Breaking Down Memory Walls: Adaptive Memory Management in LSM-based Storage Systems (Extended Version)

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ABSTRACT
Log-Structured Merge-trees (LSM-trees) have been widely used in modern NoSQL systems. Due to their out-of-place update design, LSM-trees have introduced memory walls among the memory components of multiple LSM-trees and between the write memory and the buffer cache. Optimal memory allocation among these regions is non-trivial because it is highly workload-dependent. Existing LSM-tree implementations instead adopt static memory allocation schemes due to their simplicity and robustness. In this paper, we attempt to break down these memory walls in LSM-based storage systems. We present a memory management architecture that adapts memory management to workload. We then present a partitioned memory component structure with new flush policies that better exploit the write memory to minimize the write cost. To break down the memory wall between the write memory and the buffer cache, we further introduce a memory tuner that tunes the memory allocation between these two regions. We have conducted extensive experiments in the context of Apache AsterixDB using the YCSB and TPC-C benchmarks and present the results here.

1 INTRODUCTION
Log-Structured Merge-trees (LSM-trees) [42] are widely used in modern NoSQL systems, such as LevelDB [4], RocksDB [5], Cassandra [2], HBase [3], X-Engine [26], and AsterixDB [1]. Unlike traditional in-place update structures, LSM-trees adopt an out-of-place update design by first buffering all writes in memory; they are subsequently flushed to disk to form immutable disk components. The disk components are periodically merged to improve query performance and reclaim space occupied by obsolete records.

Efficient memory management is critical for storage systems to achieve optimal performance. Compared to update-in-place systems where all pages are managed within shared buffer pools, LSM-trees have introduced additional memory walls. Due to the LSM-tree’s out-of-place update nature, the write memory is isolated from the buffer cache. Moreover, the write memory must be shared among multiple LSM-trees since each LSM-tree manages its memory component independently. Since the optimal memory allocation heavily depends on the workload, memory management should be workload-adaptive to maximize the system performance.

Unfortunately, adaptivity is non-trivial, as it is highly workload-dependent. Existing LSM-tree implementations, such as RocksDB [5] and AsterixDB [28], have opted for simplicity and robustness over optimal performance by adopting static memory allocation schemes. For example, RocksDB sets a static size limit (default 64MB) for each memory component. AsterixDB specifies the maximum number N of writable datasets (default 8) so that each active dataset, including its primary and secondary indexes, receives 1/N of the total write memory. Both systems allocate separate static budgets for the write memory and the buffer cache.

In this paper, we seek to break down these memory walls in LSM-based storage systems to maximize performance and efficiency. As the first contribution, we present a memory management architecture to enable adaptive memory management for LSM-based storage systems. In this architecture, the overall memory budget is divided into the write memory region and the buffer cache region. Within the write memory region, the memory allocation of each memory component is purely driven by its demands, i.e., write rates, to minimize the overall write amplification. The two regions are connected via a memory tuner that adaptively tunes the memory allocation between the write memory and the buffer cache.

As the second contribution of this paper, we propose a new LSM memory component structure to manage the write memory. The key insight is to adopt an in-memory LSM-tree to maximize the memory utilization and reduce the write amplification. We further present new flush policies to manage the memory components of multiple LSM-trees to minimize the overall write cost.

The third contribution of this paper is the detailed design of a memory tuner that adaptively tunes the memory allocation between the write memory and the buffer cache to minimize the system’s overall I/O cost. The memory tuner performs on-line tuning by modeling the I/O cost of LSM-trees without any a priori knowledge of the workload. This further allows the memory tuner to quickly adjust the memory allocation when the workload changes.

We have implemented all of the proposed techniques inside Apache AsterixDB [1]. We have carried out extensive experiments on both the YCSB benchmark [18] and the TPC-C benchmark [6] to evaluate the effectiveness of the proposed techniques. The experimental results show that the proposed techniques successfully reduce the disk I/O cost via adaptive memory management, which in turn maximizes system efficiency and overall performance.

The remainder of this paper is organized as follows. Section 2 discusses background information and related work. Section 3 presents our adaptive memory management architecture for LSM-trees. Section 4 describes the new memory component structure for managing the write memory. Section 5 presents the design and implementation of the memory tuner. Section 6 experimentally evaluates the proposed techniques. Finally, Section 7 concludes the paper.

2 BACKGROUND

2.1 Log-Structured Merge Trees

The LSM-tree [42] is a persistent index structure optimized for write-intensive workloads. LSM-trees perform out-of-place updates by always buffering writes into a memory component and appending log records to a transaction log for durability. Writes are flushed to
disk when either the memory component is full, called a memory-triggered flush, or when the transaction log length becomes too long, called a log-triggered flush.

A query over an LSM-tree has to reconcile the entries with identical keys from multiple components, as entries from newer components override those from older components. A range query searches all components simultaneously using a priority queue to perform reconciliation. A point lookup query simply search all components from newest to oldest until the first match is found. To speed up point lookups, a common optimization is to build Bloom filters [13] over the sets of keys stored in disk components.

To improve query performance and space utilization, disk components are periodically merged according to a pre-defined merge policy. In practice, two types of merge policies are commonly used [38], both of which organize disk components into "levels". The leveling merge policy maintains one component per level. When a component at Level \( L_i \) is \( T \) times larger than that of Level \( L_{i-1} \), it will be merged into Level \( L_i + 1 \) to form a new component. In contrast, the tiering merge policy maintains \( T \) components per level. When a Level \( L_i \) becomes full with \( T \) components, they are merged together into a new component at Level \( L_i + 1 \).

**Partitioning.** In practice, a common optimization is to range-partition a disk component into multiple (often fixed-size) SSTables to bound the processing time and temporary space of each merge. This optimization is often used together with the leveling merge policy, as pioneered by LevelDB [4]. An example of a partitioned LSM-tree with the leveling merge policy is shown in Figure 1, where each SSTable is labeled with its key range. Note that \( L_0 \) is not partitioned since its SSTables are directly flushed from memory. \( L_0 \) also stores multiple SSTables with overlapping keys to absorb write bursts. To merge an SSTable from \( L_i \) to \( L_{i+1} \), all of its overlapping SSTables at \( L_{i+1} \) are selected and these SSTables are merged to form new SSTables at \( L_{i+1} \). For example in Figure 1, the SSTable labeled 0-50 at \( L_1 \) will be merged with the SSTables labeled 0-20 and 22-52 at \( L_2 \), which produce new SSTables labeled 0-15, 17-30, and 32-52 at \( L_2 \). When the LSM-tree becomes too large, a new level must be added. To maximize space utilization, the new level should be added at \( L_i \) instead of the last level, as suggested by [23]. In this optimization, the last level is always treated as full, which in turn determines the maximum sizes of other levels. When the maximum size of \( L_i \) is larger than \( T \) times the write memory size (or the configured base level size), a new \( L_1 \) is added while all remaining levels \( L_i \) become \( L_{i+1} \). In our work, we will also focus on the partitioned leveling structure due to its wide adoption in today’s LSM-based systems.

**Figure 1: Example Partitioned LSM-tree**

| Notation | Definition | Example |
|----------|------------|---------|
| Global Notation | | |
| \( T \) | size ratio of the merge policy | 10 |
| \( P \) | disk page size | 4 KB/page |
| \( M_w \) | total write memory size | 1GB |
| Local Notation | | |
| \( e_i \) | entry size | 100 B/entry |
| \( a_i \) | ratio of an LSM-tree’s write memory to total write memory | 20% |
| \( N_i \) | number of levels (excluding \( L_0 \)) | 3 |
| \( |L_i| \) | size of Level \( L_i \) | 10 GB |
| \( C_i \) | write I/O cost per entry | 4 pages/entry |

**Write Memory vs. Write Cost.** Here we provide a simple cost analysis to show the relationship between the write memory size and the per-entry write I/O cost. Our notation is shown in Table 1. Note that since we consider multiple LSM-trees, Table 1 contains global notation that is valid for all LSM-trees and local notation that is specific to one LSM-tree. In the remainder of this paper, for the \( i \)-th LSM-tree, we add the subscript \( i \) to denote the local notation for this LSM-tree. Note that we have further introduced the notation \( a \) to denote the write memory ratio of an LSM-tree. Thus, for the \( i \)-th LSM-tree, its write memory size is \( a_i \cdot M_w \). Moreover, given a collection of \( K \) LSM-trees, we have \( \sum_{i=1}^{K} a_i = 1 \).

Each entry written to an LSM-tree is flushed to disk once and merged multiple times down to the last level. The per-flush cost is \( \frac{e}{P} \) pages/entry. Merging an SSTable at Level \( L_i \) usually has \( T \) overlapping SSTables at Level \( L_{i+1} \). Thus, to merge an entry from \( L_0 \) to the last level, the overall merge cost is \( \frac{e}{P} \cdot (T + 1) \cdot \log_T N \) pages/entry. Here the number of levels \( N \) can be expressed using other terms as follows. Given an LSM-tree whose write memory size is \( a \cdot M_w \), the maximum size of \( i \)-th level is \( a \cdot M_w \cdot T^i \). Based on the size of the last Level \( L_N \), we have \( |L_N| \leq a \cdot M_w \cdot T^N \). Thus, \( N \) can be approximated as \( \log_T \frac{M_w}{a \cdot M_w} \). Putting everything together, the per-entry write cost \( C \) is approximately

\[
C = \frac{e}{P} + \frac{e}{P} \cdot (T + 1) \cdot \log_T \frac{|L_N|}{a \cdot M_w} \tag{1}
\]

As Equation 1 shows, a larger write memory reduces the write cost by reducing the number of disk levels. Thus, it is important to utilize a large write memory efficiently to reduce the write cost.

### 2.2 Apache AsterixDB

Apache AsterixDB [1, 8, 16] is a parallel, semi-structured Big Data Management System (BDMS) for efficiently managing large amounts of data. It supports a feed-based framework for efficient data ingestion [25, 52]. The records of a dataset in AsterixDB are hash-partitioned based on their primary keys across multiple nodes of a shared-nothing cluster. Each partition of a dataset uses a primary LSM-based B+-tree index to store the data records, while local secondary indexes, including LSM-based B+-trees, R-trees, and inverted indexes, can be built to expedite query processing.

AsterixDB uses a static memory allocation scheme for simplicity and robustness [28]. It specifies static memory budgets for the
buffer cache and the write memory. Moreover, AsterixDB specifies the maximum number D of writable datasets (default 8) so that each active dataset receives 1/D of the total write memory. When a dataset’s write memory is full, all of its LSM-trees, including its primary index and secondary indexes, will be flushed to disk together. If the user writes to the D+1-st dataset, the least recently written active dataset will be evicted to reclaim its write memory. In this work, we use AsterixDB as a testbed to evaluate the proposed techniques and compare them to other baselines.

2.3 Related Work

LSM-trees. Recently, a large number of improvements have been proposed to optimize the original [42] LSM-tree design. These improvements include optimizing write performance [10, 12, 21, 22, 30, 33, 39, 40, 44, 55], supporting auto-tuning of LSM-trees [19, 20, 31], optimizing LSM-based secondary indexes [36, 43], minimizing write stalls [11, 37, 47], and extending the applicability of LSM-trees [35, 45]. We refer readers to a recent survey [38] for a more detailed description of these LSM-tree improvements.

In terms of memory management, FloDB [9] presents a two-level memory component structure to mask write latencies by first storing writes into a small hash index that is later migrated to a larger sorted index. However, it mainly optimizes for peak throughput instead of reducing the overall write cost. Accordion [14] introduces a multi-level memory component structure with memory flushes and merges. One drawback is that Accordion does not range-partition memory components, resulting in high memory utilization during large memory merges. We will further experimentally evaluate Accordion in Section 6. Monkey [19] uses analytical models to tune the memory allocation between memory components and Bloom filters. ElasticBF [29] proposes a dynamic Bloom filter management scheme to adjust Bloom filter false positives rates based on the data hotness. Different from Monkey and ElasticBF, in our work Bloom filters are managed as the same page way as SSTables through the buffer cache. It should also be noted that virtually all previous research only considers the memory management of a single LSM-tree. Except [28], which describes memory management in AsterixDB, we are not aware of any previous work that considers memory management of multiple heterogeneous LSM-trees.

Database Memory Management. The importance of memory management, or buffer management, has long been recognized for database systems. Various buffer replacement policies, such as DBMIN [17], 2Q [27], LRU-K [41], and Hot-Set [46], have been proposed to reduce buffer cache misses. These replacement policies are orthogonal to this work because we mainly focus on the memory walls introduced by the LSM-tree’s out-of-place update design.

Automatic memory tuning is also an important problem for database systems. Some commercial DBMSs have offered functionalities to tune the memory allocation among different memory regions [7, 48]. Depending on the tuning goals, the memory tuning techniques can be classified as maximizing the overall throughput or meeting latency requirements. DB2’s self-tuning memory manager (STMM) [48] is an example of the former, using control theory to tune the memory allocation. For the latter, the relationship between the buffer cache size and the cache miss rate must be predicted, using either analytical models [50] or machine learning approaches [49]. In our work, the memory tuner attempts to minimize the total I/O cost, which indirectly maximizes the overall throughput. One key difference between our memory tuner and STMM is that STMM targets a traditional in-place update system, which does not include the write memory used by LSM-trees.

There has been recent interest in exploiting machine learning to tune database configurations [24, 32, 51, 54], where memory allocation is treated as a tuning knob. These approaches usually require additional training steps and user inputs. Different from these approaches, our memory tuner uses a white-box approach; it carefully models the I/O cost of LSM-based storage systems.

3 MEMORY MANAGEMENT ARCHITECTURE

In this section, we present our memory management architecture to enable adaptive memory management. In this architecture, depicted in Figure 2, the total memory budget is divided into the write memory $M_{write}$ and the buffer cache $M_{cache}$. These two regions are further connected via a memory tuner, which periodically performs memory tuning to minimize the total I/O cost.

Write Memory. The write memory stores incoming writes for all LSM-trees. To maximize memory utilization, we do not set static size limits for the individual memory components. Instead, all memory components are managed through a shared memory pool. When an LSM-tree has insufficient memory to store its incoming writes, more pages will be requested from the pool. When the overall write memory usage is too high, an LSM-tree is selected to flush its memory component to disk.

While the basic idea of this design is straightforward, there are several technical challenges here. First, how can we best utilize the write memory to minimize the write cost? Existing LSM-tree implementations use B⁺-trees or skiplists to manage memory components and always flush a memory component entirely to disk. However, this negatively impacts memory utilization since B⁺-trees have internal fragmentation [53] and a large chunk of memory will be freed all at once during flushes. Second, since the memory component of an LSM-tree now becomes highly dynamic, how can we adjust the disk levels as the write memory changes to always make optimal performance trade-offs? Finally, given a collection of heterogeneous LSM-trees with different sizes, how can we allocate the write memory to these LSM-trees to minimize the overall write cost? We will present our solutions to these challenges in Section 4.

Buffer Cache. The buffer cache stores the (immutable) disk pages of the SSTables as well as their Bloom filters. As in traditional
database systems, all disk pages are managed together using a predefined buffer replacement policy. For example, AsterixDB uses the clock replacement policy to manage its shared buffer cache. In this work, we mainly focus on the memory allocation given to the buffer cache instead of cache replacement within the buffer cache.

**Memory Tuner.** Given a memory budget, the memory tuner attempts to find an optimal memory allocation between the write memory and the buffer cache to minimize the total I/O cost. The key property of the memory tuner is that it takes a white-box approach by carefully modeling the I/O cost of LSM-based storage systems and thus does not require any offline training. We will describe the design and implementation of the memory tuner in Section 5.

## 4 MANAGING WRITE MEMORY

Now we present our solution for managing the write memory. We first describe the memory component structure of a single LSM-tree and then extend it to multiple LSM-trees.

### 4.1 Partitioned Memory Component

Existing LSM-tree implementations use skiplists or B+-trees to manage memory components and always flush a memory component entirely to disk. As mentioned before, this causes lower memory utilization for two reasons. First, a B+-tree has internal fragmentation, as its pages are about 2/3 full [53]. Second, after a flush, a large chunk of write memory will be freed (vacated) at once. To address these two problems, we introduce a partitioned LSM-tree to manage the memory component, which is called a partitioned memory component for short. An LSM-tree achieves much higher space utilization than B+-trees. For example, with a size ratio of 10, an LSM-tree achieves 90% space utilization, which is much higher than that of a B+-tree. Moreover, since the structure is range-partitioned, it naturally supports flushing the write memory incrementally and continuously by flushing one memory SSTable at a time.

#### 4.1.1 Basic Structure. Figure 3 shows an example LSM-tree with a partitioned memory component. Compared to the basic partitioned LSM-tree design depicted in Figure 1, the new design has two key differences. First, the memory component itself is managed by a partitioned LSM-tree. This LSM-tree has an active SSTable at $M_0$ that stores incoming writes and a set of partitioned in-memory levels that contain immutable SSTables. When a memory level $M_i$ is full, one of its SSTables is merged into the next level $M_{i+1}$ using a memory merge. A greedy selection policy is used to select SSTables to merge by minimizing the overlapping ratio, i.e., the ratio between the size of the overlapping SSTables at $M_{i+1}$ and the size of the selected SSTable at $M_i$. This reduces the merge cost and provides better support for concurrent merges. Memory SSTables must be flushed to disk eventually. For a memory-triggered flush, SSTables at the last memory level ($M_2$ in Figure 3) are flushed to disk in a round-robin way. This policy ensures that the flushed SSTables always have disjoint key ranges, which minimizes write amplification. For a log-triggered flush, the SSTable with the minimum log sequence number (LSN) will be flushed to facilitate log truncation. Suppose this SSTable is at Level $M_i$. In order to flush this SSTable, all overlapping SSTables at higher levels ($M_j$ s.t. $j > i$) must be flushed together for correctness.

| Disk | Memory |
|------|--------|
| L0   | M0     |
|      | 0-100  |
|      | active |
| L1   | M1     |
|      | 0-50   |
|      | 55-99  |
|      | M2     |
|      | 0-20   |
|      | 55-80  |
|      | 81-99  |

**Figure 3:** LSM-tree with a Partitioned Memory Component

The second key difference is that the disk level $L_0$ is now range-partitioned. $L_0$ organizes its SSTables into groups, where all SSTables within each group have disjoint key ranges. Groups are ordered based on their recency, where the keys in a newer group override the keys in an older group. When the total number of groups at $L_0$ exceeds a predefined threshold, incoming flushes must be stopped. To minimize the number of groups at $L_0$, which in turns minimizes write stalls, two heuristics are used. First, when an SSTable is flushed to disk, it is always inserted into the oldest possible group where all newer groups do not have any overlapping SSTables. Otherwise, if no such group can be found, a new group is created. Consider the two groups in Figure 3, where group 0 is older than group 1. When flushing the SSTable labeled 81-99, the resulting SSTable will be inserted into the older group 0. If the SSTable labeled 25-55 is flushed, a new group will be created because group 1 contains an overlapping SSTable 25-50. Second, to merge SSTables from $L_0$ into $L_1$, the smallest group that contains the newest SSTables is always selected for the merge. Specifically, an SSTable from this group as well as any overlapping SSTables from other $L_0$ groups are merged with the overlapping SSTables at $L_1$. To reduce write amplification, the SSTable to merge is selected to minimize the overlapping ratio, i.e., the ratio between the total size of the overlapping SSTables at $L_1$ and the total size of the merging SSTables at $L_0$. Consider the example LSM-tree in Figure 3. Group 1 will be selected for the merge because it has fewer SSTables than group 0. The SSTable labeled 0-23 could be merged with the SSTable labeled 10-30 at group 0 and the SSTables labeled 0-15 and 20-35 at $L_1$, whose overlapping ratio would be 1. The SSTable labeled 25-50 could be merged with the SSTables labeled 10-30 and 32-55 in group 0 and the SSTables labeled from 0-15 to 50-60 at $L_1$, whose overlapping ratio would be 4/3. Thus, to reduce write amplification, the SSTable labeled 0-23 will be selected for the merge.

One potential issue with the above design is that memory merges and flushes may lead to deadlocks. To see this problem, consider an extreme situation where all SSTables at the last memory level are merging and the total write memory is full. As a result, memory merges cannot proceed until some write memory is reclaimed by flushes. However, flushes also cannot proceed because all of the last-level SSTables are merging. Since deadlocks are rare, our solution is to break deadlocks when they occur. Specifically, when the write memory is full and no flush can proceed, some memory merges that are blocking flushes will be aborted.

#### 4.1.2 Adjusting Disk Levels. In the new memory component architecture, the write memory allocated of each LSM-tree is allocated...
Recall that to maximize the space utilization, levels are only added or deleted at $L_1$. For each disk level $L_i$, its maximum size is $a \cdot M_w \cdot T^i$. Here we assume that the disk levels of an LSM-tree are relatively stable, i.e., the size of each level $|L_i|$ is stable, but the write memory allocated to an LSM-tree may change, i.e., $a \cdot M_w$ is dynamic. When an LSM-tree’s write memory size $a \cdot M_w$ becomes too small, i.e., $a \cdot M_w \cdot T < |L_1|$, a new $L_1$ should be added to reduce the write cost. One can simply add a new empty $L_1$ and all remaining levels $L_i$ automatically become $L_{i+1}$. In contrast, when the write memory size becomes too big, i.e., $a \cdot M_w \cdot T > |L_2|$, $L_1$ becomes redundant and can be deleted. Implementing this strategy directly can cause oscillation when the write memory is close to this threshold. To avoid this, the deletion of $L_1$ can be delayed until the write memory further grows by a factor of $f$, i.e., $a \cdot M_w \cdot T > f \cdot |L_2|$. As we will see in Section 6, delaying the deletion of $L_1$ has a much smaller impact than delaying the addition of a level. In general, a larger $f$ better avoids oscillation but may have a larger negative impact on write amplification. By default, we set $f$ to 1.5 to balance these two factors.

To delete $L_1$, all existing SSTables from $L_1$ must be merged into $L_2$. Here we describe an efficient solution to delete $L_1$ smoothly with minimal overhead. When $L_1$ needs to be deleted, SSTables from $L_0$ can be directly merged into $L_2$ along with all overlapping SSTables at $L_1$. Consider the example LSM-tree in Figure 4, where the write memory is large enough to remove $L_1$. In this case, the SSTable labeled 0-23 at $L_0$ as well as the overlapping SSTable labeled 0-46 at $L_1$ are directly merged into $L_2$. This mechanism ensures that $L_1$ will not receive new SSTables but does not itself guarantee that $L_1$ will eventually become empty. To address that problem, low-priority merges are also scheduled to merge SSTables from $L_1$ directly into $L_2$ when there are no schedulable merges at other levels. These two operations ensure that $L_1$ will eventually become empty, and it can then be removed from the LSM-tree.

4.1.3 Partial Flush vs. Full Flush. The partitioned memory component design allows for the flushing of one SSTable at a time, which we call partial flushes. For memory-triggered flushes, partial flushes reduce the disk write amplification by creating skews at the last level [31]. The reason is that since SSTables are flushed in a round-robin way, the flushed SSTable will have received the most updates.

Thus, the key ranges of these SSTables will be denser than the average key range, which in turn reduces the write amplification.

While possible, partial flushes may not always be an optimal choice. Consider the case when the total write memory is large and flushes are only triggered by log truncation. Since the oldest entries can be distributed across all memory SSTables, most memory SSTables may have to be flushed in order to truncate the log. If partial flushes are used, the flushed SSTable may have overlapping key ranges. In contrast, if a full flush is performed, which will merge-sort all memory SSTables across all levels, the flushed SSTables will have non-overlapping key ranges. Thus, for a log-triggered flush, the optimal flush choice depends on the write memory size and the maximum transaction log length.

Developing an optimal flush solution is non-trivial since it also heavily depends on the key distribution of the write workload. Here we propose a simple heuristic to dynamically switch between partial and full flushes for log-triggered flushes. The basic idea is to use a window to keep track of how much write memory has been partially flushed before the log-triggered flush, where the window size is set as the maximum transaction log length. When log truncation is needed, if the total amount of previously flushed write memory is larger than $\beta$ times the total write memory, where $\beta$ is a configurable parameter, then partial flushes will be performed. Otherwise, we flush the entire memory component using a full flush.

Based on some preliminary simulation results, we set our default value for $\beta$ to be 0.5 to minimize the overall write cost. (We leave the further exploration of the optimal choice of partial and full flushes as future work.)

4.1.4 Discussion. In summary, the partitioned memory component design described here provides additional adaptivity on top of a traditional monolithic memory component. When the write memory is small, it behaves much like a monolithic memory component because its memory merges are rarely performed. When the write memory is large, however, memory merges are performed to maximize memory utilization and to reduce write amplification. The partitioned memory component design also permits concurrent flushes and concurrent disk merges of $L_0$ because both the memory components and $L_0$ are now range-partitioned. However, one potential drawback is that memory merges incur extra CPU overhead, which may not be ideal for CPU-bound workloads. We will further evaluate this issue in Section 6.

4.2 Managing Multiple LSM-trees

When managing multiple LSM-trees, a fundamental question is how to allocate portions of the write memory to these LSM-trees. Since write memory is allocated on-demand, this question becomes how to select LSM-trees to flush. For log-triggered flushes, the LSM-tree with the minimum LSN should be flushed to perform log truncation. For memory-triggered flushes, existing LSM-tree implementations, such as RocksDB [5] and HBase [3], choose to flush the LSM-tree with the largest memory component. We call this policy the max-memory flush policy. The intuition is that flushing this LSM-tree can reclaim the most write memory, which can be used for subsequent writes. However, this policy may not be suitable for our partitioned memory components because flushing any LSM-tree will reclaim the same amount of write memory due to partial SSTable flushes.
Min-LSN Policy. One alternative flush policy is to always flush the LSM-tree with the minimum LSN for both log-triggered and
memory-triggered flushes. We call this policy the min-LSN flush
policy. The intuition is that the flush rate of an LSM-tree should be approximately proportional to its write rate. A hotter LSM-tree
should be flushed more often than a colder one, but it still receives
more write memory. This policy also facilitates log truncation,
which can be beneficial if flushes are dominated by log truncation.

Optimal Policy. Given a collection of K LSM-trees, our ultimate
goal is to find an optimal memory allocation that minimizes the
overall write cost. For the $i$-th LSM-tree, we denote $r_i$ as its the
write rate (bytes/s). The optimal memory allocation can be obtained
by solving the following optimization problem:

$$
\min a_i \sum_{i=1}^{K} \frac{r_i}{e_i} C_i, \text{ s.t. } \sum_{i=1}^{K} a_i = 1
$$

By substituting Equation 1 from Section 2.1 into Equation 2 and
using the Lagrange multiplier method, the optimal write memory
ratio $a_i^{opt}$ for the $i$-th LSM-tree is $a_i^{opt} = \frac{e_i}{\sum_j e_j} \cdot r_i$. This shows that
the write memory allocated to each LSM-tree should be propor-
tional to its write rate.

We call this policy the optimal flush policy. In terms of its imple-
mentation, we can use a window to keep track of the total number
of writes to each LSM-tree, where the window size is set as the
maximum transaction log length. When a memory-triggered flush is requested, each active LSM-tree is checked in turn and a flush is scheduled if its write memory ratio $a_i$ is larger than its optimal
write memory ratio $a_i^{opt}$.

5 MEMORY TUNER

After discussing how to efficiently manage the write memory, we
now proceed to describe the memory tuner to tune the memory
allocation between the write memory and the buffer cache. We first
provide an overview of the tuning approach, which is followed by
its design and implementation.

5.1 Tuning Approach

The goal of the memory tuner is to find an optimal memory alloca-
tion between the write memory and the buffer cache to minimize
the I/O cost per operation. This in turn should maximize the sys-
tem efficiency as well as the overall throughput. Suppose the total
available memory is $M$. For ease of discussion, let us assume the
write memory size is $x$, which implies that the buffer cache size is
$M - x$. Let write($x$) and read($x$) be the write cost and read cost
per operation when the write memory is $x$. Our tuning goal is to
minimize the weighted I/O cost per operation (pages/op)

$$
cost(x) = \omega \cdot \text{write}(x) + \gamma \cdot \text{read}(x)
$$

The weights $\omega$ and $\gamma$ allow us to instantiate the objective function
for different use cases. For example, on hard disks, one can set a
smaller $\omega$ since LSM-trees mainly use sequential I/Os for writes,
while on SSDs one can make $\omega$ larger since SSD writes are often
more expensive than SSD reads.

In general, cost($x$) is a $U$-shaped function. To see this, when $x$
is very small, the per-operation merge cost will be very large. In
contrast, when $x$ is very large, there will be a lot of buffer cache
missing caused by both queries and merges. Thus, to minimize Equa-
tion 3, our goal is to find $x$ such that the derivative $\frac{\partial}{\partial x} \text{cost}(x) = \omega \cdot \frac{\partial}{\partial x} \text{write}(x) + \gamma \cdot \frac{\partial}{\partial x} \text{read}(x) = 0$. Intuitively, write’($x$)/read’($x$) measures how the write/read cost changes if more write memory is
allocated. If we can estimate both write’($x$) and read’($x$), then we
can find the optimal $x$ using some root-finding algorithm.

Based on this idea, our memory tuner uses a feedback-control
loop to tune memory allocation, as depicted in Figure 5. The system
periodically reports workload statistics to the memory tuner. The
memory tuner then uses the collected statistics to find an optimal
memory allocation between the write memory and the buffer cache.
Note that the whole tuning process does not require any user input
nor training samples. Instead, the memory tuner continuously tunes
the memory allocation based on the current statistics as well as
some past history. Before describing the details of the memory
 tuner, we first introduce some notation used by the memory tuner
(Table 2) in addition to the LSM-tree notation listed in Table 1. Note
that with secondary indexes each operation may write multiple
entries to multiple LSM-trees.

5.2 Estimating Write Cost Derivative

For the $i$-th LSM-tree, recall that Equation 1 computes the per-entry
write cost $C_i$. Since each operation writes $\frac{N_i}{op}$ entries to this LSM-
tree, its write cost per operation write$_i$($x$) can computed as $\frac{N_i}{op} \cdot C_i$.
By taking the derivative of write$_i$($x$), we have

$$
\text{write}_i'(x) = \frac{w_i}{op} \cdot \frac{e_i}{F} \cdot \frac{1}{x \cdot \ln T}
$$

Table 2: Memory Tuner Notation

| Notation    | Definition                     | Example   |
|-------------|--------------------------------|-----------|
| $K$         | number of LSM-trees            | 8         |
| $op$        | number of operations observed  | 10K ops   |
| saved$_q$   | saved query disk I/O by the simulated cache | 0.01 page/op |
| saved$_m$   | saved merge disk I/O by the simulated cache | 0.002 page/op |
| $sim$       | simulated cache size           | 32 MB     |
| $w_i$       | number of entries written to an LSM-tree | 50K entries |
| flush$_{log}$ | write memory flushed by log truncation | 1 GB   |
| flush$_{mem}$ | write memory flushed by high memory usage | 8 GB |

Figure 5: Workflow of Memory Tuner
To reduce the estimation error, instead of collecting statistics for \( op \), \( wi \), \( ei \) and \( P \), we simply collect the total number of merge writes per operation, \( merge_i(x) \), in the last tuning cycle. By substituting \( merge_i(x) \) into Equation 4, we have

\[
write'_i(x) = -\frac{merge_i(x)}{x \cdot \ln \left( \frac{\|N_i\|}{a_i} \right)} \cdot \frac{\text{flushmem}_i}{\text{flushmem}_i + \text{flushlog}_i} \tag{5}
\]

Here we assume that the write memory of an LSM-tree is always smaller than its last level size. Thus, the estimated value of \( write'_i(x) \) in Equation 5 is always negative as long as \( merge_i(x) \) is not zero. This implies that adding more write memory can always reduce the write cost, which may not hold in practice. Once flushes are dominated by log truncation, adding more write memory will not further reduce the write cost. To account for the impact of log-triggered flushes, we further multiply Equation 5 by a scale factor \( \frac{\text{flushmem}_i}{\text{flushmem}_i + \text{flushlog}_i} \) that we also keep statistics for. Intuitively, this scale factor will be close to 1 if flushes are mainly triggered by high memory usage and it will approach to 0 if flushes are mostly triggered by log truncation. Finally, \( write'(x) \) is the sum of \( write'_i(x) \) for all LSM-trees:

\[
write'(x) = \sum_{i=1}^{K} write'_i(x) = \sum_{i=1}^{K} -\frac{merge_i(x)}{x \cdot \ln \left( \frac{\|N_i\|}{a_i} \right)} \cdot \frac{\text{flushmem}_i}{\text{flushmem}_i + \text{flushlog}_i} \tag{6}
\]

**Example 5.1.** Consider an example with two LSM-trees. Suppose that the total write memory \( x \) is 128MB. Suppose that the first LSM-tree receives 80% of the write memory \( (a_1 = 0.8) \) with a last level size of 100GB \( (\|N_1\| = 100GB) \) and that its merge cost per operation is 1 page/op \( (merge_1(128MB) = 1 \text{ page/op}) \). Similarly, for the second LSM-tree, suppose that \( a_2 = 0.2 \), \( \|N_2\| = 50GB \), and \( merge_2(128MB) = 0.8 \) page/op. For simplicity, suppose that all flushes are memory-triggered. Based on Equation 5, \( write'_1(128MB) \approx -1.08e^{-9} \text{ page/op} \) and \( write'_2(128MB) \approx -0.86e^{-9} \text{ page/op} \). Thus, \( write'(128MB) \approx -1.86e^{-9} \text{ page/op} \). This implies that if we allocate one more byte of write memory, the write cost can be reduced by \( 1.86e^{-9} \text{ page/op} \).

### 5.3 Estimating Read Cost Derivative

Estimating \( read'(x) \) is slightly more complicated because disk reads are performed by both queries and merges. Thus, we break down \( read(x) \) into \( read(x) = read_q(x) + read_m(x) \), where \( read_q(x) \) is the total number of query disk reads per operation and \( read_m(x) \) is the total number of merge disk reads per operation.

We use a simulated cache to estimate \( read'_q(x) \), as suggested by [48]. This simulated cache only stores page IDs. Whenever a page is evicted from the buffer cache, its page ID is added to the simulated cache. Whenever a page is about to be read from disk, a disk I/O could have been saved if the simulated cache contains that page ID. Suppose that the simulated cache size is \( sim \) and the saved read cost per operation is \( saved_q \), then \( read'_q(x) = \frac{saved_q}{sim} \).

To estimate \( read'_m(x) \), we first rewrite \( read_m(x) = pin_m(x) \cdot miss_m(x) \), where \( pin_m(x) \) is the total number of page pins for disk merges and \( miss_m(x) \) is the cache miss ratio for merges. Based on the derivative rule, we have \( read'_m(x) = pin'_m(x) \cdot miss_m(x) + pin_m(x) \cdot miss'_m(x) \). \( pin_m(x) \) and \( miss_m(x) \) can be obtained by counting the number of merge page pins per operation, and \( miss_m(x) = \frac{read_m(x)}{pin_m(x) \cdot \text{merge}_m(x)} \). \( pin'_m(x) \) is the number of saved merge page pins per unit of write memory. Recall that we have computed \( write'(x) \), which is the number of saved disk writes per unit of write memory. On average, each merge disk write requires \( \frac{pin_m(x)}{\text{merge}_m(x)} \) page pins. As a result, \( pin'_m(x) = write'(x) \cdot \frac{pin_m(x)}{\text{merge}_m(x)} \).

To estimate \( miss'_m(x) \), we again use the simulated cache to estimate the number of saved merge reads per operation \( saved_m \). Thus, \( miss'_m(x) = \frac{saved_m}{pin_m(x) \cdot sim} \). Putting everything together, \( read'_m(x) = write'(x) \cdot \frac{pin_m(x)}{\text{merge}_m(x)} + \frac{saved_m}{pin_m(x) \cdot sim} \).

Finally, \( read'(x) \) can be computed as

\[
read'(x) = \frac{saved_q + saved_m}{sim} + \frac{read_m(x)}{\text{merge}_m(x)} \quad \text{read'(x)} \tag{7}
\]

**Example 5.2.** Continuing from Example 5.1, suppose that the simulated cache size is 32MB. Suppose that the simulated cache reports that the saved query disk reads per operation is \( saved_q = 0.01 \text{ page/op} \) and that the saved merge disk reads per operation is \( saved_m = 0.008 \text{ page/op} \). Moreover, suppose that the total number of merge disk reads per operation is \( read_m(x) = 2.4 \text{ page/op} \). Thus, we can compute \( read'(x) = -1.94e^{-9} \text{ page/op} \). This means that allocating 1 more byte of write memory can decrease the disk read cost per operation by \( 1.94e^{-9} \text{ page/op} \), as disk reads are mainly performed by merges in this case.

### 5.4 Finding Optimal Memory Allocation

To find the optimal memory allocation \( x \), we can use the Newton-Raphson method to find the root of \( \text{cost}'(x) = \omega \cdot write'(x) + \gamma \cdot read'(x) \). The basic idea is to use a series of approximations to find the root of a function \( f(x) \). At the \( i \)-th iteration, the next approximation is computed as \( x_{i+1} = x_i - \frac{f(x_i)}{f'(x_i)} \). Since we only know the evaluations of \( \text{cost}'(x) \), we further approximate \( \text{cost}'(x) \) using a linear function. That is, we use the last \( K \) samples to fit a linear function \( \text{cost}'(x) = Ax + B \), where by default \( K \) is set to 3. Thus, at each tuning step, the next memory allocation is computed as

\[
x_{i+1} = x_i - \frac{\text{cost}'(x_i)}{A} \tag{8}
\]

To ensure the stability of the memory tuner, we employ several heuristics here. First, during the startup phase, the tuner does not have enough samples to construct the linear function. In this case, \( \text{cost}'(x) \) only tells whether the write memory should be increased or decreased but not the exact amount. To address this, a simple heuristic is to use a fixed step size, e.g., 5% of the total memory. Second, to ensure the stability of the memory tuner, the maximum step size is limited based on the memory region whose memory needs to be decreased. The intuition is that taking memory from a region may be harmful because both the write memory and the buffer cache are subject to diminishing returns. Thus, at each tuning step, we limit the maximum decreased memory size for either memory region to 10% of its currently allocated memory size. Finally, the memory tuner uses two stopping criteria to avoid oscillation. The memory allocation is not changed if the step size is too small, e.g., smaller than 32MB, or if the expected cost reduction is too small, e.g., smaller than 0.1% of the current I/O cost.
The last question for implementing the memory tuner is determining the appropriate tuning cycle length. Ideally, the tuning cycle should be long enough to capture the workload characteristics but be as short as possible for better responsiveness. To balance these two requirements, memory tuning is triggered whenever the accumulated log records exceed the maximum log length. This allows the memory tuner to capture the workload statistics more accurately by waiting for log-triggered flushes to complete. For read-heavy workloads, it may take a very long time to produce enough log records. To address this, the memory tuner also uses a timer-based tuning cycle, e.g., 10 minutes.

6 EXPERIMENTAL EVALUATION

In this section, we experimentally evaluate the proposed techniques in the context of Apache AsterixDB [1]. Throughout the evaluation, we focus on the following two questions. First, what are the benefits of the partitioned memory component compared to alternative approaches? Second, what is the effectiveness of the memory tuner in terms of its accuracy and responsiveness? In the remainder of this section, we first describe the general experimental setup followed by the detailed evaluation results.

6.1 Experimental Setup

Hardware. All experiments were performed on a single node m5d.2xlarge on AWS. The node has an 8-core 2.50GHz vCPUs, 32GB of memory, a 300GB NVMe SSD, and a 500GB elastic block store (EBS). We use the native NVMe for LSM storage and EBS for storing transaction logs. The NVMe SSD provides a write throughput of 250MB/s and a read throughput of 500MB/s. We allocated 26GB of memory for the AsterixDB instance. Unless otherwise noted, the total storage memory budget, including the buffer cache and the write memory, was set at 20GB. Both the disk page size and memory page size were set at 16KB. The maximum transaction log length was set at 10GB. Finally, we used 8 worker threads to execute benchmark operations.

LSM-tree Setup. All LSM-trees used a partitioned leveling merge policy with a size ratio of 10, which is a common setting in existing systems. Unless otherwise noted, the number of disk levels was dynamically determined based on the current write memory size. For the partitioned memory component, its active SSTable size was set at 32MB and the size ratio of the memory merge policy was also set at 10. We used 2 threads to execute flushes, 2 threads to execute memory merges, and 4 threads to execute disk merges. In each set of experiments, we first loaded the LSM storage based on the given workload. Each experiment always started with a fresh copy of the loaded LSM storage. For both memory and disk levels, we built a Bloom filter for each SSTable with a false positive rate of 1% to accelerate point lookups. Finally, both the memory flush threshold and the log truncation threshold were set at 95%.

Workloads. We used two popular benchmarks, YCSB [18] and TPC-C [6], to evaluate the proposed techniques. YCSB is a popular and extensible benchmark for evaluating key-value stores. Due to its simplicity, we used YCSB to understand the basic performance of various techniques. In all experiments, we used the default YCSB record size, where each record has 10 fields with 1KB size in total, and the default Zipfian distribution. Since YCSB only supports a single LSM-tree, we further extended it to support multiple primary and secondary LSM-trees, which is described in Section 6.2. TPC-C is an industrial standard benchmark used to evaluate transaction processing systems. We chose TPC-C because it represents a more realistic workload with multiple benchmarks and secondary indexes. It should be noted that AsterixDB only supports a basic record-level transaction model without full ACID transactions. Thus, all transactions in our evaluation were effectively running under the read-uncommitted isolation level from the TPC-C perspective. Because of this, we disabled the client-triggered aborts (1%) of the NewOrder transaction. The detailed setup of these two benchmarks is further described below.

6.2 Evaluating Write Memory Management

We first evaluated the benefits of the partitioned memory component structure for managing the write memory. Specifically, we designed the following four sets of experiments. The first set of experiments uses a single LSM-tree to evaluate the basic performance of various memory component structures. The second set of experiments uses multiple datasets, each of which has just a primary LSM-tree. The third set of experiments focuses on LSM-based secondary indexes which all belong to the same dataset. Finally, the last set of experiments uses a more realistic workload that contains multiple primary and secondary indexes. For the first three sets of experiments, we used the YCSB benchmark [18] due to its simplicity and customizability. For the last set of experiments, we used the TPC-C benchmark [6] since it represents a more realistic workload.

Evaluated Write Memory Management Schemes. First, we evaluated two variations of AsterixDB’s static memory allocation scheme. The first variation, called B-tree-static-default, uses AsterixDB’s default number of active datasets, which is 8. The second variation, called B-tree-static-tuned, configures the number of active datasets parameter setting based on each experiment. We further evaluated an optimized version of the write memory management scheme (called B-tree-dynamic) used in existing systems, e.g., RocksDB and HBase, by not limiting the size of each memory component. When the overall write memory becomes full, the LSM-tree with the largest memory component is selected to flush. Moreover, we also evaluated two variations of Accordion [14], Accordion-separates keys from values by storing keys into an index structure while putting values into a log. The first variation, called Accordion-index, only merges the indexes without rewriting the logs. The second variation, called Accordion-data, merges both the indexes and logs. Finally, for the proposed partitioned memory component structure, called Partitioned, we further evaluated three variations based on the three flush policies described in Section 4.2, namely max-memory (called Partitioned-MEM), min-LSN (called Partitioned-LSN), and optimal (called Partitioned-OPT).

6.2.1 Single LSM-tree. In this experiment, the LSM-tree had 100 million records with a 110GB storage size. We evaluated four types of workloads, namely write-only (100% writes), write-heavy (50% writes and 50% lookups), read-heavy (5% writes and 95% lookups), and scan-heavy (5% writes and 95% scans). A write operation updates an existing key and each scan query accesses a range of 100 records. Each experiment ran for 30 minutes and the first 10-minute...
We found out that the resulting 99th percentile latencies of all ways performs the worst since any one LSM-tree is only allocated 1/8 of the write memory. B-tree-static-default always performs the worst since any one LSM-tree is only allocated 1/8 of the write memory. B-tree-dynamic performs slightly better than B-tree-static-tuned because the former does not leave memory idle by preallocating two memory components for double buffering. The partitioned memory component structure has the highest throughput under write-dominated workloads since better utilizes the write memory. It also improves the overall throughput slightly under the read-heavy workload by reducing write amplification. For both B-tree-dynamic and partitioned, the throughput stops increasing after the write memory exceeds 4GB. This is because flushes are then dominated by log-truncation. Finally, Accordion does not provide any improvement compared to B-tree-dynamic. Accordion-data actually reduces the overall throughput because a large memory merge will temporally double the memory usage, forcing memory components to be flushed. Moreover, Accordion was designed for reducing GC overhead since HBase [3] uses Java objects to manage memory components. Although AsterixDB is written in Java, it uses off-heap structures for memory management [15, 28]. In all experiments, its measured GC time was always less than 1% of the total run time. Based on these results, and because Accordion is mainly designed for a single LSM-tree, we excluded Accordion for further evaluation with multiple LSM-trees.

We first evaluated the impact of different write memory sizes. In general, the write memory mainly impacts write-dominated workloads, such as write-only and write-heavy, and larger write memory improves the overall throughput by reducing the write cost. Among these structures, B-tree-static-default always performs the worst since any one LSM-tree is only allocated 1/8 of the write memory. B-tree-dynamic performs slightly better than B-tree-static-tuned because the former does not leave memory idle by preallocating two memory components for double buffering. The partitioned memory component structure has the highest throughput under write-dominated workloads since better utilizes the write memory. It also improves the overall throughput slightly under the read-heavy workload by reducing write amplification. For both B-tree-dynamic and partitioned, the throughput stops increasing after the write memory exceeds 4GB. This is because flushes are then dominated by log-truncation. Finally, Accordion does not provide any improvement compared to B-tree-dynamic. Accordion-data actually reduces the overall throughput because a large memory merge will temporally double the memory usage, forcing memory components to be flushed. Moreover, Accordion was designed for reducing GC overhead since HBase [3] uses Java objects to manage memory components. Although AsterixDB is written in Java, it uses off-heap structures for memory management [15, 28]. In all experiments, its measured GC time was always less than 1% of the total run time. Based on these results, and because Accordion is mainly designed for a single LSM-tree, we excluded Accordion for further evaluation with multiple LSM-trees.

As suggested by [37], we further carried out an experiment to evaluate the 99th percentile write latencies of each scheme using a constant data arrival process, whose arrival rate was set at a high utilization level (95% of the measured maximum write throughput). We found out that the resulting 99th percentile latencies of all schemes were less than 1s, which suggests that all structures can provide a stable write throughput with a relatively small variance, even under a very high utilization level.

Benefits of Dynamically Adjusting Disk Levels. To evaluate the benefit of dynamically adjusting disk levels as the write memory changes, we conducted an experiment where the write memory size alternates between 1GB and 32MB every 30 minutes. Each experiment ran for two hours in total. We used the partitioned memory component structure but the disk levels were determined differently. In addition to the proposed approach that adjusts disk levels dynamically (called "dynamic"), we used two baselines where the number of disk levels is determined statically by assuming that the write memory is always 32MB (called "static-32MB") or always 1GB (called "static-1GB"). The resulting write throughput, aggregated over 5-minute windows, is shown in Figure 7. The dynamic approach always has the highest throughput, which confirms the utility of adjusting disk levels as the write memory changes. Moreover, we see that having fewer levels when the write memory is small has a more negative impact than having more levels when the write memory is large since the write throughput for static-1GB is much lower under the small write memory.

6.2.2 Multiple Primary LSM-trees. In this set of experiments, we used 10 primary LSM-trees, each of which had 10 million records. Since the write memory mainly impacts write performance, a write-only workload was used in this experiment. Writes were distributed among the multiple LSM-trees following a hotspot distribution, where x% of the writes go to y% of the LSM-trees. For example, an 80-20 distribution means that 80% of the writes go to 20% of the LSM-trees, i.e., 2 hot LSM-trees, while the 20% of the writes go to 80% of the LSM-trees, yielding 8 cold LSM-trees. Within each LSM-tree, writes still followed YCSB’s default Zipfian distribution.

Impact of Write Memory. We first evaluated the impact of the write memory size by fixing the skewness to be 80-20. The
resulting write throughput is shown in Figure 8a. Note that B⁺-tree-static-default results in a much lower throughput because of thrashing. Since the default number of active datasets in AsterixDB is only 8, some LSM-trees have to be constantly activated and deactivated, resulting in many tiny flushes. Moreover, thrashing has larger negative impact under large write memory because it takes longer to allocate larger memory components. B⁺-tree-static-tuned avoids the thrashing problem, but it still performs worse than the other baselines because it does not differentiate hot LSM-trees from cold ones. B⁺-tree-dynamic allows the write memory to be allocated dynamically. However, since it always flushes the LSM-tree with the largest memory component, the memory components of the cold LSM-trees are not flushed until they are large enough or until the transaction log has to be truncated. Because of this, Partitioned-MEM, which uses the max-memory flush policy, also has a relatively lower throughput. In contrast, both the min-LSN (Partitioned-LSN) and optimal (Partitioned-OPT) flush policies improve the write throughput via better memory allocation. Moreover, the min-LSN policy has a write throughput comparable to the optimal policy, which makes it a good approximation but with less implementation complexity. Finally, all three flush policies start to have similar throughput when the write memory is larger than 2GB because flushes then become dominated by log truncation.

**Impact of Skewness.** Next, we evaluated the impact of skewness by fixing the write memory to be 1GB. The resulting write throughput is shown in Figure 8b. All memory component structures except B⁺-tree-static-tuned benefit from skewed workloads. The problem of B⁺-tree-static-tuned is that it always allocates the write memory evenly to all datasets without differentiating hot LSM-trees from cold ones. For B⁺-tree-static-default, the thrashing problem is alleviated under skewed workloads since most writes go to a small number of LSM-trees. The partitioned memory component structure also outperforms B⁺-tree-dynamic, as we have seen before. Moreover, when the workload is more heavily skewed, the performance differences among the three flush policies also become larger. Under the 50-50 workload, where each LSM-tree receives the same volume of writes, these flush policies have nearly identical behavior. When the workload becomes more skewed, the primary LSM-tree and all secondary LSM-trees share the same budget here, which is similar to B⁺-tree-dynamic.

**Impact of Number of Updated Fields.** Finally, we studied the performance impact of the number of updated fields per write, ranging from 1 to 5. The resulting throughput is shown in Figure 8c. Increasing the number of updated fields per write negatively impacts the write throughput because each logical write produces more physical writes. Because of this, the write throughput of all memory component structures decreases in the same way when each write updates more fields.

### 6.2.3 Multiple Secondary LSM-trees

We further evaluated the alternative memory component structures using multiple secondary LSM-trees for one dataset. The dataset had one primary LSM-tree and 10 secondary LSM-trees, with one secondary LSM-tree per field. The primary LSM-tree had 50 million records with 55GB storage size, and each secondary LSM-tree was about 5GB. As before, we used the write-only workload to focus on write performance. It should be noted that each write must also performs a primary index lookup to cleanup secondary indexes [36]. Unless otherwise noted, each write only updates one secondary field, but the choice of updated fields followed the same hotspot distribution as in Section 6.2.2. For each field, its values followed the default Zipfian distribution used in YCSB.

**Impact of Write Memory.** First, we varied the total write memory to evaluate its impact on the different memory component structures with secondary indexes. The resulting write throughput is shown in Figure 9a. In general, the results are consistent with the multiple primary LSM-tree case in Figure 8a. Note that the performance difference between B⁺-tree-static-tuned and B⁺-tree-dynamic becomes smaller in this case because B⁺-tree-static-tuned allocates the write memory at a dataset level, so the primary LSM-tree and all secondary LSM-trees share the same budget here, which is similar to B⁺-tree-dynamic.

**Impact of Update Field Skewness.** We further varied the skewness of updated fields to study its impact on write throughput. Figure 9b shows the resulting write throughput. As one can see, the skewness of updated fields has a smaller performance impact here compared to the multiple primary LSM-tree case in Figure 8b because the size of a secondary LSM-tree is much smaller than the primary one. However, B⁺-tree-dynamic and Partitioned-MEM, both of which used the max-memory flush policy, still benefit from a more skewed workload. The reason is that when most writes access a small number of hot secondary indexes, the size of their memory components will grow faster and they will be selected by the max-memory policy to flush.

**Impact of Number of Updated Fields.** Finally, we used the TPC-C benchmark to evaluate the alternative memory management schemes on a more realistic workload. We used two scale factors (SF) of TPC-C, i.e., 500, which results in a 50GB storage size, and 2000, which results in a 200GB storage size. Each experiment ran for one hour and the throughput was measured excluding the first 30 minutes.

The resulting throughput and the per-transaction disk writes (KB) under the two scale factors are shown in Figure 10. Note that there is only one baseline, B⁺-tree-static, because the number of active datasets in TPC-C is 8, which is the same as the default value used in AsterixDB. B⁺-tree-static still has the highest I/O cost because it allocates write memory evenly to all datasets. TPC-C contains some hot datasets, such as order_line and stock, that
receive most of the writes, as well as some cold datasets, such as warehouse and district, that only require a few megabytes of write memory. Partitioned-OPT always seeks to minimize the transaction write cost, improving the system I/O efficiency. However, note that this may not always improve the overall throughput. When the workload is CPU-bound at scale factor 500, the extra CPU overhead incurred by memory merges actually decreases the overall throughput as compared to B⁺-tree-dynamic. When the workload is I/O-bound at scale factor 2000, reducing the disk writes does increase the overall throughput. Thus, we observe that it is useful to design a memory management scheme to balance the CPU overhead and the I/O cost, which we leave as future work. Finally, the results also show that increasing the write memory may not always increase the overall transaction throughput. For example, when the scale factor is 2000, the optimal throughput is reached when the write memory is between 1GB and 2GB. This confirms the importance of memory tuning, which will be evaluated next.

6.2.5 Summary. Here we briefly summarize the findings from the evaluation of the various memory component schemes. As all of the experiments have illustrated, it is important to utilize a large write memory efficiently to reduce the I/O cost. Although AsterixDB’s static memory allocation scheme is relatively simple and robust, it leads to sub-optimal performance because the write memory is always evenly allocated to active datasets. The optimized version of the memory management scheme used by existing systems, i.e., B⁺-tree-dynamic, reduces the I/O cost by dynamically allocating the
write memory to active LSM-trees. This still does not achieve optimal performance, however, because it fails to manage large memory components efficiently and its choice of flushes does not optimize the overall write cost. Finally, the proposed partitioned memory component structure and the optimal flush policy minimize the write cost for all workloads. The use of partitioned memory components manages the large write memory more effectively to reduce the write amplification of a single LSM-tree. Moreover, the optimal flush policy allocates the write memory to multiple LSM-trees based on their write rates to minimize the overall write cost. However, the partitioned memory component structure may incur extra CPU overhead, which makes it less suitable for CPU-heavy workloads. Finally, we have observed that the min-LSN policy achieves comparable performance to the optimal policy, which makes it a good approximation but with less implementation complexity.

6.3 Evaluating the Memory Tuner

We now proceed to evaluate the memory tuner with the focus on the following questions: First, what are the basic mechanics of the memory tuner in terms of how it tunes the memory allocation for different workloads? Second, what is the accuracy of the memory tuner as compared to manually tuned memory allocation? Finally, how responsive is the memory tuner when the workload changes?

Recall that the memory tuner minimizes the weighted sum of the I/O cost. Thus, instantiating this cost function to maximize the overall throughput is hardware-dependent. To avoid this dependency on the underlying hardware in our evaluation, we set both weights to be 1 here and focus on the per-operation I/O cost, instead of the absolute throughput, in our evaluation. The I/O cost was measured by dividing the total number of monitored disk I/Os with the total number of operations. Moreover, to show the effectiveness of the memory tuner, the write memory size always starts from 64MB. The simulated cache size was set to 128MB. Unless otherwise noted, other settings of the memory tuner, such as the number of samples for fitting the linear function, the stopping threshold, and the maximum step size, all used the default values given in Section 5.4.

6.3.1 Basic Mechanics. To understand the basic mechanics of the memory tuner, we carried out a set of experiments using YCSB [18] with a single LSM-tree. As before, the LSM-tree had 100 million records with 110GB in total. We used a mixed read/write workload where the write ratio varied from 10% to 50%. The total memory budget was set at 4GB or 20GB. Each experiment ran for 1 hour.

The tuned write memory size and the corresponding I/O costs over time are shown in Figure 11. Note that each point denotes one tuning step performed by the memory tuner. We see that the memory tuner balances the relative gain of allocating more memory to the write memory and the buffer cache to minimize the overall I/O cost. As shown in Figures 11a and 11c, when the overall memory budget is fixed, the memory tuner allocates more write memory when the write ratio is increased because the benefit of having a large write memory increases. Moreover, by comparing the allocated write memory sizes in Figures 11a and 11c, we can see that when the write ratio is fixed, the memory tuner also allocates more write memory when the total memory becomes larger. This is because the benefit of having more buffer cache memory plateaus.

Finally, as shown in Figures 11b and 11d, the overall I/O cost also decreases after the memory allocation is tuned over time.

6.3.2 Accuracy. To evaluate the accuracy of the memory tuner, we carried out a set of experiments on TPC-C to compare the tuned I/O cost versus the optimal I/O cost. Here We used TPC-C because it represents a more complex and more realistic workload than YCSB. The scale factor was set at 2000. To find the memory allocation with the optimal I/O cost, we used an exhaustive search with an increment of 128MB. To show the effectiveness of the memory tuner, we included two additional baselines. The first baseline always set the write memory at 64MB, which is the starting point of the memory tuner. The second baseline divided the total memory budget evenly between the buffer cache and the write memory. We further varied the total memory budget from 4GB to 20GB. Each experiment ran for 1 hour and the I/O cost was measured after the first 30 minutes.

Figure 12 shows the I/O cost per transaction, which includes both the read and write costs, for the different memory allocation approaches. In general, the auto-tuned I/O cost is always very close to the optimal I/O cost found via exhaustive search, which shows the effectiveness of our memory tuner. Moreover, the memory tuner performs notably better than the two heuristic-based baselines. Allocating a small write memory minimizes the read cost but leads to a higher write cost. In contrast, allocating a large write memory minimizes the write cost but the read cost becomes much higher. An optimal memory allocation must balance these two costs in order to minimize the overall cost.

6.3.3 Responsiveness. Finally, we used a variation of TPC-C to evaluate the responsiveness of the memory tuner. This experiment started with the default TPC-C transaction mix and the workload changed into a read-mostly variation, one which contains 5% write transactions, i.e., new_order, payment, and delivery, and 95% read transactions, i.e., order_status and stock_level. Each experiment ran for two hours and the workload was changed after the first hour. The resulting allocated write memory and I/O cost over time are shown in Figure 13. After the workload changes, the memory tuner immediately detects the change in the next tuning cycle and begins allocating more memory to the buffer cache. Note that the write memory decreases relatively slowly because the memory tuner limits its step size to 10% of the current write memory size to ensure stability. However, we see that this does not impact the overall I/O cost too much because the buffer cache already occupies

![Figure 12: Experimental Results of Memory Tuner’s Accuracy on TPC-C](chart.png)
breaking down memory walls: adaptive memory management in lsm-based storage systems (extended version)

in this paper, we have described and evaluated a number of techniques to break down the memory walls in lsm-based storage systems. we first presented an lsm memory management architecture that facilitates adaptive memory management. we further proposed a partitioned memory component structure with new flush policies to better utilize the write memory in order to minimize the overall write cost. to break down the memory wall between the write memory and the buffer cache, we further introduced a memory tuner that uses a white-box approach to continuously tune the memory allocation. we have empirically demonstrated that these techniques together enable adaptive memory management to minimize the io cost for lsm-based storage systems.

7 conclusion

most of the memory. also note that the write memory size does not change when the total memory is 16gb or 20gb. this is because the buffer cache already occupies most of the memory and allocating more write memory would not change the total io cost too much.

to study the impact of the maximum step size on the responsiveness and stability of the memory tuner, we further carried out an experiment that varies the maximum step size from 10% to 100%. the total memory was set at 12gb. each experiment ran for four hours and the workload changed from the default tpc-c mix into the read-heavy mix after the first hour. the tuned write memory and io cost over time are shown in figures 14a and 14b respectively. as the results show, increasing the maximum step size improves responsiveness by allowing the memory tuner to change the memory allocation more quickly. however, this also negatively impacts the memory tuner’s stability and leads to some oscillation. also note that decreasing the write memory more rapidly has a very small impact on the io cost since the buffer cache already occupies most of the memory. thus, the memory tuner’s default maximum step size is set at 10% to ensure stability while providing reasonable responsiveness.

6.3.4 summary

in this set of experiments, we evaluated the memory tuner in terms of its mechanics, accuracy, and responsiveness. the memory tuner uses a white-box approach by modeling the io cost of the lsm storage system and minimizing the overall io cost based on the relative gains of allocating more memory to the buffer cache or to the write memory. the experimental results show that this white-box approach enables the memory tuner to achieve both high accuracy with reasonable responsiveness, making it suitable for online tuning.

7 conclusion

in this paper, we have described and evaluated a number of techniques to break down the memory walls in lsm-based storage systems. we first presented an lsm memory management architecture that facilitates adaptive memory management. we further proposed a partitioned memory component structure with new flush policies to better utilize the write memory in order to minimize the overall write cost. to break down the memory wall between the write memory and the buffer cache, we further introduced a memory tuner that uses a white-box approach to continuously tune the memory allocation. we have empirically demonstrated that these techniques together enable adaptive memory management to minimize the io cost for lsm-based storage systems.

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