either hash or range) a dataset into a set of regions, where each region is managed by an LSM-based storage engine. HBase supports dynamic region splitting and merging to elastically manage system resources based on the given workload. Here we focus on the storage engine of HBase.

HBase’s LSM implementation is generally based on the basic tiering merge policy. It supports some variations of the tiering merge policy as well, such as the exploring merge policy and the date-tiered merge policy. The exploring merge policy checks all mergeable component sequences and selects the one with the smallest write cost. The exploring merge policy is more robust than the default tiering merge policy, especially when components have irregular sizes due to loading and deletions. Thus, it is used as the default merge policy in HBase. The date-tiered merge policy is designed for managing time-series data. It merges components based on their time ranges, instead of their sizes, so that components will be time-range-partitioned. This enables efficient processing of temporal queries.

Recently, HBase has introduced a new option, called stripping, to partition a large region to improve merge efficiency. The idea is to partition the key space so that each partition, which contains a list of components, is merged independently. This is similar to the design proposed by PE-files [35], but is different from the partitioned tiering merge policy described in Section 2.2.1.

HBase does not support secondary indexes natively. However, a secondary index can be implemented as a separate table that stores secondary keys plus their primary keys using co-processors, as described in [26].

4.4 Cassandra

Apache Cassandra [1] is an open-source distributed data storage system modeled after both Amazon’s Dynamo [24] and Google’s BigTable [19]. Cassandra relies on a decentralized architecture to eliminate the possibility of a single point of failure. Each data partition in Cassandra is powered by an LSM-based storage engine.

Cassandra supports a similar set of merge policies to RocksDB and HBase, including the (unpartitioned) tiering merge policy, the partitioned leveling merge policy, and the date-tiered merge policy. Moreover, Cassandra supports local secondary indexes to facilitate query processing. To avoid the high point lookup overhead, secondary indexes are maintained lazily, similar to DELI [64]. During an update, if the old record is found in the memory component, then it is used to clean up secondary indexes directly. Otherwise, secondary indexes are cleaned up lazily when merging the primary index components.

4.5 AsterixDB

Apache AsterixDB [9] is an open-source Big Data Management System (BDMS) that aims to manage massive amount of semi-structured (e.g., JSON) data efficiently. Here we focus on the storage management aspect of AsterixDB [10].

AsterixDB uses a shared-nothing parallel database style architecture. The records of each dataset are hash-partitioned based on their primary keys across multiple nodes. Each partition of a dataset is managed by an LSM-based storage engine, with a primary index, a primary key index, and multiple secondary indexes. AsterixDB supports a record-level transaction model to ensure that all of the indexes are kept consistent within each partition. The primary index stores records indexed by primary keys, and the primary key index stores primary keys only. The primary key index is built to support COUNT(*) style queries efficiently as well as various index maintenance operations [44] since it is much smaller than the primary index.

Secondary indexes use the composition of the secondary key and the primary key as their index keys. AsterixDB supports LSM-based B+-trees, R-trees, and inverted indexes using a generic LSM-ification framework, which can convert an in-place index into an LSM index. For LSM-based R-trees, a linear order such as a Z-order curve or Hilbert curve is used to sort the entries in disk components, while in the memory component, deleted keys are recorded in a separate B+-tree to avoid multi-path traversals during deletes. AsterixDB further supports LSM-based inverted indexes to efficiently process full-text queries and similarity queries [38]. By default, each index’s components are merged independently using a tiering-like merge policy. AsterixDB also supports a correlated merge policy that synchronizes the merges
of all of a dataset’s indexes together to improve query performance with filters. The basic idea of this policy is to delegate merge scheduling to the primary index. When a sequence of primary index components are merged, all corresponding components from other indexes will be merged as well.

5 Future Research Directions

Categorizing and summarizing the existing LSM improvements in the literature reveals several interesting outages and opportunities for future work on LSM-based storage. We now briefly discuss some future research directions suggested by the result of this survey.

Thorough Performance Evaluation. As mentioned before, the tunability of LSM-trees has not been adequately considered in many of the research efforts to date. These improvements have typically been evaluated against a default (untuned) configuration of LevelDB or RocksDB. It is not clear how these improvements would compare against a well-tuned baseline LSM-tree for a given workload. Moreover, many of the improvement proposals have primarily evaluated their impact on query performance, but space utilization has often been neglected. This situation can be addressed in future LSM research by more carefully considering the tunability of LSM-trees.

Partitioned Tiering Structure. Tiering has been used by many LSM improvements to reduce the write amplification of LSM-trees. In Section 2.2.1, we identified two possible partitioned tiering schemes, namely horizontal grouping and vertical grouping, that cover virtually all of the tiering-related LSM improvements proposed recently. However, the performance characteristics of these two schemes are not yet clear. In general, vertical grouping permits more freedom when selecting SSTables to merge, while horizontal grouping ensures that SSTables are fixed-size. It would be an interesting future direction to systematically evaluate these two schemes and possibly design new schemes that combine advantages of both.

Hybrid Merge Policy. Until recently, most LSM improvements have assumed a homogeneous merge policy of either leveling or tiering at all of the levels of an LSM-tree. However, this has been shown to be sub-optimal for certain workloads [22]. A hybrid merge policy of leveling and tiering can provide much better write performance than leveling with little impact on point lookups, long range queries, and space amplification. As a future direction, it would be interesting to design and implement LSM-trees with hybrid merge policies and revisit some of the key questions raised by this design choice.

Minimizing Performance Variance. In practice, performance variance is as important a performance metric as absolute throughput [33,48]. Unfortunately, LSM-trees often exhibit large performance variances because they decouple in-memory writes from expensive background I/Os. As we have seen in this survey, bLSM [58] is the only attempt to minimize write stalls exhibited by LSM-trees. However, bLSM itself still has several limitations. It was designed for the unpartitioned leveling merge policy, and it only minimizes long write latencies caused by write stalls instead of the variance of the overall ingestion throughput. As future work, it would be very useful to design mechanisms to minimize the performance variance of LSM-trees.

Towards Database Storage Engines. Finally, most of the existing LSM improvements have focused rather narrowly on a key-value store setting with a single LSM-tree. As LSM-trees are gradually becoming widely used inside database system storage engines, new query processing and data ingestion techniques should be developed for this more general (multi-index) setting. Examples include adaptive maintenance of auxiliary structures to facilitate query processing, LSM-aware query optimization, and co-planning of LSM maintenance tasks with query execution.

6 Conclusion

Recently, LSM-trees have been becoming increasingly popular in modern NoSQL systems due to advantages such as superior write performance, high space utilization, immutability of on-disk data, and tunability. These factors have enabled LSM-trees to be widely adopted and deployed to serve a variety of workloads.

In this paper, we have surveyed the recent research efforts, including efforts from both the database community and the systems community, to improve LSM-trees. We presented a general taxonomy to classify existing LSM improvements based on the specific aspects they attempt to optimize, and we discussed the improvements in detail based on the proposed taxonomy. We also reviewed several representative LSM-based open-source NoSQL systems, and we identified some interesting future research directions. We hope that this survey can serve as a useful guide to the state of the art in LSM-based storage techniques for researchers, practitioners, and users.

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