

HotRAP: Hot Record Retention and Promotion for LSM-trees with tiered storage

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ABSTRACT

The multi-level design of Log-Structured Merge-trees (LSM-trees) naturally fits the tiered storage architecture: the upper levels (recently inserted/updated records) are kept in fast storage to guarantee performance while the lower levels (the majority of records) are placed in slower but cheaper storage to reduce cost. However, frequently accessed records may have been compacted and reside in slow storage, and existing algorithms are inefficient in promoting these “hot” records to fast storage, leading to compromised read performance. We present HotRAP, a key-value store based on RocksDB that can timely promote hot records individually from slow to fast storage and keep them in fast storage while they are hot. HotRAP uses an on-disk data structure (a specially-made LSM-tree) to track the hotness of keys and includes three pathways to ensure that hot records reach fast storage with short delays. Our experiments show that HotRAP outperforms state-of-the-art LSM-trees on tiered storage by up to 3.3× compared to the second best for read-only and read-write-balanced workloads with common access skew patterns.

1 INTRODUCTION

Log-Structured Merge-trees (LSM-trees) [17, 28] are widely adopted to build key-value stores [5, 11, 15, 24] and database storage engines [1, 2, 16, 18, 21] because of their superior write performance. To achieve better cost efficiency, systems tend to leverage the tiered storage by locating the upper levels of the LSM-tree in fast local solid-state drives (SSDs) while storing the lower levels (i.e., the majority of the records) in slower but cheaper cloud storage or hard disk drives (HDDs). Such a storage-tier separation is inherently efficient for the write operations (i.e., inserts, updates, deletes) because the append-only nature of the LSM-tree keeps the most recent writes automatically in the fast storage. However, records that are considered “hot” (i.e., frequently accessed) may not overlap with those that are frequently updated (although “read-hot” and “write-hot” are often correlated in real-world scenarios). This leads to a majority of the hot records sitting in slow storage with higher latency and lower bandwidth and thus compromising the read performance of the LSM-tree.

The problem can be mitigated by caching frequently accessed records in memory, and prior studies have proposed numerous caching algorithms [31, 33, 35, 39, 41]. However, memory is often a limiting resource for systems [22, 37, 38], and the size of the hot records can be far larger than the memory capacity. RocksDB, therefore, introduces the secondary cache on fast SSDs for caching recently-accessed data blocks [26]. Solutions such as Mutant [36], LogStore [23], and MirrorKV [30] propose to adjust the placement of blocks/SSTables across the storage tiers periodically according to their access frequencies. These approaches, nonetheless, cannot

fully leverage the capacity of the expensive fast storage because they move data at a coarse granularity where many cold records in the identified hot blocks/SSTables are piggybacked to the fast storage.

Moreover, the above solutions can only promote hot SSTables to fast storage through the LSM-tree compaction. To deal with read-heavy workloads where compactions happen infrequently, several systems [23, 29] allow triggering compactions proactively, but they must wait for the hot records to accumulate in the slow storage before promoting them. Such a promotion delay is harmful to read performance because it could overstep the time window when a record is still hot.

In this paper, we present HotRAP (Hot record Retention And Promotion), an LSM-tree implementation based on RocksDB on tiered storage that can promote hot records timely from the slow disk (abbr. as *SD* hereafter) to the fast disk (abbr. as *FD* hereafter) and retain them in *FD* as long as they stay hot. HotRAP addresses the aforementioned three limitations of previous solutions. First, instead of tracking the hotness of records in memory, HotRAP logs each record access in a small specially-made LSM-tree, called *RALT* (Recent Access Lookup Table), located in *FD*. *RALT* tracks the access history for each logged key and maintains a hotness score for the key using exponential smoothing. *RALT* then evicts low-score keys periodically from itself to stay under a size limit that can be automatically tuned according to the workload.

Using *RALT*, HotRAP addresses the second limitation by supporting retention and promotion at *record level* rather than at block/SSTable level, thus preventing cold records from being piggybacked to *FD*. Third, besides waiting for LSM-tree compactions to retain/promote hot records, HotRAP introduces a small in-memory *promotion cache* that logs each key-value access to *SD* and timely promotes the hot records (via checking *RALT*) by flushing them to the top level (i.e. *L0*) of the LSM-tree. Specifically, HotRAP provides the following three pathways for hot records to reside in *FD*: retention, promotion by compaction, and promotion by flush.

Both *retention* and *promotion by compaction* take place when compacting SSTables from *FD* to *SD*. During such a compaction, HotRAP checks the hotness of each record in the selected SSTables in *FD* (i.e., retention) and within the compaction key range in the promotion cache (i.e., promotion by compaction). Both checks are efficiently performed by scanning the corresponding key range in *RALT* sequentially. The identified hot records are then written back to *FD* instead of merged down to the SSTables in *SD*. When the promotion cache becomes full because of insufficient LSM-tree compactions, HotRAP triggers *promotion by flush* that bulk-inserts the hot records (identified via consulting *RALT*) to *L0* of the LSM-tree to keep the size of the promotion cache small. To prevent promotion by flush from overwriting records with a newer version

(i.e., promoting a stale record to L0 that has a higher level than the newly updated version), we perform extra checks and carry out a concurrency control mechanism to guarantee correctness.

We evaluated HotRAP extensively using YCSB-based workloads on AWS instances with fast local NVMe SSDs and slower cloud storage. Compared to the state-of-the-art LSM-trees on tiered storage (e.g., RocksDB with secondary cache [26], Mutant [36], and PrismDB [29]), HotRAP achieves 3.3× speedup over the second best for read-only workloads and 2.5× speedup for read-write-balanced workloads, while maintaining a competitive performance for write-heavy and update-heavy workloads. Our experiments also show that HotRAP adds < 3% overhead to the plain RocksDB under uniform workloads and is robust against hotspot shifts where it can recover the FD hit rate in a relatively short amount of time.

We make three primary contributions in this paper. First, we propose an on-disk data structure (i.e., RALT, a specially-made LSM-tree) for tracking the hotness of key-value records. Second, we design three pathways in a tiered LSM-tree for timely promoting/retaining hot records to/in fast storage. Our algorithms operate at the record level so that the system can fully utilize the limited space of the fast storage. Finally, we build HotRAP, a key-value store based on RocksDB that outperforms state-of-the-art LSM-trees on tiered storage because of its efficiency in hot record tracking and movement.

2 BACKGROUND & RELATED WORK

2.1 LSM-trees and Tiered Storage

A Log-Structured Merge-tree (LSM-tree) consists of an in-memory buffer (i.e., MemTable) and multiple levels L_0, \dots, L_n on disk. The capacity of level L_i is T times larger than L_{i-1} , where T is called the size ratio of the LSM-tree. Records are first inserted into MemTable. When MemTable is full, it becomes immutable and then flushed to L_0 as an SSTable (i.e., a file format called Sorted String Table). When level L_{i-1} reaches its capacity, it will trigger the compaction process to merge its content into the next level L_i . There are typically two kinds of compaction policies: leveling and tiering. Leveling only allows one sorted run per level while tiering allows multiple. We focus on the leveling policy in this paper because it is RocksDB’s default [24]. RocksDB also adopts partial compaction: each compaction picks an SSTables from L_{i-1} whose key range overlaps with a minimal number of SSTables in L_i to merge to the next level. Such a compaction strategy leads to a write amplification of $\approx \frac{T}{2}(n-1)$ [10].

A lookup in an LSM-tree first checks the MemTable and then searches the levels from top to bottom until a matching key is found. A block index in memory is used to determine which SSTable data block to search for a particular key in a sorted run. Per-SSTable Bloom filters are used to reduce the number of candidate SSTables to further save I/Os. RocksDB provides snapshot isolation via multi-version concurrency control (MVCC) to prevent compactions from blocking normal read operations. A snapshot in RocksDB, called a supervision, is created after a flush or a compaction completes. An old snapshot is garbage collected when none of the active queries refer to it.

Although many LSM-trees such as RocksDB are initially designed for local SSDs, the multi-level nature of LSM-trees fits the

tiered storage architecture. The upper levels contain the recently inserted and updated records and are therefore kept in fast storage such as local SSDs because they are more likely to be accessed in the near future. To improve the system’s cost efficiency, the majority of records in the lower levels are placed in HDDs [12, 13] or low-tier cloud storage based on HDDs [14]. HDDs exhibit higher latency and lower bandwidth than SSDs, but they are much cheaper. For example, the unit price for a 20TB Seagate Enterprise HDD Exos X20 today is 6.75× cheaper than a 7.68TB SAMSUNG Enterprise SSD PM9A3 [3, 4]. That means a tiered storage with a size ratio of 1:10 based on these hardware can reduce the storage cost by 77% compared to pure SSDs of the same capacity.

2.2 Hot/cold separation in LSM-trees

Tracking the access history of (potentially) hot records in memory can incur a large footprint. According to the Twitter trace [34], for example, 50% of the records have a value size smaller than 5× the key size. That means if the size of the hot records (or local SSD) is 1 TiB, we need at least $(0.5 \times 1024)/6 = 85.3$ GiB memory to track those hot keys.

Mutant tracks access frequencies of SSTables and adjusts the placement of SSTables periodically to store the hottest SSTables in the faster storage [36]. LogStore maintains histograms in memory to track the hotness of SSTables and retains/promotes hot SSTables in/to the faster storage [23]. They all separate hot/cold data in the granularity of SSTables, which is too coarse because there can be considerable cold data in an SSTable that is considered hot.

RocksDB introduces the secondary cache on the fast disk to cache data blocks colder than blocks in the in-memory block cache [26]. However, the granularity of blocks is still too coarse because small objects are prevalent in large-scale systems [22], and there can be many cold tiny records in a hot data block.

MirrorKV splits the LSM-tree into the key LSM-tree and the value LSM-tree and caches the most frequently accessed key SSTables in the faster storage [30]. Additionally, MirrorKV retains the hottest blocks (e.g., 10%) during compactions from L1 to L2 [30]. Similarly, the granularity of SSTables and blocks are both too coarse.

SA-LSM accurately predicts cold data using historical information with survival analysis and demotes cold records from the faster storage to the slower storage [40]. However, SA-LSM does not support promoting hot records back to the faster storage, and the training cost of the survival model is heavy.

PrismDB uses Optane SSDs (or other non-volatile memory such as Z-NAND) as its faster tier [29]. Considering that the write granularity of Optane SSDs is small [32], PrismDB stores records within Optane SSDs in unsorted slabs instead of SSTables. PrismDB estimates key popularity with the clock algorithm, and the clock bits are indexed with a hash table. Hot records are retained/promoted in/to Optane SSD during compactions. However, PrismDB requires a B+ tree to index records in unsorted slabs within Optane SSD. The B+ tree and the hash table used to index clock bits can consume considerable memory if records are small.

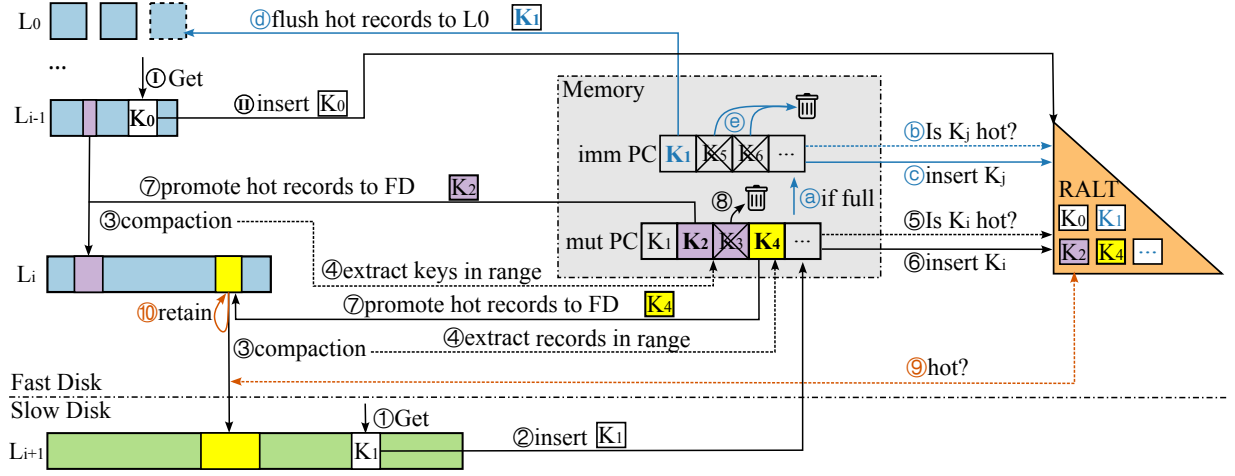


Figure 1: Overview of HotRAP. PC stands for the promotion cache. Solid arrows are data flow. Dashed arrows are control flow. The accessed keys in SD are firstly inserted into the mutable promotion cache (① & ②). Compactions can piggyback hot records in their range to FD (③ to ⑧). If the mutable promotion cache becomes full, hot records in it will be flushed to Level 0 (⑨ to ⑩).

3 DESIGN & IMPLEMENTATION

3.1 Overview

The overview of HotRAP is shown in Figure 1. There are two components to facilitate the retention and promotion: Recent Access Lookup Table (RALT) and the promotion cache. RALT is responsible for tracking the hotness of records. It maintains a set of hot records that are worth promoting and retaining, and it ensures that the total size of hot records does not exceed a limit. The promotion cache is an in-memory cache that resides between the last level of FD and the first level of SD, that is, the version of records in it is older than the levels in FD and as the same as the newest version in SD. To read a key, HotRAP first searches in MemTables and levels in FD, then searches in the promotion cache, and at last searches levels in SD. The promotion cache consists of the mutable promotion cache and a list of immutable promotion caches. Immutable promotion caches are flushed to disk as soon as possible.

When a record in FD is accessed (①), its key will be inserted into RALT to record the access (⑩). When a record in SD is accessed, HotRAP first inserts the key into the mutable promotion cache (②) (unless checks in §3.3 fail). It is inserted into RALT later because HotRAP needs to check its hotness before this access.

Promotion by compaction. When a compaction to the last level of FD or a compaction to the first level of SD occurs (③), the records in the range will be extracted (④). For the example in Figure 1, K_2 and K_3 are extracted because they are in the range of the compaction from L_{i-1} to L_i , and K_4 is extracted because it is in the range of the compaction from L_i to L_{i+1} . Promoting all accessed records to FD can incur significant overhead because cold records are also promoted, especially under the uniform workload in which all accessed records are cold records (see §4.5). Therefore, HotRAP consults RALT whether keys are hot in RALT (⑤). HotRAP inserts keys into RALT after consulting their hotness (⑥) so that the newly inserted access record can keep the promoted already-hot records hot for a long time. Hot records (K_2 and K_4) are written to the last level in FD (⑦). Cold records (K_3) are dropped (⑧).

Retention. During a compaction to the first level of SD, HotRAP constructs a RALT iterator whose range is the key range of FD’s input SSTables. Advancing the RALT iterator can iterate hot records by the order of keys. Records from the last level of FD are read sequentially, also by the order of keys. Therefore, their hotness can be checked by advancing the compaction iterator and the RALT iterator in the sort-merge style (⑨). Hot records from the last level of FD are retained in FD, i.e., written to new SSTables in FD (⑩). The I/O incurred by the RALT iterator is small because RALT does not store values of HotRAP records.

Promotion by flush. For read-heavy workloads, there may not be enough compactions. In this case, promotion by compactions is not sufficient to keep the mutable promotion cache small. Therefore, when the size of the mutable promotion cache grows to the target size of SSTables (64 MiB by default), HotRAP converts it to an immutable promotion cache, and a new mutable promotion cache will be created (⑨). For the example in Figure 1, K_2 , K_3 , and K_4 are promoted by compaction. Therefore, only K_1 , K_5 , \dots are packed into an immutable promotion cache. Similar to promoting by compaction, the immutable promotion cache consults RALT whether the records are hot (⑥) and then inserts the key into RALT (⑥). Hot records (K_1) will be flushed to disk (⑩), while other records (K_5 , K_6) are dropped (⑩). Records promoted by flush will be compacted level by level again, which incurs non-negligible I/O. Therefore, promotion by compaction is still needed to reduce the cost of promotion.

3.2 Recent Access Lookup Table (RALT)

RALT is a lightweight LSM-tree. The overview is shown in figure 2. Each record in RALT consists of 3 parts: key, value length, and data for scoring. Keys are considered as hot if they are in RALT and their scores are greater than a score threshold. RALT has two arguments: hot set size limit and physical size limit. We refer to the size of the corresponding HotRAP record of a RALT record as the *hot size* of the RALT record, while the size of the ralt record itself as the *physical size* of the record. It ensures that the total hot size

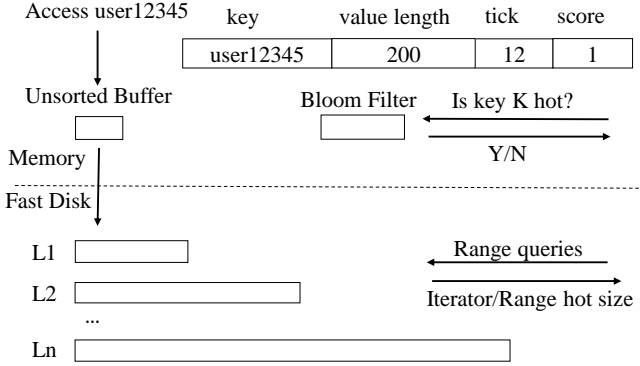


Figure 2: Overview of RALT. Suppose key user12345 is accessed and HotRAP is inserting the key, the value length of HotRAP record is 200B. Suppose we use exponential smoothing and the current time slice sequence number is 12. The RALT record is as shown in the figure. The hot size of the record is $200 + \text{len}(\text{user12345}) = 209$ bytes. The physical size is $(4 + 9) + (8 \times 3) = 37$ bytes if we allocate 4 bytes for the length of the key, and 8 bytes each for value length, tick, and score.

of RALT records (aka. the hot set size of RALT records) in HotRAP does not exceed the hot set size limit and that the occupied disk space does not exceed the physical size limit.

Overview of RALT. RALT supports 5 operations: (1) Insert a RALT record. (2) Calculate the total hot size of RALT records with keys in a range. (3) Scan a range of keys. (4) Check if a key is hot. (5) Evict keys when the total hot size or the occupied space of RALT exceeds the limit. RALT stores exact keys to support range scan. When HotRAP inserts a key, it first generates a RALT record, then inserts it into an in-memory unsorted buffer. The in-memory unsorted buffer cannot be seen by queries. We use an unsorted buffer to improve performance because a sorted memory table does not benefit much (if a key is accessed again while the last access is not flushed, then it should be super hot and promoted very fast). If the unsorted buffer is full, it is sorted and flushed to FD. There are several levels on FD and they follow the leveling compaction strategy. If the total hot size or the occupied disk space of RALT records exceeds the limit, an *eviction* is triggered, and all RALT records are merged into a single sorted run. To ensure the I/O cost is not high, RALT evicts 10% of the RALT records.

For checking hotness, RALT uses an in-memory bloom filter to avoid random reads on FD. For calculating range hot size, RALT stores the prefix sum of hot size in index blocks to reduce FD I/O. For range scan, RALT constructs iterators on each level, like other LSM-trees. To avoid blocking reads, RALT maintains multiple versions of the LSM-tree structure.

Calculating score. RALT supports any scoring method that can be calculated separately, i.e. there exists a scoring function f and a function g on the access history $H = H_1 || H_2$ ($||$ means concatenation) of a key so that $f(H) = g(f(H_1), f(H_2))$. For example, for LRU, $f(H)$ is the maximum access time in H and $f(H_1 || H_2) = \max(f(H_1), f(H_2))$. This ensures that we can calculate the score of a key by merging the scores at each level. Many methods such

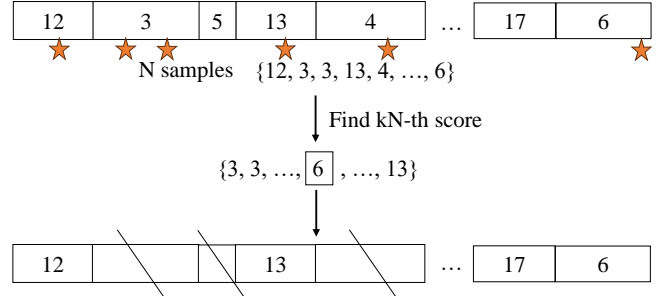


Figure 3: Eviction in RALT. The first line is the records in RALT, the length of records represents the size (hot size or physical size), and the numbers represent the scores. Stars are samples. The records with longer lengths have more samples in expectation.

as LRU, CLOCK, and exponential smoothing [19] satisfy this condition. In RALT, we use exponential smoothing to calculate score, because it utilizes history information. The score in exponential smoothing for a key is $\sum_{i=1}^N t_i \alpha^{t-i}$ where N is the number of time slices, t is the time slice sequence number, and $t_i = 1$ if the key is accessed in the i -th time slice, $t_i = 0$ otherwise. In every record in RALT, we store a pair $(tick, score)$ for scoring, where $tick$ is the most recent time slice sequence number (i.e., timestamp) of the record, and $score = \sum_i t_i \alpha^{tick-i}$. RALT maintains the current number of time slices t . For every key accessed in this time slice, their $tick$ is set to t . RALT increments t every time β (size of FD data is accessed). Although the stored scores in RALT are not updated when t is incremented, their real score is multiplied by α , i.e., the real score of the record $(tick, score)$ is $\alpha^{t-tick} \cdot score$. For two records $(tick_i, score_i)$, $(tick_j, score_j)$ which have the same key, suppose $tick_i < tick_j$ without loss of generality, the merged record $(tick^*, score^*)$ satisfies $score^* = \alpha^{tick_j-tick_i} \cdot score_i + score_j$, and its most recent time slice sequence number $tick^* = tick_j$.

Eviction. If the hot set size or the physical size of RALT exceeds the limit, RALT scans all the data and calculates a score threshold to evict 10% records. It evicts those with scores smaller than the score threshold. Since the records in RALT are sorted by key, not by score, we cannot get the threshold directly. Instead, we use an approximation algorithm to estimate it. The steps of the algorithm are shown in Figure 3.

We can formalize the problem as follows: Each record i has a size A_i (which can be hot size or physical size) and a score S_i . The size threshold is A' . We want to find a score threshold S' , so that the total size of records with scores greater than S' is near A' , i.e., $\sum_{i \in RALT, S_i \geq S'} A_i \approx A'$. S' exists because $A_i \ll A'$.

To solve it, we sample record i with probability $p = \frac{A_i}{\sum_{i \in RALT} A_i}$. Thus, the probability of sampling a record with score $\geq S'$ is p . Then, if we sample N records, there are pN records with score $\geq S'$ in expectation. Then we can estimate S' by calculating the pN -th score of the N records.

In practice, we cannot sample the records directly because there may be duplicated records in different levels. Instead, we first sample N values a_i from $[0, \sum_{i \in RALT} A_i]$, and find the corresponding record of a_i by a full scan. The corresponding record x of a_i satisfies $\sum_{j < x} A_j < a_i \leq \sum_{j \leq x} A_j$. The error of total hot size of records with

score \geq the calculated score threshold is less than the difference of the two adjacent sampled values a_i, a_{i+1} satisfying $a_i \leq A' \leq a_{i+1}$. It can be proved that the probability that the difference $\geq \alpha A/N$ is decreased exponentially as α rises.

For the hot set size limit and physical size limit, we calculate two thresholds and physically evict records with a score less than the physical size score threshold. For records with a score less than the hot set score threshold but not less than the physical size score threshold, we still store the records in RALT. RALT uses filters in checking hotness and scans so that they cannot be seen by queries.

After calculating the score thresholds, RALT merges all records and evicts. To ensure the temporary occupied space is not big, RALT merges data step by step. At each step it picks some SSTables in the largest level that are not merged and SSTables that are overlapping with them in the other levels, ensuring the total number of SSTables doesn't exceed a small constant (e.g. 10). In this way, the temporary occupied space is limited by the constant. It then merges them and updates the version of the LSM-tree. Since RALT maintains multiple versions, the old SSTables cannot be deleted if the old version is being used. The merging process pauses until all references to the old version are released and the old version is deleted.

Range queries. RALT can calculate the number of hot keys in a range for HotRAP to select which SSTable to compact (details in §3.5). Similar to a normal LSM-tree, we have data blocks and index blocks in SSTables. For each 8KB data block, its first key and the sum of the hot size of keys in previous data blocks are added to index blocks. For a range query, at each level, we read 2 index block records and calculate the difference of the sum to calculate the sum of the hot size of the range. Since the hot size of one or two data blocks at the edge of the range is small, it does not matter if we do not read them. We sum up the query results of each level. The result is overestimated because there may be duplicated keys in different levels. But if the number of levels is small and the multiplier between levels is big, we can expect the overestimation rate to be small. For example, if the multiplier is 10, the result of the second largest level is 10% of the result of the largest level on average. So the overestimation rate is about 10% on average.

Checking hotness. HotRAP checks if a key is hot when flushing the promotion cache. The cost of searching keys by reading from SSTs is high, so RALT stores bloom filters in memory for each SST. Each bloom filter contains the hot keys (keys with scores higher than the threshold) in its SST. When checking whether a key is hot, RALT checks the bloom filters at each level and returns true if any bloom filter gives a positive result. Since the overall false positive rate is low ($\leq 1\%$), we do not need a double-check.

Cost analysis. Suppose RALT has N_L levels, the size ratio between level $i+1$ and level i is α . The write amplification is $\frac{\alpha}{2}(N_L-1)$. Suppose evictions evict β of data (in our implementation, $\beta = 10\%$). The total write amplification is $\frac{\alpha}{2}(N_L-1) + \frac{1}{\beta}$. The read amplification is $\frac{\alpha}{2}(N_L-1) + \frac{2}{\beta}$ because we need an additional full scan to calculate the score threshold. Thus, the total I/O of RALT is $(\alpha(N_L-1) + \frac{3}{\beta}) \cdot (\text{average size of RALT record}) \cdot N$, where N is the number of accesses. N Since every point lookup in LSM-trees at least needs to read a data block from disk if it is not cached, the read I/O of LSM-tree is $\geq (\text{data block size})N$. Since data block size is at least 4KB, and in some industrial systems it can be 16KB [25], while

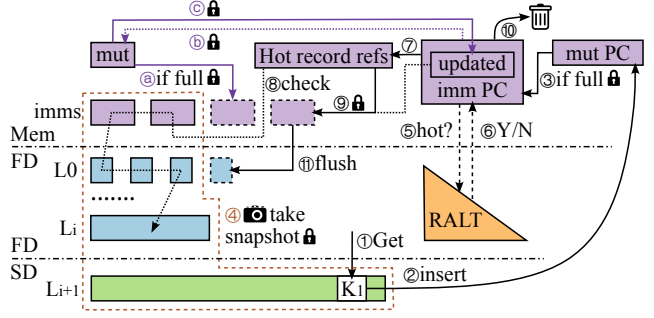


Figure 4: Concurrency control of promotion by flush. ⑧ ensures that no newer versions exist in the snapshot of the LSM-tree. ① to ③ insert all updated keys in immutable promotion caches into their *updated* fields. Hot records with updated keys are excluded in ⑨. The snapshot is taken (④) after the creation of the immutable promotion cache (③), therefore, a key updated before ⑨ is either found out by ⑧ or by ①–③.

key length is small, the I/O cost of RALT comparing to random reads is small, i.e. $(\alpha(N_L-1) + \frac{3}{\beta}) \cdot (\text{average size of RALT record}) \ll (\text{data block size})$.

3.3 Checks before inserting to promotion cache

The promotion cache resides between FD and SD. Therefore, before promoting a record into the promotion cache, it is crucial to verify the absence of a newer version of this record in SD. Although for a point read that retrieves the latest available version, it is known that there is no newer version of this record in the read's supervision (a snapshot of LSM-tree's state, see 2.1 for details), it is still possible that a newer version of the record is compacted into SD before the record is inserted into the promotion cache. Consequently, the next read of this key will return the promoted outdated record instead of the newer version in SD, leading to an incorrect result.

To address this issue, HotRAP marks SSTables as being or having been compacted when setting up compaction jobs with the promotion cache lock held. During the client access, all SD SSTables whose range contains the key are recorded. Before inserting a record into the promotion cache, HotRAP acquires the lock and then checks whether any of the recorded SSTables is being or has been compacted. If none, the record can be safely inserted into the promotion cache. The abort rate is low because of the small number of compaction jobs. Our experiments show that the checking only aborts less than 1% of insertions into the promotion cache.

3.4 Concurrency control of promotion by flush

Figure 4 shows the concurrency control of promotion by flush. The processes with lock icons are protected by the DB mutex lock.

When a record in SD is read (①), before returning it to the caller, HotRAP stores it in the in-memory mutable promotion cache (②). When the mutable promotion cache is full, it will become an immutable promotion cache and a new empty mutable promotion cache will be created (③). Then a snapshot is taken by incrementing the reference count of the caller's supervision (④). We pass the

immutable promotion cache’s reference and the snapshot (i.e., a reference to the supervision) to a background thread called *Checker*. *Checker* will handle the rest part of promotion by flush. In this way, promotion’s influence on foreground read operations is minimized.

The background thread *Checker* checks with RALT whether the records in the immutable promotion cache are already hot (⑤ & ⑥). Hot records are picked out (⑦). Then *Checker* looks for newer versions of the hot records in the snapshot’s immutable memory tables and levels in FD (⑧). Hot records without a newer version will be packed into a new immutable memory table (⑨), and the immutable promotion cache is then deleted (⑩). Those records will eventually be flushed into Level 0 (⑪).

However, there is still a corner case here: newer versions can be flushed into Level 0 when HotRAP is looking for newer versions. To address this issue, HotRAP attaches an *updated* field to each immutable promotion cache. When the mutable memory table becomes immutable (Ⓐ), for every record in them, HotRAP checks whether the same key exists in immutable promotion caches (Ⓑ), if so, then HotRAP inserts the key into the *updated* field of the corresponding immutable promotion cache (Ⓒ). The records whose keys exist in the *updated* field will not be packed into the immutable memory table (Ⓓ).

To ensure that the list of immutable promotion caches does not change during the creation of immutable memory tables so that *updated* field is correct, we create immutable promotion caches with DB mutex (the only major lock in RocksDB) held. Since in RocksDB, flushes are protected by DB mutex, there are only 2 cases and both cases are correct: (1) An immutable memory table is created, then an immutable promotion cache is created. If the immutable memory table has newer versions of records, then they will be detected in the checking process. (2) An immutable promotion cache is created, then an immutable memory table is created. If the immutable memory table has newer versions of records, then they will be added into *updated* field and be detected.

3.5 How to pick an SSTable to compact

In the leveling compaction strategy, every time a level reaches its capacity, we pick an SSTable and merge it into the next level. Typically, we calculate a score for each SSTable and pick the one with the highest score. For example, RocksDB defines the score as $\frac{FileSize}{OverlappingBytes}$ by default, in which *OverlappingBytes* represents the number of bytes in the input SSTables (the overlapping SSTables at the target level) of the target level. It is substantially a cost-benefit metric: *FileSize* is the benefit, and $(FileSize+OverlappingBytes)$ is the cost, in which *FileSize* is optimized out without affecting the ordering of scores.

However, the benefit-cost score needs some revision in HotRAP. During an inter-tier compaction in HotRAP, i.e., the start level is in FD while the target level is in SD, hot records in the chosen SSTable in the start level will be retained in the start level. Therefore, the benefit should be $(FileSize-HotSize)$, the cost should be $(FileSize+OverlappingBytes)$, and the benefit-cost score should be $(FileSize-HotSize)/(FileSize+OverlappingBytes)$.

HotRAP estimates the *HotSize* of an SSTable by summing up the size of hot records in the corresponding range in each level of RALT. The estimated *HotSize* is an over-estimated value. Therefore,

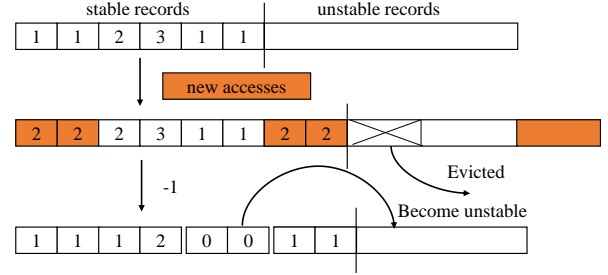


Figure 5: Auto-tuning overview. Orange regions have keys that are in new accesses. Some of the new accesses hit stable records and their counters are added by 1 (Suppose $\Delta_c = 1$). Some hit unstable records so that they become stable records, and their counters are also added by 1. Some do not hit any record, so they become new unstable records. Old unstable records are evicted. All counters are decreased by 1 periodically, stable records with a counter equal to 0 will become unstable and be evicted.

it is possible, although very unlikely, that all benefit values are zero. If we choose the SSTable with the minimum cost value in this case, infinite compactions can occur: a hot SSTable is chosen over and over again without compacting any record to the target level. To address this issue, HotRAP chooses the oldest SSTable for compaction if all benefit values are zero.

3.6 Write amplification of retention

Since some data in the last level of FD is retained, the efficiency of inter-tier compaction decreases. For example, if an SSTable is compacted to the last level of FD, suppose half of the level is hot data, then we need 2 compactions to compact data of SSTable size to SD. It results in write amplification as two times as normal value. Generally speaking, suppose the size ratio of the LSM-tree is T , the fraction of cold data is p , then the write amplification is $\approx \frac{1}{2} \cdot \frac{T}{p}$. We can consider the "real" size of the last level of FD reduces to p times, thus, the levels of SD should also reduce to p times, i.e. let the size of the last level of FD be S , then the sizes of levels of SD are pST, pST^2, pST^3 and so on. The size ratio between the last level of FD and the first level of SD is pT . Since we can set the size ratio of the last level of SD to $1/p$ (i.e. the size ratios are $pT, T, \dots, T, 1/p$), the write amplification is only increased by $\frac{1}{2} \cdot \frac{1}{p}$. It can be lowered by tuning the size ratios of levels or adding more levels.

3.7 Auto-tuning

In section 3.2, RALT initially takes 2 arguments: maximum hot set size and maximum physical size. The two arguments limit the size of hot records and the occupied space of RALT. However, users often do not know the distribution of their workload. Moreover, the distribution can be dynamic over time. Thus we need a method to estimate the most suitable hot set size and physical size.

Assume that over a relatively long period of time, key k has an access probability of p_k . Assume the hot set size is between L_{hs} and R_{hs} . The problem is to find a set K as small as possible such that $\sum_{k \in K} p_k \geq (\max_{K'} \sum_{k \in K'} p_k) - \delta$, where the hot set size of K' is less than the maximum hot set size and $\delta > 0$ is negligible for the performance of HotRAP. For many skewed distributions, we can

find a threshold p_t so that K is the set of keys with probability $\geq p_t$. If we have a p_t , this problem can be considered as a frequent items problem. Several algorithms have been proposed to solve it, such as counter-based approaches[20, 27] or sketch-based approaches[7]. But the counter-based approaches need to maintain a set of size $\frac{1}{p_t}$ which is too big, while sketch-based approaches need to maintain expensive data structures. Thus, we propose a novel algorithm.

We store a counter c and a tag t in each record. Records with $c > 0$ and $t = 1$ are called stable records. Records with $c = 0$ or $t = 0$ are called unstable records. For every access, we initially insert a record with $c = \Delta_c$ and $t = 0$. The hot set size limit is $1.1 \times$ the total hot size of stable records. RALT periodically evicts old unstable records. If a record is hit, then we update c to $\min(c + \Delta_c, c_{max})$ and t to 1. If an unstable record is hit before it is evicted, then it becomes stable. We can control the speed by setting the period time. Every time the hot size (the size of key-value pair) of accesses reaches a limit R , e.g. the size of FD, we decrement counters of all the records by one. If the workload changes, cold keys are evicted after accessing at most $c_{max}R$ data, so c_{max} should not be large.

We lazily update counters and tags in compactions and update the hot set size limit for every eviction. The period time is controlled by setting the physical size limit to the sum of the physical size of stable records and the maximum physical size of unstable records. We update the physical size limit every few evictions to allow time for disk space adjustments.

Analysis. This algorithm ensures that hot keys will become stable, while the number of stable cold keys is limited. Suppose accesses are i.i.d.. Suppose the probability of key $k \in K$ is p_k . Suppose by limiting the physical size of unstable records, there are at most D accesses between two unstable records. Then the probability that k becomes stable at least once during $N(D \ll N)$ accesses equals the probability that there exists two accesses of k separated by $\leq D$ accesses. Let $E_{k,t}$ be the number of accesses of k during t accesses. The expectation of the number of two accesses of k separated by $\leq D$ is $E_{k,N}E_{k,D} = p_k^2 ND$. The probability of becoming stable is then $\leq p_k^2 ND$. When $p_k^2 ND \ll 1$, the probability of becoming stable can be estimated by $p_k^2 ND$. Then for N accesses, we have $\leq DN \sum_{k \in K} p_k^2$ stable records.

The intuition is that, for a cold key set K_{cold} and a hot key set K_{hot} , the difference between $\sum_{k \in K_{hot}} p_k$ and $\sum_{k \in K_{cold}} p_k$ may not be large because the number of cold keys can be very large, but the difference between $\sum_{k \in K_{hot}} p_k^2$ and $\sum_{k \in K_{cold}} p_k^2$ is typically large. Thus, by this approach, hot keys are identified because hot keys become stable faster than cold keys. If the eviction speed of cold keys is faster than the speed of becoming stable, then the size of cold keys is limited.

Suppose we have a probability threshold p_t . Let $R\Delta_c p_t = 1 + \delta$, where $\delta > 0$ is a constant. δ is set to make sure keys with probability $\geq p_t$ are stable with high probability. Now we calculate the extra space taken by keys with $p_k < \epsilon p_t$, $\epsilon(1 + \delta) < 1$. For a key k with $p_k = \epsilon p_t$ occasionally becomes stable, suppose c be the counter c_k when it becomes stable, we have $c \leq 2R\Delta_c$ when it is accessed twice. Since it loses $\epsilon p_t R\Delta_c - 1 = \epsilon(1 + \delta) - 1$ in expectation, the expectation time it becomes unstable ($c_k = 0$) is $\frac{c}{1 - \epsilon(1 + \delta)}$. Then the

extra space is

$$\leq \frac{2R\Delta_c}{1 - \epsilon(1 + \delta)} (D \sum_{k \in K} p_k^2) \leq \frac{2R\Delta_c (D(\epsilon p_t)^2 \frac{1}{\epsilon p_t})}{1 - \epsilon(1 + \delta)} = \frac{2\epsilon(1 + \delta)D}{1 - \epsilon(1 + \delta)}$$

Typically when $\epsilon(1 + \delta) < \frac{1}{3}$, the extra space is less than D . Let $\delta = \frac{1}{3}$, then the extra space for $\epsilon < \frac{1}{4}$ is D , which is small enough.

Range of hot set size limit. The range of hot set size limit $[L_{hs}, R_{hs}]$ is preset. R_{hs} can be large when the workload is read-heavy, or small when the workload is write-heavy. By shrinking the first level of SD (see section 3.6), the write amplification increased by hot set limit is $\leq \frac{1}{2} \frac{\text{FD last level size}}{(\text{FD last level size}) - R_{hs}}$. To avoid changing the size of the first level of SD when the hot set size limit changes, we can let the size of the first level of SD be the same as the last level of FD. The write amplification remains the same. We can determine R_{hs} by the maximum acceptable write amplification.

Implementation details. We set $L_{hs} = 0.05(\text{FD last level size})$. For write-heavy workloads (50% write and 50% read, see section 4), experiments show that it does not affect much if the write amplification increases by ≤ 3 . So we set $R_{hs} = 0.8(\text{FD last level size})$. We set the maximum size of unstable records to $0.05R_{hs}$. The probability threshold p_t is set to $\frac{1}{5R_{hs}}$ by default. We set R to R_{hs} and c_{max} to 10 so that cold keys are evicted in at most $10R_{hs}$ accesses. The experiments are shown in section 4.7.

3.8 Support scan

HotRAP can support short-range scan. Long-range scan is more dependent on throughput so we do not consider it. A possible implementation is as follows. RALT tracks the hotness of ranges by logging scan ranges. During each scan, HotRAP stores records read from SD. After the scan finishes, HotRAP inserts them as a range record into the promotion cache. When HotRAP flushes an immutable promotion cache, it consults RALT whether the range is hot. If not hot, HotRAP drops the range record. If hot, HotRAP promotes all the records in the range record to FD (by compaction or by flush) and marks the range as promoted in RALT. Subsequent scans do not need to read SD if the range is marked as promoted. When a range becomes cold, records in it will be compacted into SD during compactions from FD to SD, and the range will be marked as not promoted or evicted directly. However, tracking the hotness of ranges is non-trivial. We leave this to future work.

4 EVALUATION

4.1 Experimental setup

Testbed. We evaluate HotRAP on AWS EC2 i4i.2xlarge instances with 8 vCPU cores, 64GiB memory, and an 1875GiB local AWS Nitro SSD. The performance of the attached disks is shown in Table 1. We use local SSDs as FD and gp3 as SD. Since HDD RAID arrays can achieve thousands of IOPS and high throughput, we set the maximum IOPS and throughput of gp3 to 16000 and 500MiB/s respectively to simulate the most performant HDD RAID arrays. None of our tests are bounded by the throughput of gp3.

Sizes of tiers and memory. We set the ratio between tiers to 10 and the memory budget to 1GB, so that the expected used size of FD is set to 10GB and the initial expected used size of SD is set to

100GB. The 1GB memory budget is only used to limit the memory usage of HotRAP. Other compared systems are not bounded by it. **Compared systems.** We compare HotRAP with Mutant [36], PrismDB [29], and several variants of RocksDB. *RocksDB(FD)* is a variant of RocksDB that all data are stored in FD, which is used to indicate the maximum performance that HotRAP can achieve. *RocksDB-secondary-cache* [26] is a variant of RocksDB that enables secondary cache, which is an additional block cache stored in FD. The size of the last level in FD is tuned so that the levels and the secondary cache use 10GB of FD in total. *RocksDB-fat* is a variant of RocksDB that the size of the last level in FD is increased so that the total size of levels in FD is 10GB, which is the same as HotRAP.

Configurations. HotRAP is configured with an 8MiB block cache. Since HotRAP has a 64MiB promotion cache, other systems are configured with an 8+64=72MiB block cache. To minimize the deflection of the file system cache, direct I/O is used for HotRAP and RocksDB. To reduce the memory usage of block indexes, the block size of all systems is set to 16KiB following Meta’s practice [25]. The maximum number of background jobs is set to 4 for HotRAP and RocksDB. All systems are configured with 10-bit bloom filters. To save memory, we disable bloom filters in the last level for workloads with a 200B record size. Other configurations are set to default. For Mutant and PrismDB, since it is difficult to enable direct I/O due to their old versions of RocksDB/LevelDB, we limit their memory with `systemd-run` to reduce page cache size. All experiments are run with 16 threads.

Methodology. We evaluate HotRAP with YCSB[8] workload generator with read-write ratios shown in Table 2. *RO* i.e., read-only, tests the effectiveness of promotion by flush. *RW* and *WH*, i.e., read-write and write-heavy, test the effectiveness of retention. *UH*, i.e., update-heavy, is the worst case for HotRAP. In YCSB update-heavy workloads, the key distributions of reads and updates are the same. Therefore, the newer version of read-intensive records are frequently inserted into the database and flushed into FD, making the proactive promotion of HotRAP useless.

We test three skewness types: hotspot-5%, Zipfian, and uniform. In the hotspot-5% distribution, 5% of records are hot records, and 95% of operations uniformly access them. The other 5% of operations uniformly access the other 95% of records. In the Zipfian distribution of N records, the access probability of the k -th hottest record is $f(k, N, s) = \frac{1}{H_{N,s}} \frac{1}{k^s}$, in which $H_{N,s} = \sum_{k=1}^N \frac{1}{k^s}$ [6]. In our experiments, $s = 0.99$. In the uniform distribution, the access probability of all records is the same.

In all workloads, the client first loads 110GB of records into the LSM-tree, which is called the load phase. After that, the client executes read/insert operations, which is called the run phase. For workloads with 1KiB record size (≈ 24 B key and 1000B value), 1.1×10^8 read/insert operations are executed in the run phase of HotRAP and RocksDB by default. For workloads with 200B record size (≈ 24 B key and 176B value), 5.5×10^8 read/insert operations are executed in the run phase. PrismDB and Mutant have long enough run phases to stabilize their performance. This paper only shows the performance in the run phase. We set the default hot set size limit of HotRAP to 60% of the FD size, i.e., 6GB. 60B of physical size is allocated for each key in the hot set. The secondary cache size of RocksDB is also set to 6GB.

We do not turn on auto-tuning on these workloads because it will bias the results of HotRAP. We test it independently in §4.7.

Table 1: Performance of attached disks on our EC2 instances

	Fast Disk	Slow Disk
Type	AWS Nitro SSD	gp3
8 threads rand 16K read IOPS	≈ 210000	16000^1
Sequential read bandwidth	≈ 1.4 GiB/s	500MiB/s
Sequential write bandwidth	≈ 1.1 GiB/s	500MiB/s

Table 2: Read-write ratios of YCSB workloads in our tests

Notation	Meaning	Read-write ratio
RO	read-only	100% read
RW	read-write	75% read, 25% insert
WH	write-heavy	50% read, 50% insert
UH	update-heavy	50% read, 50% update

4.2 Comparison with other systems

Figure 6 shows the stable phase throughput of systems under different read-write ratios and skewness with 1KiB record size. Figure 7 shows the stable phase throughput under workloads with 200B record size. In both figures, the performance of HotRAP is close to RocksDB(FD) under hotspot-5% workload, which demonstrates the effectiveness and efficiency of RALT and HotRAP.

Under read-only (RO) workloads with skewed distribution, HotRAP promotes hot records to the fast disk, thus outperforming other systems. HotRAP achieves almost the same performance as RocksDB(FD) under the hotspot distribution, because HotRAP promotes all hot data into FD successfully and achieves about 95% hit rate. RocksDB(FD) outperforms HotRAP much under the Zipfian distribution because the Zipfian distribution allows only 82% hit rate.

Under the hotspot distribution, RocksDB-secondary-cache and Mutant show negligible improvement compared to RocksDB-fat because they promote data in a too-coarse granularity: data blocks for RocksDB-secondary-cache and SSTables for Mutant. PrismDB shows negligible improvement compared to RocksDB-fat due to its inefficient promotion mechanism. While under the Zipfian distribution, RocksDB-secondary-cache, Mutant, and PrismDB can perform better than RocksDB-fat because the Zipfian distribution is so skewed that caching the hottest 10^3 records in memory can achieve 35% hit rate.

Under read-write (RW) workloads, HotRAP still has a high performance, because it retains the hot data. For write-heavy (WH) workloads, the performance of HotRAP becomes lower compared to Rocksdb(FD) because the write performance of SD is worse than FD. But HotRAP still outperforms other systems, showing the effectiveness of retention and promotion. More detailed analysis on retention can be found in 4.4.

For the uniform distribution, the performance of HotRAP is similar to other systems, showing its low overhead. It is because

¹The maximum allowed IOPS of gp3 is 16000.

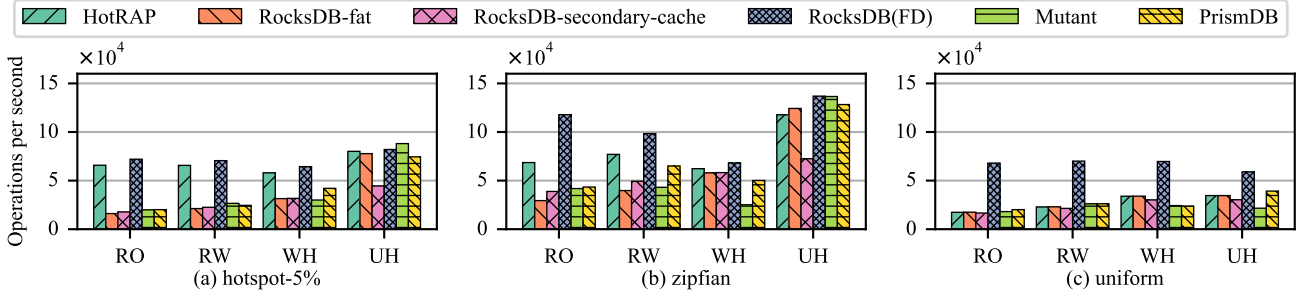


Figure 6: Throughput of stable phases under workloads with 1KiB record size

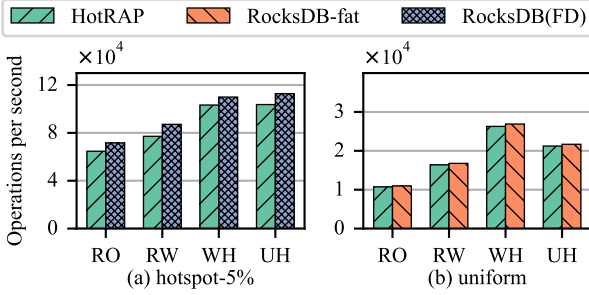


Figure 7: Throughput of stable phases under workloads with 200B record size

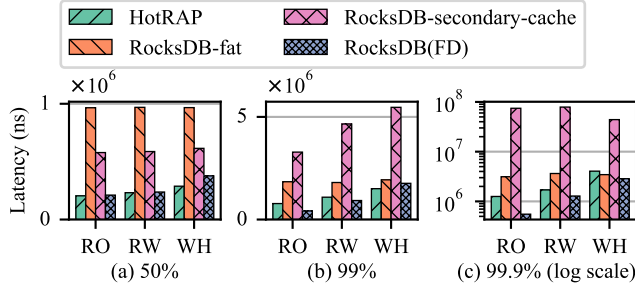


Figure 8: Get tail latencies of stable phases under hotspot-5% workloads with 1KiB record size

HotRAP only promotes hot records. More detailed analysis can be found in 4.5.

For update-heavy (UH) workloads, since the updated data has a skewed distribution, update operations can be considered promotions. Thus, the performance of all systems is higher. Mutant outperforms because it allows the size of levels in FD to temporarily exceed the 10GiB limit, while other systems do not. RocksDB-secondary-cache has a relatively low performance because secondary-cache frequently evicts and promotes data blocks, thus incurring much FD I/O.

Figure 8 shows the tail latencies of systems under hotspot-5% workloads with 1KiB record size. HotRAP achieves low tail latency under read-heavy workloads (RO & RW) because HotRAP reduces the accesses to SD. RocksDB(FD), HotRAP, and RocksDB-fat have similar tail latencies under write-heavy workloads (WH) because frequent compactions deteriorate the tail latency of FD.

4.3 Breakdown of costs

Figure 9 and Figure 10 show the breakdown of the CPU time and I/O under workloads with 200B record size, in which case the size of RALT is more than 1.5GB, exceeding the 1GB memory budget. The results show that RALT is only responsible for 4.2%–11.6% of total CPU time and 7.6%–12.8% of total I/O, showing the efficient design of RALT. The dividing point of the warm-up phase and the stable phase is the first time that the hit rate of HotRAP reaches 95% of the maximum hit rate.

In the run phase of uniform workloads, HotRAP consumes more CPU time than RocksDB-fat because most accesses are in SD and thus the records are inserted into the promotion cache. However, few records are promoted into FD due to the hotness checking (⑤ & ⑥ in Figure 1), therefore they have similar compaction I/O.

In the stable phase of hotspot workloads, most hot records already have been promoted into FD, therefore HotRAP and RocksDB-fat have similar Read CPU time. HotRAP still incurs more compaction I/O because retention increases the write amplification.

Figure 11 shows the breakdown of device throughput under the read-write (75% read, 25% insert) hotspot-5% workload. HotRAP promotes and retains hot records in FD. Therefore, the number of *Get* operations served by FD increases over time, and thus the total throughput of *Get* also increases over time until it is near the *Get* throughput of RocksDB(FD). Most of *Get* operations in RocksDB-fat are served by SD. Therefore, the total throughput of *Get* is bound by the throughput of SD. RocksDB-secondary-cache is similar to RocksDB because the block granularity of the secondary cache is too coarse, and few records are cached by the secondary cache. Additionally, RocksDB-secondary-cache incurs much FD I/O because the secondary cache constantly evicts and promotes data blocks.

4.4 Effectiveness of retention

To show the effectiveness of retention, we remove the retention mechanism from HotRAP and call the version *no-retain*. We compare its throughput, hit rate, and promoted bytes with HotRAP. The results are shown in Figure 12. Although *no-retain* still promotes records into FD, the promoted records are compacted into SD again during compactions. Therefore, the promoted bytes are much higher than HotRAP's because the hot records have to be promoted repeatedly. Its max hit rate also drops to 74.3%.

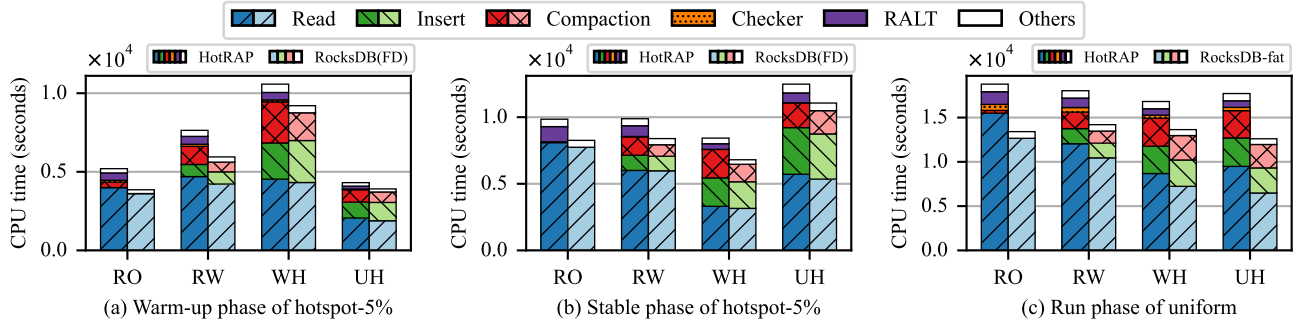


Figure 9: Breakdown of the CPU time under workloads with 200B record size

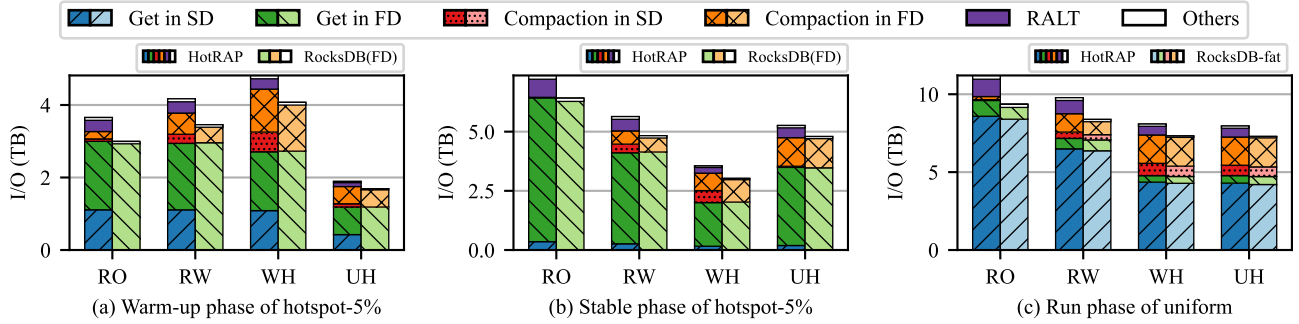


Figure 10: Breakdown of the I/O under workloads with 200B record size

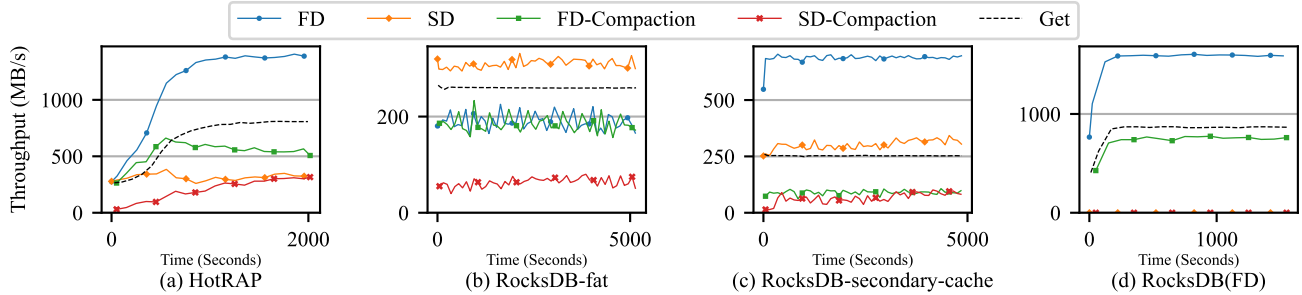


Figure 11: Breakdown of device throughput under the 75% read, 25% insert hotspot-5% workload with 1KiB record size. For readability, the throughput is averaged every 100 seconds. Markers are used to make lines distinguishable in greyscale. *Get* is the measured throughput of disk reads during *Get* operations, which is an indicator of the end-to-end performance.

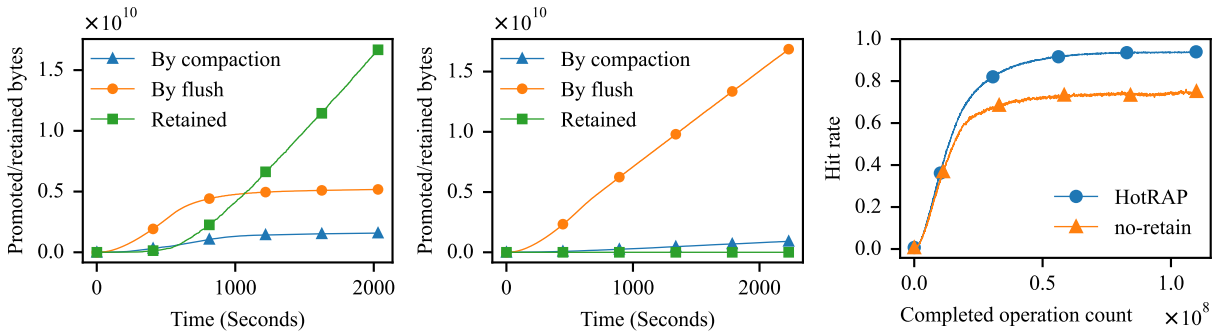


Figure 12: Effectiveness of retention. 75% read, 25% insert, hotspot-5% with 1KiB record size

4.5 Other promotion policies

HotRAP only promotes hot records to reduce overhead introduced by promotion. To show the effectiveness of this policy, we remove

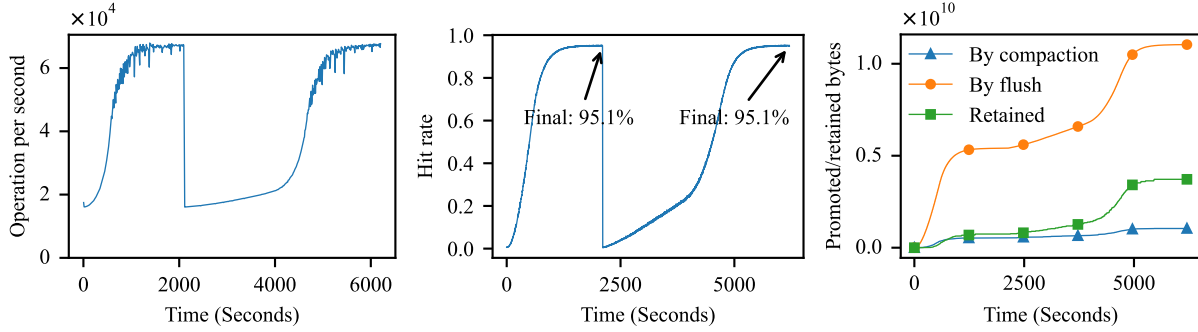


Figure 13: HotRAP under the read-only hotspot-shifting-5% workload with 1KiB record size. The first phase executes 1.1×10^8 *Get* operations, the second phase executes 1.5×10^8 *Get* operations. The 5% hotspots in the two phases are non-overlapping.

Table 3: Promotion costs without hotness checking under the 100% read uniform workload with 1KiB record size

Version	Promoted	Retained	Compaction
HotRAP	4.7GB	279.8MB	226.9GB
promote-accessed	116.9GB	56.4GB	4525.1GB

Table 4: Promotion costs without promotion by compaction under the 75% read, 25% insert, hotspot-5% workload with 1KiB record size

Version	Promoted	Compaction	Final hit rate
HotRAP	6.8GB	1504.6GB	93.8%
no-by-compaction	7.1GB	1582.6GB	92.4%

this hotness checking and promote all accessed records. We call this version *promote-accessed*. Table 3 shows that *promote-accessed* promotes 24.0 \times more records and thus incurs 18.9 \times more compaction I/O than HotRAP.

HotRAP also promotes by compactions to reduce the costs of promotion. To show its effectiveness, we remove the promote-by-compaction policy and only promote hot records by flushing them to Level 0 of the LSM-tree. We call this version *no-by-compaction*. Table 4 shows that *no-by-compaction* incurs 5.2% more compaction I/O than HotRAP because the records originally promoted by compaction are flushed to Level 0 and compacted to deeper levels again. Therefore, the promote-by-compaction policy is effective in reducing compaction I/O caused by promotions.

4.6 Hotspot shifting

To show that RALT is responsive to changes in the access pattern, we evaluate HotRAP under the hotspot-shifting-5% workload. The hotspot shifting workload contains two phases, in which the hot data is different. In the first phase, the workload executes 1.1×10^8 *Get* operations, 95% of which reads 5% of loaded records (the hotspot in the first phase). In the second phase, the workload executes 1.5×10^8 *Get* operations, 95% of which target a different, non-overlapping 5% of loaded records, distinct from those in the first phase (i.e., the hotspot shifts to another record set). Figure 13 shows the results. When the hotspot shifts, both the throughput and the hit rate of HotRAP drops to their initial levels observed at the outset. However, RALT reacts adaptively to the hotspot shifting and starts

to promote the new hot data. The promotion is slower than in the first phase because it needs to wait for the high scores of old hot keys to decay. At last, both the throughput and the hit rate increase and ultimately reach their peak performance in the first phase.

4.7 Auto-tuning

We evaluate the hot set size under RO workload with 8.25×10^8 operations under uniform, hotspot-1%, hotspot-2%, hotspot-5% distributions. The hot data size of hotspot-1% is 1% of the workload, and the hot data size of hotspot-2% is 2% of the workload. The fraction of operations operating hot data is 0.95. L_{hs} is 0.05GiB and R_{hs} is 7GiB. All other parameters are the same as in the experiments above. The hot set size under uniform distribution is smaller than L_{hs} . The hot set size under hotspot-1%, hotspot-2%, and hotspot-5% distribution converge to the size of hot data. It also shows that the keys with smaller probability are promoted more slowly. Then, to show the performance under a dynamic workload, we evaluate the hot set size under 2 hotspot-shifting workloads. In each phase of all hotspot-shifting workloads, we execute 8.25×10^8 operations. The first workload is hotspot shifting-5%, i.e. shifting from 5% to another 5%. The second workload is shifting from 5% to another 2%. The hot set size of the 5% data is 2.5 \times the hot set size of the 2% data. It shows that the cold keys are evicted quickly and new hot keys become stable quickly. The hot set size limit gets to the maximum value of 7GiB temporarily because old hot keys are not evicted and new hot keys are added quickly. It shows that RALT can find the suitable hot set size under dynamic workload.

4.8 Efficiency of different scoring methods

We study the hit rate of 3 scoring methods under hotspot-5% WH workload: LRU, CLOCK[9] and exponential smoothing [19]. The result is shown in figure 15. It shows that the hit rate of exponential smoothing is the best, about 93%, while CLOCK is 88%, and LRU is 85%. LRU is bad because hot keys can be easily evicted because there are some recent cold accesses. CLOCK is better because it records the access counts, but it can cause the counters of hot keys to be decremented unnecessarily. We implement LRU and CLOCK by modifying the merging function of RALT. For LRU, the score is the maximum access time, and the merging function is the maximum function of two maximum access times. For CLOCK, we store a 32-bit integer as the clock bit, and the merging function is the sum

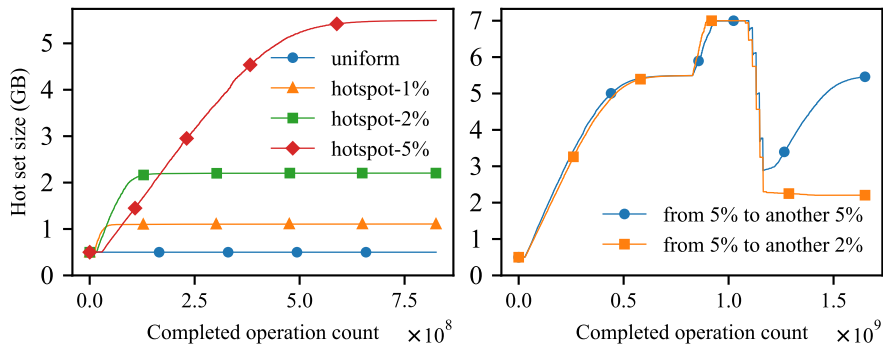


Figure 14: Hot set size of HotRAP with auto-tuning turned on

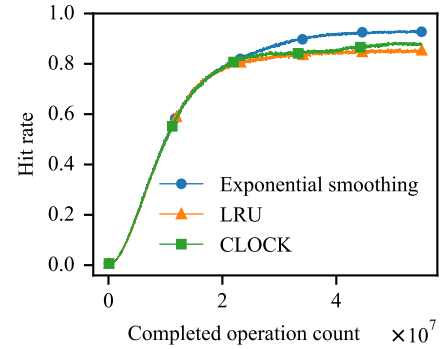
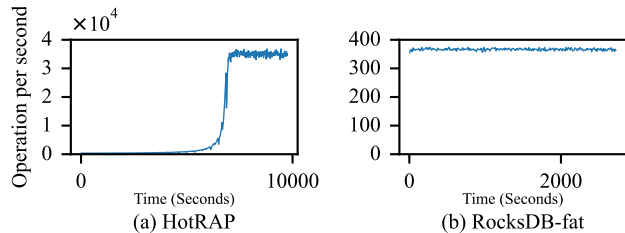


Figure 15: Hit rate of different scoring methods

Table 5: Performance of disks in the HDD test

	Fast Disk	Slow Disk
Type	NVMe	HDD
8 threads rand 16K read IOPS	≈56000	≈330
Sequential read bandwidth	≈5GiB/s	≈260MiB/s
Sequential write bandwidth	≈4GiB/s	≈250MiB/s

Figure 16: Throughput of HotRAP and RocksDB-fat in the HDD test under the 100% read hotspot-1% workload with 1KiB record size. RocksDB-fat only runs 10^6 operations to save test time. HotRAP runs 1.1×10^8 operations as usual.

function of two clock bits. We do not calculate the score threshold, instead, we maintain a clock hand as in the CLOCK algorithm.

4.9 The Hard Disk Drive (HDD) test

Although most of our experiments are conducted with gp3 as the slow disk, HotRAP can also achieve significant performance improvement with other types of slow disks. In this subsection, we evaluate HotRAP using a hard disk drive (HDD) as the slow disk, which is likely to be a common choice in the industry due to its large capacity and cost-effectiveness. The experiments are conducted on an Intel NUC with an i7-1165G7 CPU (2.80GHz, 8 vCPU cores), 32GB DRAM, and a Samsung 980PRO NVMe SSD as the fast disk. The performance of disks is shown in Table 5. Figure 16 shows the evaluation results. The throughput of HotRAP is 92× to the throughput of RocksDB-fat, which shows that HotRAP can achieve even higher performance improvement if the slow disk is a real HDD instead of gp3 due to the larger performance gap between FD and SD.

5 CONCLUSION

We introduced HotRAP, an LSM-tree-based key-value store on tiered storage. Unlike previous solutions, HotRAP adopts an on-disk hotness tracker along with record-level retention and promotion algorithms that can be independent of LSM-tree compactions. These techniques allow HotRAP to move data efficiently across tiers to fully utilize the fast storage for keeping hot records even under read-heavy workloads. The source code of HotRAP is available at <https://github.com/hotrap>.

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