Abstract

Zoned storage devices, such as zoned namespace (ZNS) solid-state drives (SSDs) and host-managed shingled magnetic recording (HM-SMR) hard-disk drives (HDDs), expose interfaces for host-level applications to support fine-grained, high-performance storage management. Combining ZNS SSDs and HM-SMR HDDs into a unified hybrid storage system is a natural direction to scale zoned storage at low cost, yet how to effectively incorporate zoned storage awareness into hybrid storage is a non-trivial issue. We make a case for key-value (KV) stores based on log-structured merge trees (LSM-trees) as host-level applications, and present HHZS, a middleware system that bridges an LSM-tree KV store with hybrid zoned storage devices based on hints. HHZS leverages hints issued by the flushing, compaction, and caching operations of the LSM-tree KV store to manage KV objects in placement, migration, and caching in hybrid ZNS SSD and HM-SMR HDD zoned storage. Experiments show that our HHZS prototype, when running on real ZNS SSD and HM-SMR HDD devices, achieves the highest throughput compared with all baselines under various settings.

1 Introduction

Conventional storage software stacks leverage the block interface to bridge host-level applications and storage devices, but the block interface poses performance penalties due to its mismatch with modern storage hardware characteristics. Specifically, both NAND-flash-based solid-state drives (SSDs) and Shingled Magnetic Recording (SMR) hard-disk drives (HDDs) build on append-only writes by nature. To comply with the block interface, they must be coupled with a translation layer that maps the logical addresses of application data to the physical addresses of storage devices. Such a translation layer also necessitates device-level garbage collection, which incurs I/O interference and performance variability to applications. Zoned storage [9,11,12,19] has been advocated to replace the block interface with a new zoned interface. By exposing the zoned interface to applications and letting applications have fine-grained control in storage management, zoned storage not only maintains performance predictability by freeing the costly translation layers and hence on-device garbage collection [12], but also enables applications to customize the software stacks and exploit the full performance potential of modern storage hardware.

Zoned namespace (ZNS) SSDs and host-managed SMR (HM-SMR) HDDs are two mainstream zoned storage devices available today. ZNS SSDs offer better I/O performance, while HM-SMR HDDs can provide high capacity at much lower cost [15]. It is natural to support hybrid zoned storage to combine the benefits of both types of devices, while preserving performance predictability by eliminating translation layers via zoned storage.

Hybrid storage is a well-studied topic in the literature (e.g., [15,26,44,45]), yet existing hybrid storage solutions still build the block interface for storage management. While some wisdom in conventional hybrid storage can be applied to hybrid zoned storage (e.g., storing frequently accessed data in high-performance devices), there are unique design challenges in hybrid zoned storage. In particular, zoned storage devices organize data in units of zones of hundreds of MiB, while the data in a zone must be reset at once before being overwritten. If the data objects of different lifetimes are stored in the same zone, there will be both high space amplification due to the occupied space by stale data and high write amplification due to the relocation of live data from a reset zone. Hybrid zoned storage incurs additional data movement between heterogeneous zoned storage devices (i.e., ZNS SSDs and HM-SMR HDDs). An effective hybrid zoned storage design should incorporate zone awareness into the data management of hybrid zoned storage devices.

Our insight is that applications now have fine-grained control in zoned storage management as opposed to legacy storage hardware, so they can provide hints [15] (e.g., application-level semantics and access patterns) for instructing how zoned storage devices should manage data. Application hints have been extensively used to improve storage performance, such as data prefetching and caching [23,29,55], CPU consumption reduction [40], and throughput improvements [34,38]. In this work, we make a case for key-value (KV) storage based on log-structured merge trees (LSM-trees), and show how hints facilitate the deployment of LSM-tree KV stores atop hybrid zoned storage. LSM-tree KV stores are good fits for zoned storage since they issue append-only writes to physical storage (in KV objects) [12,50]. In fact, RocksDB [3], a production LSM-tree KV store, exports the write lifetime hint for zone selection [12]. Nevertheless, the usage of hints in RocksDB remains preliminary, not to mention hybrid zoned storage.

In this paper, we present HHZS, a middleware system
that implements hinted hybrid zoned storage that bridges the upper-layer LSM-tree KV store with the underlying hybrid ZNS-SSD and HM-SMR HDD zoned storage. HHZS leverages hints provided by the internal operations (e.g., flushing, compaction, and caching) of the LSM-tree KV store to address three data management aspects in hybrid zoned storage: (i) data placement in different zoned storage devices on the write path, (ii) data migration across zoned storage devices in the background, and (iii) caching of frequently accessed data in SSD storage.

We prototyped HHZS by modifying the LSM-tree KV store RocksDB [3] and the zone-aware file system ZenFS [6]. We evaluate our HHZS prototype on real ZNS-SSD and HM-SMR HDD devices, and show that HHZS achieves the highest throughput compared with the baselines under various workloads and parameter settings. For example, under the six YCSB core workloads [17], HHZS achieves 28.0-69.3% higher throughput than the automated placement scheme in SpanDB (an LSM-tree KV store for hybrid storage) [15].

2 Background

We provide the background details on zoned storage (§2.1) and LSM-trees (§2.2). We also present analysis to show the limitations of basic data placement schemes (§2.3) and motivate the challenges of deploying LSM-tree KV stores on hybrid zoned storage (§2.4).

2.1 Zoned Storage

Zoned storage offers higher storage capacities, increased throughput, and lower latencies via the cooperation of host-level applications and storage devices [9]. There are two main types of zoned storage devices, ZNS SSDs and HM-SMR HDDs. ZNS SSDs build on NAND-flash-based SSDs, in which each flash page must be erased before being programmed with new written data. As erase operations must be performed in units of blocks with hundreds of flash pages each, ZNS SSDs prohibit in-place updates and issue writes in an append-only manner. HM-SMR HDDs build on the SMR technologies that overlap adjacent disk tracks for substantially increasing the disk areal density. In-place updates can disturb the data in adjacent disk tracks. Thus, HM-SMR HDDs also issue writes in an append-only manner. As a result, zoned storage respects the physical nature of ZNS SSDs and HM-SMR HDDs by exposing append-only writes to applications. Recent studies show that applications with zoned storage interfaces achieve better performance than with block interfaces (e.g., 44% higher throughput and 50% less tail latency using a ZNS SSD than using a multi-stream SSD [12], and 3.8× throughput gain using an HM-SMR HDD compared with a conventional HDD [50]).

Zoned storage unifies the abstraction of both ZNS SSDs and HM-SMR HDDs. It divides the physical address space into append-only zones, each of which has a writable zone capacity of hundreds of MiB (e.g., 1,077 MiB for ZNS SSDs and 256 MiB for HM-SMR HDDs [50]). Each zone represents a contiguous address space. It can be read in any order, but can only be written sequentially. It is associated with a write pointer, which indicates the offset of the next write. The write pointer initially references the beginning of the zone, and moves forward by the number of bytes written for each write request. Zoned storage exposes zones to applications, which can then specify the zones via which data is read or written. To update (or overwrite) any data in a zone, applications must first issue a reset command to make the write pointer reference again the beginning of the zone.

In this work, we explore hybrid zoned storage that comprises both ZNS SSDs and HM-SMR HDDs. For brevity, our discussion refers to ZNS SSDs and HM-SMR HDDs as SSDs and HDDs, respectively if the context is clear.

2.2 LSM-Trees

LSM-tree KV stores issue the writes or updates of KV objects as sequential writes to storage. They are friendly to zoned storage that builds on append-only writes [12, 50]. We now provide a high-level overview of a typical LSM-tree KV store (e.g., LevelDB [2] and RocksDB [3]), as shown in Figure 1.

**LSM-tree structure.** An LSM-tree (Figure 1) organizes KV objects in $n + 1$ levels, referred to as $L_0, L_1, \ldots, L_n$, where $L_j$ is a higher level than $L_i$ for $0 \leq i < j \leq n$. It maintains KV objects in immutable files called SSTables (SSTs) of several MiB each (e.g., 64 MiB in RocksDB). Each SST is divided into multiple data blocks (of several KiB each) and maintains an index block that stores the key ranges and the offsets of all data blocks in the SST. To support efficient range queries, each SST keeps all KV objects sorted by keys, and all SSTs at the same level (except $L_0$) have disjoint key ranges.

Each level is configured with a target size that specifies the expected maximum amount of KV objects being stored. The target sizes across levels typically increase exponentially; for example, the default target size of $L_{i+1}$ is $10 \times$ that of $L_i$ for $i \geq 1$ in LevelDB [2] and RocksDB [3].

**Writes.** To write a KV object, an LSM-tree KV store appends the KV object into both an on-disk write-ahead log (WAL) for crash consistency and an in-memory write buffer called the MemTable for batched writes (the LSM-tree KV store may allocate multiple MemTables). When the size of a MemTable...
with the SST from (iii) it finally searches the KV object within the data block. To accelerate reads, each SST maintains a Bloom filter [14].

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**Table 1:** Performance statistics and prices in May 2022 of our ZNS SSD and HM-SMR HDD devices (the price of the ZNS SSD is estimated with that of an NVMe SSD).

|                      | ZN540 (ZNS SSD) | ST14000NM0007 (HM-SMR HDD) |
|----------------------|-----------------|-----------------------------|
| Sequential reads (MiB/s) | 1039.6          | 210.0                       |
| Sequential writes (MiB/s) | 1002.8          | 210.0                       |
| Random reads (IO/s)    | 16928.3         | 115.0                       |
| Price (US$/GiB)        | 0.28 [7,8]      | 0.021 [5]                   |

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reaches a limit (e.g., 64 MiB by default in RocksDB [3]), the LSM-tree KV store makes the MemTable immutable, flushes the immutable MemTable as an SST into $L_0$, and deletes the flushed KV objects from the WAL. If the size of a level $L_i$ ($i \geq 0$) exceeds its target size, the LSM-tree KV store triggers compaction to merge the SSTs of $L_i$ and the next higher level $L_{i+1}$. Specifically, it retrieves an SST from $L_i$ and the SSTs at $L_{i+1}$ that have overlapping key ranges with the SST from $L_i$. It then merge-sorts the KV objects in the retrieved SSTs, and discards any older versions of a KV object. Finally, it writes back all sorted KV objects as new SSTs into $L_{i+1}$. Both flushing and compaction operations are done in the background, and multiple compaction operations can be issued simultaneously if they do not have SSTs with overlapping key ranges.

**Reads.** To read a KV object, an LSM-tree KV store first searches for the key in all MemTables. If unsuccessful, it searches each level, starting from $L_0$, until the key is found at a level or does not exist at all levels. Since each level is sorted, searching for a KV object at a level can be done by binary search: (i) it first searches for the SST whose key range covers the searched key, (ii) it then searches the index block for the data block that possibly contains the searched key, and (iii) it finally searches the KV object within the data block. To accelerate reads, each SST maintains a Bloom filter [14] and the search within an SST is done only if the key probably exists. The frequently accessed data blocks and index blocks can also be cached in an in-memory block cache (e.g., in RocksDB) to mitigate the disk I/O overhead.

### 2.3 Motivating Analysis

Hybrid zoned storage requires effective data management across zoned storage devices. We now motivate via experiments that na"ıve data management can lead to significant performance degradations.

We consider two real zoned storage devices, a 4-TiB Western Digital Ultrastar DC ZN540 ZNS SSD [8] and a 14-TiB Seagate ST14000NM0007 HM-SMR HDD [5], with the zone capacities of 1,077 MiB and 256 MiB, respectively. We analyze the cost-performance trade-off of both devices, as shown in Table 1. We measure the throughput of sequential reads/writes (with 1 MiB requests) and random reads (with 4 KiB requests) for both devices, using fio [1] with a queue depth of one. We also report the prices (in US$/GiB) for both devices; since the price of the ZNS SSD is not yet publicly available at the time of the writing, we use the 3.84-TiB Ultrastar DC SN640 block-interface NVMe SSD for cost estimation given that both ZN540 and SN640 models have similar throughput and the same form factor [7,8]. In short, the ZNS SSD provides much higher throughput than the HM-SMR HDD (e.g., 147.2 × higher in random reads), yet its price per GiB is 13.1 × higher. This motivates us to explore hybrid zoned storage to balance the cost-performance trade-off.

We set up a hybrid zoned storage environment as follows. We mount RocksDB [3] on ZenFS [6], which we have modified to support hybrid zoned storage devices (S3,6). We configure RocksDB based on the RocksDB tuning guide [4], and run the modified ZenFS on the both devices.

We further implement a set of basic data placement schemes to understand their limitations. The basic schemes make the placement decision based on (i) the filename of the written file and (ii) the LSM-tree level of the SST (if the written file is an SST). We use the filename, which is specified by RocksDB during file writes, to determine if the written file belongs to the WAL or a newly written SST. For the latter case, we modify the FileOptions structure in RocksDB to include the LSM-tree level of the newly written SST. Then the basic schemes attempt to store both the WAL and the low-level SSTs in the SSD, and the high-level SSTs in the HDD. The rationale is that the WAL lies on the critical I/O path and WAL writes are perceived by users, so the WAL should be stored in high-speed storage [15]. Also, the low-level SSTs store the recently written KV objects that are more likely accessed than the high-level SSTs, so they are also stored in the SSD for low-latency access. Note that the similar rationale is also adopted in [15]. To avoid extra I/Os of data migration and hence long stalls, if the SSD is full, the basic schemes simply issue the writes of the WAL or low-level SSTs to the HDD, and the SSD space can be reused if some SSTs are removed by the LSM-tree compaction.

In our evaluation, we vary the level threshold, denoted by $h$, that differentiates the low and high LSM-tree levels. Let $B/h$ be the basic scheme that puts the SSTs at levels $L_0, \ldots, L_{h-1}$ in the SSD and the SSTs at levels $L_h$ or higher in the HDD. We make four key observations on the basic schemes.

**O1: The actual size of SSTs at each level can significantly exceed the target size during runtime.**

We first examine whether the basic schemes (where $1 \leq h \leq 4$) can effectively put the low-level SSTs in the SSD. We use YCSB [17] to load into RocksDB 200 GiB of 1-KiB KV objects, each with a 24-byte key and a 1,000-byte value. We limit the available SSD space as 20 zones (i.e., $20 \times 1,077$ MiB = 21.0 GiB) and set the target sizes of $L_0, L_1, L_2, L_3,$ and $L_4$ as 1 GiB, 1 GiB, 10 GiB, 10 GiB, and 1,000 GiB, respectively.

We sample the actual sizes of the WAL and $L_0 \sim L_4$ at one-minute intervals when the KV objects are loaded (which takes about eight hours in total). Figure 2(a) shows the boxplots (in-
including the minimum, lower quartile, median, upper quartile, and maximum) of the samples from B4; the results of B1-B3 are similar and omitted from our plots. The maximum sizes of \( L_0 \), \( L_1 \), and \( L_2 \) can reach 40.3 GiB, 29.7 GiB, and 49.1 GiB, or equivalently 40.3 \( \times \), 29.7 \( \times \), and 4.9 \( \times \) their target sizes, respectively, and their medians also achieve 4.0 \( \times \), 5.2 \( \times \), and 1.4 \( \times \) their target sizes, respectively. The reason that the actual size can grow beyond the target size is that the compaction operations cannot catch up with the write speed under write-intensive workloads due to the limited I/O bandwidth of the SSD/HDD. Thus, it is ineffective to statically determine the reserved space for each level based on its target size.

**O2:** The load throughput degrades when \( h \) is too small since the SSD is not fully utilized, or when \( h \) is too large since the WAL and low-level SSTs cannot be entirely stored in the SSD.

We study the throughput (in operations per seconds (OPS)) of loading KV objects by tuning \( h \). Figure 2(b) shows the percentage of write traffic that goes to the SSD with respect to the total write traffic for each basic scheme \( B_h \); recall that \( B_0 \) may issue the writes of the WAL and low-level SSTs (i.e., at levels from \( L_0 \) to \( L_{k-1} \)) to the HDD if the SSD is full. For \( h = 1 \) or \( h = 2 \), both B1 and B2 can issue most of the writes of the WAL and low-level SSTs to the SSD. B2 has higher throughput than B1 as it can put the SSTs at \( L_1 \) in the SSD as well (but not for B1). However, for \( h = 4 \), large fractions of the SSTs at \( L_0 \) and \( L_1 \) are written to the HDD (84.4% and 89.1%, respectively). The reason is that some SSTs at level \( L_3 \) occupy the SSD space and prohibit the future writes of SSTs at \( L_0 \) and \( L_1 \) to the SSD.

Figure 2(c) shows the load throughput for the basic schemes. B3 has the highest load throughput among all basic schemes, while B4 has 11.3% lower throughput than B3 even though it attempts to put more low-level SSTs in the SSD. However, B3 still has significant fractions of writes of the WAL (68.2%) and low-level SSTs (68.2% at \( L_0 \), 49.4% at \( L_1 \), and 67.2% at \( L_2 \)) that go to the HDD.

**O3:** Throttling writes cannot address the limitations of the basic data placement schemes.

To prevent writes from outpacing compaction, one possible solution is to rate-throttle writes. Here, we use the \(-\text{target}\) option in YCSB to throttle the rate of writing KV objects to 6,000 OPS, which is smaller than the load throughput of the basic schemes without throttling as shown in Figure 2(c). Figure 2(d) shows the boxplots of the samples from B4 with the throttled loading rate of 6,000 OPS. Unfortunately, the actual sizes of \( L_0 \), \( L_1 \), and \( L_2 \) still exceed their target sizes, with the maximum sizes of 10.0 \( \times \), 10.7 \( \times \), and 2.4 \( \times \) their target sizes, respectively. While the numbers are smaller than without throttling (Figure 2(a)), throttling writes not only degrades performance, but also cannot entirely prevent an
We examine the number of SST reads at without throttling. In particular, for B3, even with write throttling, the total sizes of WAL and SSTs in $L_0$, $L_1$, and $L_2$ can exceed the total SSD size, so some WAL data or $L_0$ files will be stored in the HDD (Figure 2(e)). Also, we find similar throughput degradations for B1 and B4 compared with B2 and B3 (whose throughput is upper-bounded at 6,000 OPS due to throttling), since too few SSTs (in B1) or too many SSTs (in B4) are written to the SSD.

**O4: Frequently read SSTs can reside in the HDD, thereby leading to the degraded read throughput.**

Figure 2(e) shows the percentage of write traffic to the SSD, and Figure 2(f) shows the load throughput, when writes are throttled to 6,000 OPS. We find similar observations to without throttling. In particular, for B3, even with write throttling, the total sizes of WAL and SSTs in $L_0$, $L_1$, and $L_2$ can exceed the total SSD size, so some WAL data or $L_0$ files will be stored in the HDD (Figure 2(e)). Also, we find similar throughput degradations for B1 and B4 compared with B2 and B3 (whose throughput is upper-bounded at 6,000 OPS due to throttling), since too few SSTs (in B1) or too many SSTs (in B4) are written to the SSD.

We first consider the distribution of the number of reads to each of the SSTs at $L_3$ in B4, in which $L_3$ is sizable enough that its SSTs may be stored in both the SSD and the HDD. We examine the number of SST reads at $L_3$ in B4 in both the SSD and the HDD for $\alpha = 0.9$, while the results are similar for $\alpha = 1.2$. After the load operation, five SSTs at $L_3$ are in the SSD, and the remaining SSTs (98 in total) are in the HDD.

Here, we present the numbers of reads of the five SSTs in the SSD together with the top-five frequently read SSTs in the HDD, as shown in Figure 2(g). We see that there exist much more reads issued to the top-five SSTs at $L_3$ in the HDD than to the five SSTs in the SSD, implying that the read throughput can be significantly slowed down. The reason is that the basic schemes are unaware of the upper-layer access patterns, and the frequently read KV objects may be stored in the HDD.

Figure 2(h) shows the percentage of read traffic that goes to the HDD over all read traffic. For $\alpha = 0.9$, all basic schemes have most of the read traffic (79.7-98.2%) issued to the HDD. For $\alpha = 1.2$ (which represents a more skewed distribution), although the in-memory block cache has absorbed much more read traffic, there are still non-negligible fractions of HDD read traffic (35.8-49.5%) in the basic schemes.

Finally, we examine the actual read throughput of each basic scheme. Figure 2(i) shows the read throughput of each basic scheme for $\alpha = 0.9$ and $\alpha = 1.2$. Since the basic schemes have high fractions of HDD reads, the throughput is bottlenecked by the slow random reads of the HDD (Table 1).

### 2.4 Challenges

From [2,3] we summarize three challenges on designing an efficient hybrid zoned storage system.

**Challenge 1: Data placement.** Our goal is to put as many low-level SSTs as possible in the SSD with high SSD utilization. O1 shows that the target sizes of the LSM-tree levels are inaccurate indicators for the actual sizes of the LSM-tree levels, and O2 further shows that statically pinning low-level SSTs for the SSD can lead to sub-optimal performance. O3 shows that throttling writes still cannot effectively address the limitations of basic data placement. Thus, a dynamic data placement algorithm is necessary for SST storage management. In particular, for hybrid zoned storage, it is critical to properly place SSTs in the SSD or the HDD without compromising the performance predictability, which is a key design feature of zoned storage devices [12].

**Challenge 2: Data migration.** O4 reveals that without considering the read access patterns, a naive data management scheme cannot effectively handle the read disparity of SSTs at the same level. Thus, the migration of SSTs across the SSD and the HDD is inevitable (e.g., moving the frequently read KV objects from the HDD to the SSD). However, data migration in hybrid zoned storage is particularly non-trivial due to the large zone capacities (e.g., hundreds of MiB). If the migration only moves partial data of a zone, it causes fragmentation within the zone. On the other hand, if the migration moves data on a per-zone basis, it incurs substantial I/O traffic that leads to interference to foreground activities.

**Challenge 3: Data caching.** O4 also reveals that a significant fraction of read traffic can go to the HDD, thereby degrading the overall read performance. Effective data placement and data migration can reduce the amounts of HDD reads, but the frequently read KV objects may be scattered across SSTs in the HDD. Such frequently read KV objects should be specifically cached for fast read performance. Enlarging the in-memory cache space is one possible solution but is expensive. Caching the KV objects in the SSD can resolve the tension of in-memory caching. However, due to the append-only writes of ZNS SSDs, we need to design specific caching strategies based on the append-only interface. Also, we should carefully balance the SSD space, which is now shared by the WAL, low-level SSTs, and cached KV objects.

### 3 HHZS Design

HHHZS is a middleware system that leverages hints to bridge LSM-tree KV stores and hybrid zoned storage, with the primary goal of achieving both high I/O throughput and low latencies in KV operations (e.g., reads, writes, scans, and updates) subject to the limited SSD space.

#### 3.1 Hints and Design Techniques

HHHZS builds on three types of hints that describe the internal operations in an LSM-tree. The LSM-tree KV store passes a
hint to HHZS along with the corresponding operation. Each hint is of small size with tens of bytes, and its passing incurs limited overhead.

- **Flushing hint**: A flushing operation passes a flushing hint that identifies the flushed SST (at $L_0$).
- **Compaction hint**: A compaction operation passes a compaction hint in three phases: (i) when the compaction operation is triggered, it passes a compaction hint that identifies the current SSTs selected for compaction and the level with which the SSTs are merged; (ii) when the compaction operation generates an SST, it passes a compaction hint that specifies the level at which the SST resides; and (iii) when the compaction operation completes, it passes a compaction hint that identifies the SSTs generated from compaction.
- **Cache hint**: The in-memory block cache passes a cache hint after it evicts a data block. The cache hint identifies the SST in which the data block resides and the offset of the data block in the SST.

HHZS leverages the hints to control how to manage KV objects across the SSD and the HDD in hybrid zoned storage. It builds on three design techniques:

- **Write-guided data placement**: Instead of statically reserving SSD zones for specific LSM-tree levels as in the basic schemes ($\S 2.2$), HHZS adaptively reserves SSD zones for the low-level SSTs, by calculating how many zones are needed by each level on the fly using both flushing hints and compaction hints. It monitors the actual sizes of the LSM-tree levels and avoids putting too few or too many SSTs in the SSD. Thus, it keeps a large fraction of low-level SSTs in the SSD and maintains high SSD utilization.

- **Workload-aware migration**: HHZS monitors the workload characteristics on the fly, so as to migrate the KV objects across the SSD and the HDD. Specifically, it monitors the currently occupied SSD space and the read access patterns using both the flushing hints and compaction hints, so as to decide when to trigger data migration operations. It also rate-limits the data migration operations to limit their interference to foreground activities.

- **Application-hinted caching**: HHZS keeps the frequently accessed HDD data blocks that are evicted from the in-memory block cache in the SSD using the cache hints. Thus, it maintains high read performance for the frequently accessed KV objects, without redundantly caching the KV objects in both the in-memory block cache and the SSD.

### 3.2 Architectural Overview

Figure 3 shows the architecture of HHZS. An LSM-tree KV store issues I/O requests via HHZS to the zoned storage devices. It also issues hints to HHZS, which then manages KV objects in the zoned storage devices based on the hints.

**Zone organization**: With limited SSD space, HHZS dedicately allocates different numbers of SSD zones to the WAL and the SSTs at different levels. We reserve a number of SSD zones for the WAL and the cached data blocks, called the WAL zones and the cache zones, respectively. We fix the total number of WAL zones and cache zones as the pre-configured maximum size of the WAL divided by the SSD zone capacity, while the respective numbers of WAL zones and cache zones vary based on the access patterns ($\S 3.3$). This ensures that all WAL data can be accommodated in the SSD, but some WAL zones may be switched to serve as the cache zones if necessary. The remaining SSD zones other than the WAL zones and cache zones are used to keep SSTs.

Recall that our SSD and HDD devices have zone capacities of 1,077 MiB and 256 MiB, respectively ($\S 2.3$). Our rationale is to configure the size of an SST to be slightly smaller than the SSD zone capacity to achieve high space utilization in each SSD zone ($\S 2$), while an SST can span across multiple HDD zones (which have smaller zone capacities). Thus, we set the SST size as 1,011.2 MiB, so that it can fit in one SSD zone (93.9% of the SSD zone capacity) or four HDD zones (100% of the HDD zone capacity for the first three HDD zones, and 95% for the last HDD zone). Note that HHZS does not use the write lifetime hint from RocksDB [3] for zone selection ($\S 2$), as it always assigns a new SST to one (for the SSD) or multiple (for the HDD) empty zones.

**Writes**: The LSM-tree KV store generates new SSTs via either flushing or compaction operations. When a new SST is generated, the LSM-tree KV store also issues a flushing hint or a compaction hint to HHZS, which then determines the level of the SST and hence whether the SST should be stored in the SSD or the HDD ($\S 3.3$). Also, HHZS maintains the mappings between each SST and its associated zone using the `std::map` structure in the C++ standard template library, as in the original ZenFS [6].

**Reads**: To read a KV object, the LSM-tree KV store first checks both its MemTable and in-memory block cache for the KV object. If it is not found, the LSM-tree KV store requests the KV object via HHZS from an SST in zoned storage. HHZS first checks if the KV object resides in the
SSD (either in an SSD zone or in a cache zone). If so, it returns the KV object; otherwise, it checks the HDD for the KV object.

3.3 Write-Guided Data Placement

HHZS aims to write as many low-level SSTs as possible to the SSD and achieve high SSD space utilization based on both the flushing hints and the compaction hints. Given the flushing hints, HHZS attempts to write the SSTs from flushing to the SSD, as such SSTs reside at the lowest level \( L_0 \). Given the compaction hints, HHZS assigns the SSTs from compaction to either the SSD or the HDD, depending on the levels at which the SSTs reside. However, the actual sizes in LSM-tree levels can be significantly large (see O1 in §2.3), which leads to fewer low-level SSTs that can be actually written into the SSD. To adapt to the varying actual sizes in each LSM-tree level, HHZS monitors the actual sizes of the LSM-tree levels, so as to dynamically allocate the SSD zones for the low-level SSTs that are being written. HHZS performs the following four steps.

**Step 1: Calculating storage demands.** HHZS calculates the storage demand of each LSM-tree level, defined as the number of SSTs that need to be generated by the ongoing flushing and compaction operations, whenever an SST is to be written. Given the SST size and both SSD and HDD zone capacities, the storage demand of each LSM-tree level can be translated to the number of zones that are needed to store the SSTs for the level in the SSD or the HDD.

HHZS first computes the storage demand of \( L_0 \), at which the SSTs are generated by flushing. The storage demand of \( L_0 \) is the total size of MemTables that currently contain KV objects divided by the SST size. Note that HHZS is unaware of the storage status of MemTables, which are managed by the LSM-tree KV store. Nevertheless, it knows the current number of WAL zones being used, as each KV object in the MemTable also has a copy in the WAL (§2.2). Thus, HHZS sets the storage demand of \( L_0 \) as the current number of WAL zones.

HHZS next computes the storage demand of each higher level \( L_i \), where \( i \geq 1 \), at which the SSTs are generated by the ongoing compaction operations. When a compaction operation is triggered or issues writes of SSTs, it also sends a compaction hint to HHZS to update the storage demand. Specifically, when there is no compaction operation that writes SSTs to \( L_i \), the storage demand of \( L_i \) is zero. When the LSM-tree KV store triggers a compaction operation that writes SSTs to \( L_i \) (we call this compaction operation \( C \)), HHZS increments the storage demand of \( L_i \) by the number of the selected SSTs from \( C \); this is the maximum number of SSTs being generated by \( C \). Each time when \( C \) writes an SST to \( L_i \), HHZS decrements the storage demand by one. When \( C \) finishes, HHZS decrements the storage demand by the difference of the number of selected SSTs minus the actual number of generated SSTs from \( C \).

**Step 2: Determining the tiering level.** Given the current allocation of SSTs and storage demands of different LSM-tree levels, HHZS determines the tiering level \( L_t \), such that the SSTs at any level lower or higher than the tiering level are put in the SSD and the HDD, respectively, while the SSTs at the tiering level are stored in either the SSD or the HDD. Specifically, HHZS allocates the available zones in the SSD (aside the WAL zones and cache zones) from low to high levels, until the SSTs of a level (i.e., the tiering level) cannot be fully stored in the SSD. Let \( A_i \) be the currently allocated zones for \( L_i \), \( D_i \) be the storage demand of \( L_i \), and \( C_{ssd} \) be the number of available SSD zones for SSTs. Given that an SST is stored in one SSD zone, HHZS calculates \( t = \arg\min_i \sum_{j=0}^{i-1} (A_j + D_j) \geq C_{ssd} \).

**Step 3: Reserving SSD zones for \( L_t \).** Given that \( L_t \) is determined, HHZS further calculates the number of SSTs that can be stored in the SSD, given by \( C_{ssd} - \sum_{j=0}^{t-1} (A_j + D_j) \). The remaining SSTs at \( L_t \) will be stored in the HDD.

**Step 4: Selecting zones for a written SST.** Finally, HHZS determines the new zone being allocated for a written SST. HHZS attempts to select an empty SSD zone for a written SST if (i) a flushing hint informs that the written SST is generated from flushing; (ii) a compaction hint informs that the written SST is from compaction and at levels lower than \( L_t \); or (iii) a popularity migration informs that the written SST is at \( L_t \), while there are still available SSD zones reserved for \( L_t \). Otherwise, if there is no empty SSD zone or the above three conditions are violated, HHZS selects empty HDD zones for the written SST.

3.4 Workload-Aware Migration

HHZS performs workload-aware migration to refine the data placement in the SSD and the HDD in the background. We introduce two types of migration: (i) capacity migration, which moves SSTs from the SSD to the HDD to free up SSD zones for the low-level SSTs; and (ii) popularity migration, which moves the frequently read SSTs in the HDD to the SSD for improved read performance.

**SST priorities.** We first define the priority of an SST, so as to determine if the SST should be migrated. The priority of an SST is based on the SST level (indicated by both flushing hints and compaction hints) as well as the read rate (in IOPS) of the SST, defined as the ratio between the total number of reads and the age of the SST. We say that for two SSTs, say \( X \) and \( Y \), \( X \) has a higher priority than \( Y \) if (i) \( X \) is at a lower level than \( Y \); or (ii) \( X \) and \( Y \) are at the same level while \( X \) has a higher read rate than \( Y \). Our workload-aware migration follows the priority rule to move a higher-priority SST from the HDD to the SSD. Note that the SSTs selected by current compaction operations (identified by the compaction hints) will be deleted at the end of compaction, so HHZS avoids selecting them for migration regardless of their priorities.

To track SST priorities, HHZS keeps the mappings between
each SST and its level, total number of reads, and age in memory. It simply iterates all mappings once to identify the SST priorities. Note that the mappings incur limited memory overhead (§3.6).

**Capacity migration.** When the storage demands of the lower levels increase, HHZS needs to reserve more SSD zones for the lower levels. Also, it may switch the tiering level to a lower level, meaning that the SSTs in the original tiering level should now be moved to the HDD. Thus, HHZS performs capacity migration to move some high-level SSTs in the SSD to the HDD. Specifically, HHZS checks whether the tiering level has more SSTs than the number of SSD zones reserved for the tiering level, and checks there exists any SST in the SSD that belongs to a higher level than the tiering level. If either condition holds, HHZS iterates all SSTs in the SSD and selects the SST with the lowest priority. It moves the selected SST from the SSD to the HDD.

**Popularity migration.** Recall that some SSTs receive much more reads than others at the same level under skewed workloads (see O4 in §2.3). HHZS performs popularity migration to move frequently accessed SSTs in the HDD to the SSD. Specifically, if it detects that the read rate over all SSTs in the HDD exceeds half of the maximum random read IOPS of the HDD (i.e., the read rate is bottlenecked by the HDD), it starts popularity migration. It first identifies the SST with the highest priority in the HDD. It then moves the SST to the SSD if the number of empty SSD zones is larger than the total storage demands of all levels lower than the tiering level; or swaps the SST with the one that has the lowest priority in the SSD otherwise.

**Rate-limiting.** To limit the interference of migration into foreground activities, HHZS rate-limits migration operations. It currently sets the rate limit as 4 MiB/s, which is much smaller than the HDD bandwidth (at around 200 MiB/s). With rate-limiting, the SST priorities may change at the end of migration due to the migration delay and the varying read rates of SSTs. Nevertheless, we expect that the SST priorities do not change drastically, while rate-limiting can effectively mitigate the interference caused by migration.

### 3.5 Application-Hinted Caching

HHZS leverages cache hints passed from the LSM-tree KV store to cache the frequently accessed data blocks that are scattered across the HDD in the SSD. Since the in-memory block cache in the LSM-tree KV store has already cached the frequently read data blocks in its in-memory block cache, HHZS can coordinate with the in-memory block cache to cache only the data blocks evicted from the block cache to avoid redundant caching. Figure 4 shows the workflow of application-hinted caching in HHZS.

**Cache admission.** Recall that HHZS reserves a fixed number of WAL and cache zones (§3.2). Initially, HHZS reserves WAL zones only without any cache zone. When HHZS receives a cache hint (which specifies the details of an evicted data block), it converts an empty WAL zone into an active cache zone that stores the incoming data block. Referring to Figure 4, the in-memory block cache of the LSM-tree KV store indexes each cached data block by the ID of the SST at which the data block resides and its offset in the SST. When the LSM-tree evicts a data block (1), it issues a cache hint about the evicted data block, as well as the data block content, to HHZS. If HHZS finds that the data block is stored in the HDD and has not been cached in the SSD yet, it appends the data block into the active cache zone (2); otherwise, it discards the data block. If the active cache zone is full, HHZS finds a new empty zone (either a WAL zone or a cache zone) and converts it into a new active cache zone. If no empty zone is available, HHZS calls cache eviction (see below). To efficiently identify a cached data block, HHZS maintains an in-memory mapping table to track the HDD location (i.e., the SST ID and the offset in the SST) for each cached data block in the SSD cache location (i.e., the caching address in the SSD).

**Reads to cached data blocks.** Reads can fetch the cached data block if it is tracked by the in-memory mapping table. For example, referring to Figure 4, suppose that the LSM-tree KV store issues a read to data block b1 with the SST ID 4 and offset offset4 (3), while b1 is not cached by the in-memory block cache. HHZS finds that b1 is in its mapping table, so it fetches directly b1 from the SSD (4) and returns b1 to the LSM-tree KV store (5). Suppose now that the LSM-tree KV store issues a read to data block b5, which does not appear in the mapping table of HHZS. Then HHZS retrieves b5 from
the HDD.

**Cache eviction.** HHZS evicts cached blocks if it runs out of space of the reserved zones when admitting new cached blocks or writing new WAL data. In both cases, it follows the first-in-first-out (FIFO) policy to select an evicted zone, which is always the oldest zone among all cache zones (Figure 2). It examines all cached data blocks in the evicted zone, and removes their corresponding HDD locations from its mapping table. It then resets the evicted zone and makes it available for new writes.

To identify data blocks in the evicted zone, HHZS also keeps the HDD location and SSD cache location for each data block in an in-memory FIFO queue (in addition to the mapping table). When HHZS admits a new data block, HHZS also appends its HDD location and SSD cache location into the queue. When a zone is evicted, HHZS also dequeues the location information of the data blocks in the evicted zone. Thus, it can quickly identify the HDD location and SSD cache location of each data block in the evicted zone.

### 3.6 Implementation Details

We have built our HHZS prototype on the LSM-tree KV store RocksDB v6.22.1 [3] and the C++ user-space zone-aware file system ZenFS v0.2.0 (which provides a plugin for RocksDB) [6]. Specifically, we modify RocksDB to export the three hints. For ZenFS, we modify its zone management module and I/O module to support multiple zoned storage devices (note that ZenFS currently supports a single zoned storage device only) and HHZS’s design techniques by parsing the hints from the modified RocksDB. Our implementation includes 533 LoC of changes in RocksDB and 2.9 K LoC of changes in ZenFS.

**Memory usage.** HHZS incurs limited memory overhead, which mainly comes from the maintenance of SST priorities (§3.4) and cached blocks (§3.5).

For SST priorities, HHZS keeps the mappings between each SST and its level, total number of reads, and age (§3.4). The memory overhead is small due to the large zone capacity. For example, if the SST ID and other fields are of size 8 bytes each (i.e., each mapping is of size 32 bytes), for the storage of 1-TiB KV objects with a zone capacity of 256 MiB, the memory overhead is 128 Kib only.

For cached blocks, HHZS maintains the in-memory mapping table for tracking the HDD location and the SSD cache location, as well as the in-memory FIFO queue for tracking the next evicted cached blocks (§3.5). If the SST ID, the data offset in the HDD, and the SSD cache location are of size 8 bytes each, each cached data block incurs 48 bytes for storing the information in both the mapping table and the FIFO queue. If the cache size is 2 GiB and the data block size is 4 KiB, the maximum memory usage is 24 MiB only.

### 4 Evaluation

#### 4.1 Experiment Settings

**Testbed.** We conduct our experiments in a machine that runs Ubuntu 21.04 LTS with Linux kernel 5.11. The machine is equipped with a 16-core Intel Xeon Silver 4215 CPU and 96 GiB DRAM. It has two real zoned storage devices: a 4-TiB Western Digital Ultrastar DC ZN540 ZNS SSD [8] and a 14-TiB Seagate ST14000NM0007 HM-SMR HDD [5], with zone capacities of 1,077 MiB and 256 MiB, respectively (§2.3). Both devices have a block size of 4 KiB.

**Setup.** We set the target SST size in RocksDB as 1,011.2 MiB (§3.2). We reset a zone to reclaim its space only when the WAL data or the SST in the zone is deleted by RocksDB. We set the migration rate of HHZS as 4 MiB/s.

We configure RocksDB based on the RocksDB tuning guide [4]. We set the MemTable size as 512 MiB, flush MemTables when there are at least two MemTables, and keep at most four MemTables in memory. We set the maximum total size of WAL and cache zones as 2.1 GiB (i.e., 2 SSD zones, for application-hinted caching in §3.5), the target sizes of both $L_0$ and $L_1$ as 1 GiB, and the target size of each level higher than $L_1$ as $10 \times$ the target size of its lower level. We set a total of 12 threads for flushing and compaction.

To understand the performance impact of the constrained SSD size, we restrict the available SSD size as 21.0 GiB (i.e., 20 SSD zones) and do not limit the HDD size, while we also evaluate the impact of different SSD sizes (Exp#5). The total KV object size is 200 GiB, and each KV object has a 24-byte key and a 1,000-byte value. The in-memory block cache is 8 MiB (the default in RocksDB).

Before evaluating each workload in all experiments, we always first clear the storage and load the KV objects, so that each workload is independently evaluated. We enable direct I/O for SST reads and writes, so as to reduce the impact of the page cache.

**Schemes.** We consider the basic schemes B1-B4 (§2.3) and the automated placement (referred to as AUTO) in the hybrid LSM-tree KV store SpanDB [15]. AUTO controls the maximum level, such that all LSM-tree levels up to the maximum level are put in fast storage (i.e., the SSD in our case) based on the current throughput and the remaining space in fast storage. We re-implement AUTO in our testbed based on the open-source implementation of SpanDB. Specifically, when the SSD throughput is less than 40% or higher than 65% of the sequential write throughput (Table 1), AUTO increases or decreases the maximum level by one, respectively. When the remaining SSD space is less than 13.3% of the total SSD space, AUTO fixes the maximum level as one; if the remaining space of SSD is less than 8% of the total SSD space, AUTO does not write any SST data to the SSD. Note that AUTO reserves the SSD space for the WAL, as in HHZS.
4.2 Results

Summary of findings. HHZS achieves the highest throughput compared with all baselines under different YCSB workloads (Exp#1). Our breakdown analysis shows that each design technique contributes to the performance gain of HHZS (Exp#2). Also, HHZS maintains its high throughput subject to different skewness factors (Exp#3), read-write ratios (Exp#4), and SSD space sizes (Exp#5). Its default migration rate of 4 MiB/s incurs low interference (Exp#6).

Exp#1 (YCSB workloads). We first evaluate HHZS with the YCSB benchmark. YCSB provides six core workloads: A (50% reads and 50% updates), B (95% reads and 5% updates), C (100% reads), D (95% latest reads and 5% writes), E (95% range queries and 5% writes), and F (50% reads and 50% read-modify-writes). Each workload has 1 M operations. All workloads (except workload D) follow a Zipf distribution with a skewness parameter $\alpha = 0.9$ [28], while workload D reads the latest written keys. For workload E, the starting point of each scan is selected according to the Zipf distribution. We compare HHZS with B3 (the fastest basic scheme; see §3.3) and AUTO.

Figure 5(a) shows the throughput of loading all KV objects and workloads A-F, and Figure 5(b) shows the percentages of data that resides in the SSD at each level at the end of workload A (similar results are also observed in workloads B-F). HHZS shows higher load throughput than B3 and AUTO (with a gain of 7.8% and 18.3%, respectively). In particular, it shows higher throughput in workloads A-F than B3 and AUTO (with a gain of 21.0-56.4% and 28.0-69.3%, respectively), mainly because it manages to store all SSTs at $L_0-L_2$ and some frequently read SSTs in $L_3$ in the SSD (Figure 5(b)). AUTO has even slower throughput than B3 in all cases, as its maximum level tuning can be sensitive to the throughput thresholds that are used to update the maximum level. This causes AUTO to put frequently accessed SSTs in the HDD.

Figure 6: Exp#2 (Breakdown). The number above each bar is the throughput of B3 in OPS. The x-axis shows the load and the percentages of reads and skewness factors for W1-W4.

Compared with B3, HHZS better utilizes SSD zones with migration and caching, while compared with AUTO, HHZS correctly puts low-level SSTs in the SSD with write-guided data placement.

Exp#2 (Performance breakdown). We provide a performance breakdown to show how each design technique contributes to the performance gain of HHZS. We start with B3 and then consider the following schemes:

- B3+M: It combines B3 with workload-aware migration (M) (§3.4). It moves the SSTs at $L_0-L_2$ in the HDD to the SSD under $M$. Note that it does not move SSTs at $L_3$ from the HDD to the SSD (even though there are empty zones in the SSD), as B3 requires to keep all SSTs at $L_3$ and $L_4$ in the HDD.
- P: It deploys write-guided data placement (P), without migration and caching.
- P+M: It deploys write-guided data placement (P) and workload-aware migration (M), without caching.
- P+M+C: It deploys write-guided data placement (P), workload-aware migration (M), and application-aware caching (C). It is equivalent to the whole design of HHZS.

We first load 200 GiB KV objects in each scheme. After loading the KV objects, we run a workload of 5 M operations following a Zipf key distribution for a read-write ratio and a skewness factor $\alpha$. We consider four types of workloads: W1 (10% reads and $\alpha = 0.9$); W2 (50% reads and $\alpha = 0.9$); W3 (50% reads and $\alpha = 1.2$); and W4 (100% reads and $\alpha = 1.2$). We choose $\alpha = 1.2$ for high skewness, given that practical workloads have skewness factors no more than 1.2 [47].

Figure 6 shows the normalized throughput of different schemes with respect to B3. Compared with B3, write-guided data placement (P) itself shows improved throughput in some cases, but is sometimes worse. P has higher throughput by 5.5%, 18.0%, and 18.8% in load, W1, and W2, respectively, but less throughput by 1.4% and 5.9% in W3 and W4, respectively. For load, the throughput improvement of P comes from the higher fractions of SSTs at $L_0$ and $L_1$ being stored in the SSD. For W1 and W2, B3 may write the SSTs at $L_0$ and $L_1$ to the HDD due to the amplified actual sizes of $L_2$, while P always writes the SSTs at $L_0$ and $L_1$ to the SSD. For W3 and W4, both P and B3 issue non-negligible fractions of reads to the SSTs at $L_2$ being stored in the HDD, so P cannot achieve performance gains and it has even less throughput than B3.
With migration, both B3+M and P+M improve their counterparts without migration (B3 and P, respectively) in W1-W4, and migration works better with P than B3. As depicted by Figure 6, P+M has higher throughput than B3+M by 14.5%, 8.8%, 9.4%, and 5.9% in W1, W2, W3, and W4, respectively. The reason is that both P and M aim to allocate SSD zones adaptively based on the storage demands. As a result, P+M can efficiently fix the placement violation of P under workload changes. In contrast, B3 follows static SSD space reservation and does not use the available SSD zones to store the frequently accessed SSTs.

Caching further improves the throughput of P+M in W1-W4, and the improvement is more obvious for a higher fraction of reads or a higher skewness factor. For load, caching has no effect and the throughput remains the same as P+M. P+M+C increases the throughput of P+M by 5.3%, 6.8%, 7.4%, and 173.7% in W1, W2, W3, and W4, respectively. A higher fraction of reads implies that more copies in the SSD cache are less likely updated, so the SSD cache receives more cache hits. Also, a higher skewness factor implies that the SSD cache has more read hits as more reads are aggregated on a smaller set of KV objects.

Exp#3 (Impact of the workload skewness). We study the impact of the workload skewness (i.e., the skewness factor $\alpha$) on the performance of HHZS. We run workloads with 5 M operations and vary $\alpha$ from 0.8 to 1.2. We also fix 50% of reads and 50% of writes. Figure 7 shows the throughput of B3, AUTO, and HHZS. HHZS has 27.3-43.3% of throughput gain for different workload skewness over B3. It also has 51.6-77.1% of throughput gain over AUTO. The throughput gain comes from the higher SSD utilization (compared with B3) or the placement of more low-level SSTs in the SSD (compared with AUTO).

Exp#4 (Impact of the read-write ratio). We study the impact of the read-write ratio. We run a workload with 5 M operations. We vary the percentage of reads from 10% to 90%, and fix $\alpha = 0.9$. Figure 8 shows the throughput of B3, AUTO, and HHZS. For small read percentages of 10% and 30%, HHZS has 40.4% and 42.4% higher throughput than B3, respectively, as well as 67.7% and 68.4% higher throughput than AUTO, respectively. For high read percentages at least 50%, HHZS has 42.5-60.0% and 54.1-65.3% higher throughput than B3 and AUTO, respectively. Due to the slow HDD random reads, smaller read percentages imply higher throughput since a read is much slower than a write. Thus, the overall performance of different schemes is mainly constrained by the slow HDD reads, while HHZS accelerates reads by performing popularity migration and caching.

Exp#5 (Impact of the SSD size). We examine how the SSD size affects the performance of HHZS. We vary the size of the available SSD space from 21.0 GiB (i.e., 20 zones) to 84.1 GiB (i.e., 80 zones). We first load 200 GiB KV objects and compare HHZS with the four basic schemes B1-B4, AUTO, and P (i.e., write-guided data placement in Exp#2). Figure 9(a) shows the throughput of different schemes in load. P is robust in maintaining high throughput in various SSD sizes. Compared with the basic schemes and AUTO, its throughput is 5.5%, 1.1%, 7.9%, and 6.6% higher than the best schemes among the basic schemes and AUTO under 20, 40, 60, and 80 available SSD zones, respectively. The full design HHZS further increases the load throughput of P by 2.2%, 5.3%, 7.7%, and 10.8% in four SSD sizes, respectively, with the help of capacity migration.

We also run a workload of 1 M operations with 50% reads, 50% writes, and $\alpha = 0.9$ for different SSD sizes. Figure 9(b) shows the results. For all SSD sizes, both P and HHZS have higher throughput than other schemes. Under four SSD sizes, compared with the best among all basic schemes and AUTO, P increases the throughput by 18.8%, 2.6%, 12.5%, and 6.2%, respectively, while HHZS increases the throughput by 34.8%, 15.5%, 28.5%, and 13.6%, respectively.

Exp#6 (Impact of the migration rate). Recall that HHZS rate-limits migration to reduce interference with foreground traffic (§3.3). We study the impact of the migration rates on the tail latencies. We do not consider application-hinted caching and use P+M as in Exp#3. We vary the migration rates from 1 MiB/s to 64 MiB/s. We load 200 GiB of 1-KiB KV objects, and run a workload with 50% reads, 50% writes, and $\alpha = 0.9$. We focus on the read latencies.

Figure 10 shows the 99th, 99.9th, and 99.99th percentile read latencies versus the migration rate. The 99th percentile read latencies are lower when HHZS uses a migration rate of 1 MiB/s. The 99.9th and 99.99th percentile read latencies are lower when HHZS uses a migration rate of 4 MiB/s. The 99.99th percentile read latencies are lower when HHZS uses a migration rate of 16 MiB/s. The 99.99th percentile read latencies are lower when HHZS uses a migration rate of 64 MiB/s.
latency remains similar for all migration rates, with less than 10% of variations. The 99.9th percentile latency is the lowest for migration rates of 2 MiB/s and 4 MiB/s, while the highest 99.9th percentile latency is on the migration rate of 64 MiB/s, which is 23.0% and 25.4% higher than those of 2 MiB/s and 4 MiB/s, respectively. It shows that a large migration rate increases the interference with foreground reads. The 99.99th percentile latency shows an increasing trend with the increasing migration rate, and increases by 104% from 1 MiB/s to 64 MiB/s. Our default setting selects 4 MiB/s as the migration rate for our evaluation without significantly increasing the tail latency.

5 Related Work

Zoned storage. Prior to zoned storage, previous studies expose internal SSD features to applications (e.g., Software-Defined Flash [34], Application-Managed Flash [25], and Open-Channel SSDs [13, 29]) for fine-grained storage management. Such proposals are specific to SSDs. In contrast, zoned storage provides a unified zoned interface for both ZNS SSDs and HM-SMR HDDs (§2.1).

There have been various storage system proposals for SMR drives [11, 21, 31, 33, 36, 41, 44, 46, 48, 50] and ZNS SSDs [12, 16, 19, 32]. To name a few, Duchy [45] proposes a hybrid storage design of SSDs and SMR drives by enabling SSD caching and regulating the number of written zones in SMR drives to bound the recovery time. GearDB [50] is an LSM-tree KV store for HM-SMR HDDs, using a gear compaction algorithm to eliminate on-device garbage collection. BlueStore [11] adapts RocksDB to HM-SMR HDDs and provides a zoned storage backend for distributed storage. Choi et al. [10] design a garbage collection scheme based on hot-cold data segregation for ZNS SSDs. ZNS+ [19] proposes a new interface to accelerate segment compaction in zone-aware log-structured file systems. Björling et al. [12] adapt F2FS [24] and RocksDB to ZNS SSDs, and show improved throughput and decreased tail latencies. Maheshwari [32] proposes an abstraction for storing variable-size data in ZNS SSDs. Compared with existing zoned storage designs, HHZS proposes a hinted design for hybrid zoned storage.

KV stores for hybrid storage. Some KV stores combine traditional NAND-flash-based SSDs with the faster but more expensive non-volatile memory (NVM) for cost-efficient and high-speed storage [15, 22, 27, 37, 51]. GTSSL [39] stat-ically pins an LSM-tree level to the SSD or the HDD, and re-inserts frequently read KV objects into low levels to reduce HDD reads. Mutant [51] dynamically balances the cost-performance trade-off by organizing the placement of SSTs among fast and slow storage. SLM-DB [22] uses the B+-tree in NVM for indexing and stores KV objects in a single-level organization in SSDs. HiLSM [27] proposes log-structured designs in NVM and efficient data migration from NVM to SSDs. PrismDB [37] monitors the access frequencies of KV objects, and places high-frequency KV objects in NVM and low-frequency KV objects in SSDs. SpanDB [15] combines NVMe SSDs and SATA SSDs, by storing most KV objects in SATA SSDs and relocating write-ahead logs and the top levels of the LSM-tree to NVMe SSDs. Some KV stores (e.g., HiKV [43], Flashfield [18], and AC-Key [32]) use DRAM for efficient indexing or caching, and use SSDs for persistent storage. In contrast, HHZS supports LSM-tree KV stores on hybrid storage with ZNS SSDs and HM-SMR HDDs.

Hinded storage. Application hints improve storage performance in many aspects [23, 29, 30, 34, 35, 38, 40]. Informed prefetching and caching [35] uses application hints to exploit I/O parallelism and dynamically allocate file buffers in file systems. CLient-Informed Caching (CLIC) [29] uses client-based hints to improve read hit ratios of storage server caches. Quiver [23] proposes an informed storage cache policy for deep learning training jobs in GPU clusters. PAIO [30] uses the context of each I/O request for configuring I/O optimization policies. Hints are also used in boosting the performance of distributed systems [10, 38], flash memories [34], and NVMe devices [40]. In contrast, HHZS focuses on the co-design of the LSM-tree (i.e., RocksDB) and the zoned file system (i.e., ZenFS), and leverages hints provided by the LSM-tree KV store to manage data in hybrid zoned storage.

6 Conclusion

HHZS is a middleware system that leverages hints issued by the upper-layer LSM-tree KV store to perform efficient data management on hybrid SSD and HDD zoned storage. It builds on three techniques to aim for high performance: (i) write-guided data placement adaptively reserves SSD zones for low-level SSTs; (ii) workload-aware migration dynamically moves SSTs between the SSD and the HDD with rate-limiting; and (iii) application-hinted caching keeps copies of the frequently accessed data blocks in the SSD. Experimental results demonstrate the throughput gain of HHZS prototype over the baselines in hybrid zoned storage.

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Figure 10: Exp #6 (Impact of the migration rate).
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