Kreon: An Efficient Memory-Mapped Key-Value Store for Flash Storage

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Persistent key-value stores have emerged as a main component in the data access path of modern data processing systems. However, they exhibit high CPU and I/O overhead. Nowadays, due to power limitations, it is important to reduce CPU overheads for data processing.

In this paper, we propose *Kreon*, a key-value store that targets servers with flash-based storage, where CPU overhead and I/O amplification are more significant bottlenecks compared to I/O randomness. We first observe that two significant sources of overhead in key-value stores are: (a) The use of compaction in LSM-Trees that constantly perform merging and sorting of large data segments and (b) the use of an I/O cache to access devices, which incurs overhead even for data that reside in memory. To avoid these, *Kreon* performs data movement from level to level by using partial reorganization instead of full data reorganization via the use of a full index per-level. *Kreon* uses memory-mapped I/O via a custom kernel path to avoid a user-space cache.

For a large dataset, *Kreon* reduces CPU cycles/op by up to 5.8×, reduces I/O amplification for inserts by up to 4.61×, and increases insert ops/s by up to 5.3×, compared to RocksDB.

CCS Concepts: • **Information systems → Key-value stores**; **Flash memory**; *B-trees*; *Hierarchical storage management*; • **Software and its engineering** → *Virtual memory*;

Additional Key Words and Phrases: Key-Value Stores, LSM-Tree, Copy-On-Write, Memory-Mapped I/O

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1 INTRODUCTION

Persistent key-value stores [2, 25, 31, 34] are a central component for many analytics processing frameworks and data serving systems. These systems are considered as write-intensive because

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they typically exhibit bursty inserts with large variations in the size of data items [16, 68]. To better serve write operations, key-value stores have shifted from the use of B-trees [8], as their core indexing structure, to a group of structures known as write-optimized indexes (WOIs) [41]. This transition took place because even though B-trees [8] are asymptotically optimal in the number of block transfers required for point and range queries, their write performance degrades significantly as the index grows [47].

A prominent data structure in the WOIs group is LSM-Tree (Log-Structured Merge-Tree) [60]. LSM-Tree has two important properties: (a) it amortizes device write I/O operations (I/Os) over several insert operations and (b) it is able to issue only large I/Os to the storage devices for both reads and writes, essentially resulting in sequential device accesses. These properties have made LSM-Tree appropriate for hard disk drives (HDDs) that suffer from long seek times and their throughput drops by more than two orders of magnitude in the presence of random I/Os. However, these desirable properties come at the expense of significant CPU overhead and I/O amplification. LSM-Tree needs to constantly merge and sort large data segments which leads to both high CPU utilization and increased I/O traffic [64, 76].

Another key point is that modern key-value stores incur significant CPU overhead for caching data in their address space [38]. Key-value stores need to cache data in user-space to avoid frequent user-kernel crossings and accesses to devices. Therefore, at runtime, there is a need to maintain a lookup structure for data items that reside in memory. Lookup operations occur in the common path and are required not only for misses but also for hits, when data reside in memory. These common path lookup operations incur significant cost in CPU cycles. Harizopoulos *et al.* [38] claim that about one-third of the total CPU cycles of a database system is spent in managing the user-space cache when the dataset fits in memory. Furthermore, the cache needs to manage I/O to the devices via the system call interface that is expensive for fine-grain operations and requires data copies for crossing the user-kernel boundary. In our work, we find that cache and system call overheads in RocksDB [31], a state-of-the-art persistent key-value store, are up to 28% of the total CPU cycles used (see Table 3).

With current technology limitations and trends, these two issues of high CPU utilization and I/O amplification are becoming a significant bottleneck for keeping up with data growth. Server CPU is the main bottleneck in scaling today's infrastructure due to power and energy limitations [48, 53, 67]. Therefore, it is important to increase the amount of data each CPU can serve, rather than rely on increasing the number of CPUs in the datacenter. In this context, flash-based storage, such as solid state drives (SSDs), introduces new opportunities by narrowing the gap between random and sequential throughput, especially at higher queue depths (number of concurrent I/Os). Figure 1 shows the throughput of an SSD and two NVMe (Non-Volatile Memory express) devices with random I/Os and increasing request size. At a queue depth of 32, an I/O request size of 32 KB for SSDs and 8 KB for NVMe achieve almost the maximum device throughput. Therefore, increased traffic due to I/O amplification is becoming a more significant bottleneck than I/O randomness. This trend will be even more pronounced with emerging storage devices that aim to achieve sub-μs latencies.

In this paper we present *Kreon* [62], a key-value store that aims to reduce CPU overhead and I/O traffic by trading I/O randomness. *Kreon* combines ideas from LSM [60] (multilevel structure), bLSM [68] (B-Tree index), Atlas/WiscKey [48, 54] (separate value log), and Tucana [61] memory-mapped I/O. Additionally, *Kreon* uses a fine-grain spill mechanism which partially reorganizes levels to provide high insertion rates and reduce CPU overhead and I/O traffic. *Kreon* uses a write optimized data structure that is organized in *N* levels, similar to LSM-Tree, where each level *i* acts as a buffer for the next level *i+1*. To reduce I/O amplification, *Kreon* does not operate on sorted buffers, but instead it maintains a B-tree index within each level. As a result, it generates smaller

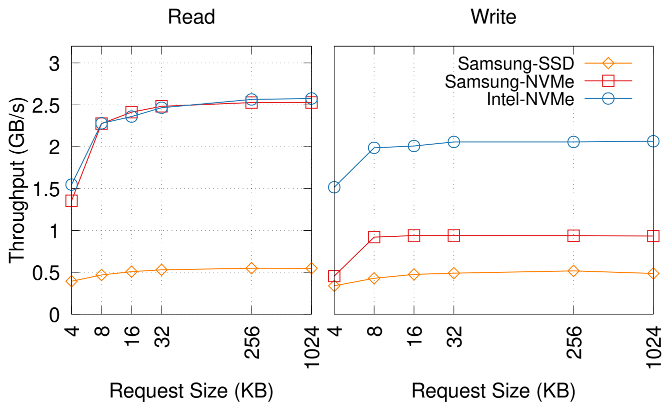


Fig. 1. Throughput vs. block size (using iodepth 32) for Samsung SSD 850 Pro 256 GB, Samsung 950 Pro NVMe 256 GB, and Intel Optane P4800X NVMe 375 GB devices, measured with FIO [3].

I/O requests in favor of reduced I/O amplification and CPU overhead. *Kreon* still requires and uses multiple levels to buffer requests and amortize I/O operations.

Furthermore, *Kreon* uses memory-mapped I/O to perform all I/O between memory and (raw) devices. Memory-mapped I/O essentially replaces cache lookups with valid memory mappings, eliminating the overhead for data items that are in memory. Misses incur a page fault and require an I/O operation that happens directly from memory without copying data between user and kernel space. However, the asynchronous nature of memory-mapped I/O means that I/O happens at page granularity, resulting in many and small I/Os, especially for read operations. In addition, memory-mapped I/O does not provide any type of consistency, recoverability, nor the ability to tune I/O for specific needs. To overcome these limitations, we implement a custom memory-mapped I/O path, *kmmap*, as a Linux kernel module. *kmmap* addresses these issues and provides all the benefits of memory-mapped storage: it removes the need to use DRAM caching both in kernel and user space, eliminates data copies between kernel and user space, and removes the need for pointer translation.

Key-value stores typically serve both local (same node) and remote (network) clients. Since we are interested in reducing CPU overhead, it is important to examine the overhead of efficient network protocols. For this reason we implement an RDMA-based (Remote Direct Memory Access) protocol for remote clients and we examine its relative cost in CPU cycles on the server side compared to index manipulation and I/O in *Kreon*.

We implement *Kreon* and evaluate its performance by using YCSB (Yahoo! Cloud Serving Benchmark) and large datasets of up to 6 billion keys. We compare *Kreon* with RocksDB [31], a state-of-the-art, LSM-Tree based, persistent key-value store which has lately been optimized for SSDs [26]. Our results show that using both datasets that stress I/O and datasets that fit in memory, *Kreon* reduces the amount of cycles/op by up to 8.3x. Additionally, *Kreon* reduces I/O amplification for insert-intensive workloads by up to 4.6x and increases ops/s by up to 5.3x. Our analysis of CPU overheads also shows that a saturated *Kreon* server can achieve up to 2.4M YCSB insert requests/s. Our network communication analysis shows that RDMA overhead in persistent key-value stores is low and that a 40 Gbps link should be able to serve 64 cores with *Kreon*.

Overall, the contributions of this paper are:

(1) The combination of multilevel data organization with full indexes at each level and a fine-grain spill mechanism that all together reduce CPU overhead and I/O traffic at the expense of increased I/O randomness.
(2) The design and implementation of *kmmap* a custom memory-mapped I/O path to reduce the overhead of explicit I/O and address shortcomings of the native *mmap* path in Linux for modern key-value stores.
(3) The implementation and detailed evaluation of a full key-value store compared to a state-of-the-art key-value store in terms of absolute performance, CPU and I/O efficiency, execution time breakdown, tail latencies, and device behavior.

Our work in this paper extends Kreon [62], as follows. We design and evaluate an efficient approach for concurrency control and increased parallelism in the write path. The initial version of *Kreon* provides a single-writer/multiple-readers concurrency model. In addition, we provide an analysis of the design for garbage collecting the value log of *Kreon*. Furthermore, and to allow efficient access to *Kreon* from network clients, we design and evaluate in terms of CPU cycle overhead, an RDMA-based network protocol for remote client access to key-value stores. In this work we are particularly interested on the overhead of the protocol in the server (*Kreon*) side. Finally, to show the effectiveness of *Kreon* as the storage engine in modern software stacks, we use *Kreon* as the storage engine in MongoDB [58] and we provide an evaluation using YCSB.

The rest of this paper is organized as follows: Section 2 provides a background on persistent key-value stores. Section 3 presents our design and implementation of *Kreon*. Section 4 presents our evaluation methodology and experimental results. Section 5 reviews related work and Section 6 provides our conclusions.

2 BACKGROUND

2.1 Write-Optimized Key-Value Stores

B-tree [8] is asymptotically optimal in the number of block transfers required for point (lookups) and range (scans) queries. However, write performance degrades as the index grows [47]. The increasing interest for systems that are able to absorb bursty writes has led to the emergence and broad use of write-optimized data structures, which aim to improve writes while keeping read performance close to B-tree. A popular data structure in this group is LSM-Tree [60]. LSM-Tree organizes its key-value pairs in multiple hierarchical levels in order to amortize write operations. O'Neil *et al.* [60] do not provide specific information on how each level is organized and two alternatives are in use today: (a) sorted arrays per-level or (b) a full index per-level. HDDs favor the use of the first alternative.

Inserts in LSM-Tree are served from memory, by typically using a skip-list [31]. Data are gradually moved to lower levels, as the current level fills up. To move data between levels and eliminate updated values, LSM-Tree uses *compactions* (see Figure 2). Compaction moves data from L_i to L_{i+1} by reading and sorting large buffers in memory and subsequently writing them to storage at L_{i+1}. Compactions have the advantage that they generate only large I/O requests which makes LSM-Tree preferable to other index structures for hard disk drives (HDDs). On the other hand, compactions result both in I/O amplification and CPU overhead due to moving data from one level to another. *Kreon* uses a different approach and introduces a full index per-level rather than sorted arrays, in order to reduce I/O amplification and CPU overheads.

2.2 B-tree Concurrency Protocols

An application can increase concurrency by breaking the dataset in multiple shards where each shard maps to a separate B-tree. However, in workloads with *Zipfian* distribution, a small subset

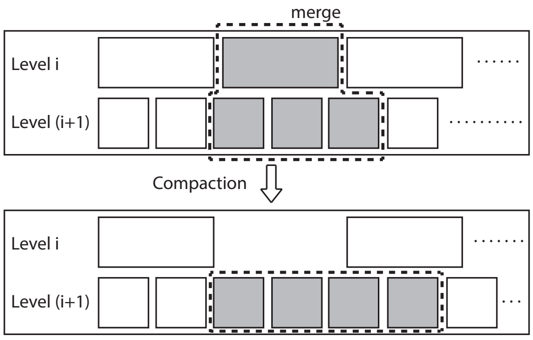


Fig. 2. Organization of an LSM-Tree.

of the shards can receive a large number of requests, which makes concurrency within a B-tree important.

Each node in a B-tree (except the root) contains $[\frac{B}{2}, B]$ elements, where B is the fan out of the tree. In the case of a node overflow (more than B) or underflow (less than $\frac{B}{2}$), B-tree applies one of the following rebalance operations: (1) split, (2) left/right merge, and (3) left/right rotate as defined in [9]. These rebalance operations make fine-grain concurrency in B-tree complicated.

Bayer *et al.* [9] propose three protocols for increased concurrency during insert operations in a B-Tree. Using the first protocol, an insert operation starts from the root and acquires a per-node lock until the leaf node. The second protocol is similar to the first, except that for each index node the lock is acquired as a read lock and only for the leaf node the lock is acquired as a write lock. Finally, the third protocol tries to achieve concurrency within the leaves by introducing a new type of lock named *update lock*. This lock is initially acquired as a read lock and is converted to a write lock only when the address of the insert operation is computed.

3 DESIGN

3.1 Overview

Kreon, similar to Atlas [48], Tucana [61], and Wisckey [54], stores key-value pairs in a log to avoid data movement during reorganization from level to level. *Kreon* organizes its index in multiple levels of increasing size and transfers data between levels in batches to amortize I/O costs, similar to LSM-Tree. But unlike LSM-Tree, within each level, *Kreon* organizes keys in a B-tree with leaves of page granularity similar to bLSM [68]. However, unlike bLSM, *Kreon* transfers data between levels via a *spill operation*, rather than full reorganization of the data in the next level. Spills are a form of batched data compaction that merge keys of two consecutive levels $[L_i, L_i + 1]$. However, spills do not read the entire L_{i+1} during merging with L_i and do not reorganize data and keys on a sequential part of the device [68]. Instead, *Kreon* spills read/write level L_{i+1} partially using the full B-tree index of each level.

The trade-off is that during spills, *Kreon* generates random read I/O requests at large queue depth (high I/O concurrency) to significantly reduce I/O traffic and CPU overhead. On the other hand, write I/O requests are relative large for writing updated parts of L_{i+1} index. This is because *Kreon* B-tree uses Copy-on-Write for persistence [35] and a custom segment allocator so updated leaves are written close on the device.

Furthermore, *Kreon* uses memory-mapped I/O to eliminate redundant copies between kernel and user space and constant pointer translation. *Kreon*'s memory-mapped I/O path is designed to provide efficient support for managing I/O memory addressing shortcomings of the default *mmap* path in the Linux kernel. These shortcomings are: (a) It does not provide explicit control over data eviction, as with an application-specific cache, (b) it results in an I/O even for pages that include garbage, and (c) it employs eager evictions to free memory, which results in excessive I/O, in order to avoid starving other system components.

Figure 3 depicts the architecture of *Kreon* showing two levels of indexes, the key-value log, and the device layout. Next, we discuss our design for the system index and memory-mapped I/O in detail.

3.2 Index Organization

Kreon offers a dictionary API (insert, delete, update, get, scan) of arbitrary sized keys and values stored in groups named *regions*. Each region can map either to a table or shards of the same table. For each region it stores key-value pairs in a single append-only *key-value log* [54, 61] and keeps a multilevel index. The index in each level is a B-tree [8], which consists of two types of nodes: internal and leaf nodes. Internal nodes keep a small log where they store pivots, whereas leaf nodes store key entries. Each key entry consists of a tuple with a pointer to the key-value log and a fixed-size key prefix. Prefixes are the first M bytes of the key used for key comparisons inside a leaf. They reduce significantly I/Os to the log since leaves constitute the vast majority of tree nodes. If the effectiveness of prefixes is reduced due to low entropy of the keys, existing techniques discuss how they can be recomputed [12].

During inserts, *Kreon* appends the key-value pair to the key-value log, then it performs a top-down traversal in its L_0 B-tree, from the root to the corresponding leaf, and adds a key entry to the leaf. Get operations examine hierarchically levels from L_0 to L_N and return the first match. Since inserts propagate with the same order as get operations, the version of the retrieved key is the most recent. Delete operations mark keys with a tombstone and defer the actual delete operation. During system operation we use the marked key entries for subsequent inserts that reuse the index entry and mark as free the deleted (old) key-value pair in the log. Marked and unused entries in the index are reclaimed during spills. Marked space in the log is reclaimed asynchronously, as discussed in Section 3.2.2. Update operations are similar to a combined insert and delete. Scan operations create a scanner per-level and use the index to fetch keys in sorted order. They combine the results of each level to provide a global sorted view of the returned keys. Scans, similar to other systems [31], access all data inserted to the system up to the scanner creation time and they operate on an immutable version of each tree which is facilitated by the Copy-On-Write approach used by *Kreon* (Section 3.4).

Similar to LSM-Tree, L_0 in *Kreon* always resides entirely in memory. Portions of $levels \geq 1$ are brought in memory on demand. *Kreon* enforces memory placement rules for different levels by using *kmmap* and explicit priorities (Section 3.3).

3.2.1 Spill Operations. When level i, L_i, fills up beyond a threshold, *Kreon* merges L_i into L_{i+1} via a *spill* operation. Spills are conceptually similar to LSM-Tree compactions [31, 34, 68], however, they operate differently. Spills avoid sorting by using the B-tree of the level to scan L_i keys in lexicographic order and to insert them in L_{i+1}. Spills effectively move a large portion of keys from one level to the next. This batching of insert operations results in amortizing device I/Os over multiple keys due to the lexicographic retrieval of L_i keys: *Kreon* fetches a leaf of L_{i+1} once and performs all updates in the batch related to this leaf before writing it back to storage. Furthermore, *Kreon* spills involve only metadata while data remain in the append-only log. Compared to LSM-Tree based key-value stores [31, 52, 68], where compactions move and reorganize the actual data as well, this reduces overhead at the expense of leaving unorganized data on the device.

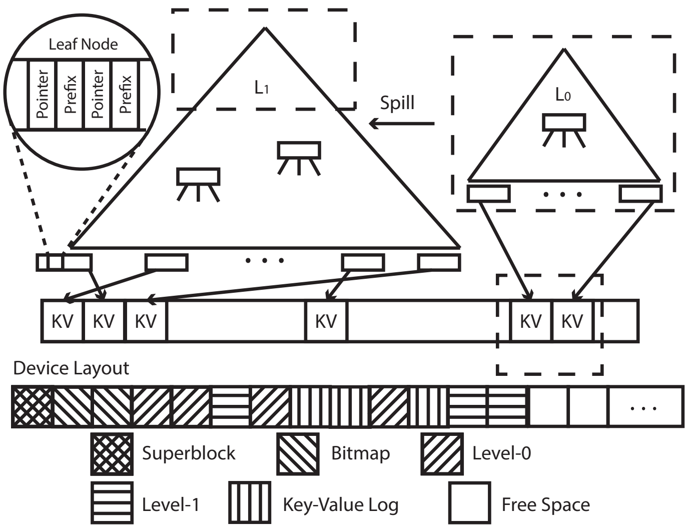


Fig. 3. The main structures of *Kreon* showing two levels of indexes, the key-value log, and the device layout. Dashed rectangles include portions of the data structures that are kept in memory via *kmmap*.

During spills, *Kreon* produces random and relatively small read requests (4 KB) for leaves of L_{i+1}. However, due to the use of Copy-on-Write in *Kreon* (Section 3.4) writes to the next level happen always to newly allocated blocks within contiguous regions of the device, which results in efficient merging of write I/Os into larger requests. Additionally, during spills, *Kreon* creates many concurrent I/Os by using multiple spill threads.

For spills to be effective, each level needs to be able to buffer a substantial amount of keys compared to the size of the lower (and larger) level, similar to compactions in LSM-Tree. We determine empirically that buffering about 5-10% of the metadata of the next level (key-value pairs themselves are not part of the indexes) results in effective amortization of I/O operations. This growth factor of 10-20x between successive levels refers only to metadata and depends also on the distribution of the inserted keys. Zipf-like distributions, that are considered more typical today compared to uniform, behave well with buffering a (relatively) small percentage of the next level. We evaluate the impact of the growth factor in Section 4.5.

To achieve bounded latency for inserts during spills, *Kreon* allows inserts to L_0 to be performed concurrently with spills, as follows. It creates a new L'_0 tree where it performs new inserts, while spilling from L_0 to L_1. Pages freed from the spill operation can be reused by the new L'_0 index. Therefore, L'_0 grows at the same rate as L_0 shrinks. Freeing pages from the old index and adding them to the new index involves memory unmap and remap operations (via *kmmap*) but no device I/O.

3.2.2 Device Layout and Access. *Kreon* manages storage space as a set of segments. Each segment is a contiguous range of blocks on a device or a file. To further reduce overhead we access devices directly rather than use a file system in between. Our measurements show that files result in a 5-10% reduction in throughput due to file system overhead. Each segment hosts multiple regions and it has its own allocator to manage free space.

Kreon's allocator stores its metadata at the beginning of each segment, which consists of a *superblock* and a *bitmap*. The *superblock* keeps pointers to the latest consistent state of the segment and its regions. The *bitmap* contains information about the allocation status (free or reserved) of each 4 KB block. The *bitmap* is accessed directly via an offset and at low overhead, while for searches we use efficient bit parallel techniques [13].

Kreon allocates space eagerly for regions in large units, currently 2 MB, consuming them incrementally in smaller units. This approach avoids frequent calls to the allocator that is shared across regions in each segment. It also improves average write I/O size by letting each region grow in a contiguous part of the device.

Similarly, the key-value log in *Kreon* is organized in large chunks, also 2 MB. At the start of each chunk we keep metadata about the garbage bytes as done in other systems [59]. Delete operations update the deleted bytes counter of the corresponding chunk. When this counter reaches a threshold the valid key-value pairs are moved to the end of the log. We locate these keys in the index via normal lookups and we update the leaf pointers accordingly. Finally, we release the chunk to be available for subsequent allocations.

3.2.3 Partial Reorganization. Scan operations in *Kreon* for small key-value pairs (less than 4 KB) produce read amplification due to page size access granularity. To address this, *Kreon* reorganizes data during scan operations, at leaf granularity. Reorganization takes place only for $L \geq 1$ leaves, since L_0 leaves are always in memory. During reorganization the key-value pairs belonging to the same leaf are written in a continuous region of the key-value log and their previous space is marked free. The reorganization criterion is currently based on a counter per leaf, which is incremented every time a leaf is written. During scans, if this counter exceeds a threshold (currently, half the leaf capacity) the leaf is reorganized and the counter is reset. We leave as future work additional adaptive policies for data reorganization.

3.2.4 Number of Levels. In our projected work, we claim that two levels in *Kreon* are adequate for most practical cases, given current and projected DRAM and Flash density and cost. If we assume a growth factor R of about 10-20x between levels, we can calculate the dataset that can be handled with M bytes of memory devoted to L_0, which needs to fit in memory. If we assume that space amplification in B trees is 1.33 [47] and N keys are buffered in L_0 then the size of L_0 is $M = 1.33 * N * P_k$, where P_k is the size of the metadata for each key (pointer and prefix). *Kreon* uses 20 bytes of metadata for each key, which results in $M = 26 * N$. Similarly, the size of the dataset is $D = R * N * (S_k + S_v)$, where S_k and S_v are the size of the keys and values respectively, in the dataset. If we conservatively assume $R = 10, S_k = 10$, and $S_v = 100$, then $D = 1100 * N$ and $M/D = 0.02$. However, more typical sizes for keys and values are $S_k = 20$ and $S_v = 1000$. If we also assume $R = 20$, then $D = 20600 * N$ and $M/D = 0.001$. Assuming that the cost ratio of DRAM over Flash is about 10x per GB, then the cost of DRAM for L_0 in a 2-level *Kreon* configuration is conservatively 20% (M/D=0.02) cost of Flash to store the data and more realistically 1% (D/M=0.001) or less.

Similar to our analysis, previous work has claimed that three levels are adequate for most purposes [52, 68]. However, in previous cases the index contains the key-value pairs as well, while in *Kreon* key-value pairs are placed in a separate log, further reducing the index size. Finally, if two levels are not adequate, *Kreon* introduces additional levels to the hierarchy. In this case however, there will be a need to also use bloom filters for avoiding out of memory lookups for all levels, similar to other systems [23, 31, 68].

3.2.5 Deletes, Updates, Garbage Collection. In this section we describe the design of delete operations and the associated garbage collection mechanism in *Kreon*. We use the algorithm proposed by Bayer et al. [8, 42] to implement deletes for the B-tree, as follows.

During a delete operation, *Kreon* searches all levels to delete every instance of the key since, due to updates, a key may be present at multiple levels. After locating a key within a level, we remove its associated metadata from the corresponding leaf (prefix, pointer). If the node underflows (fewer keys than half of maximum leaf capacity) we perform the appropriate rebalance operations (merge, rotate). During deletes and updates the key-value pair is removed or updated accordingly from the index and no writes occur in the log.

Deletes, similar to updates, produce variable size chunks of free space in the key-value log. *Kreon* implements a garbage collection (GC) mechanism to reclaim free space in the log similar to Atlas [48] and WiscKey [54]. In *Kreon* we use a dedicated GC thread which is invoked either synchronously when the system is under capacity pressure to reclaim space for issued operations or asynchronously, after a time interval. This is configurable and in our case we provide both an aggressive and a lazy policy. The aggressive policy invokes the GC thread every 30 seconds to reclaim the space as soon as possible, while the lazy invokes the daemon every 20 minutes. The GC thread scans the segments of the log and uses *Kreon*'s index to check which entries in the segment are valid.

The GC thread appends the valid key-value pairs at the end of the log and updates their locations in the index. After this step we reclaim the space of the segment. During this move operation of valid keys at the end of the log, there is a case where a key could be simultaneously updated. We detect this by comparing the pointer stored in the index with the address of the key-value pair in the log. If we identify that the new key is the same as a key that is being updated then we abort the (re)insertion of the key.

3.2.6 Single-Region Scalability. Within each region, the original version of *Kreon* [62] supports a single-writer/multiple-readers concurrency model. Readers operate concurrently with writers using Lamport counters [49] for each tree node. Furthermore, it uses a single lock per region for writers.

To increase concurrency for writers we use the first two protocols of Bayer et al. [9], as described in Section 2.2. In the common path we use the second protocol which allows higher concurrency in the index nodes, compared to the first protocol, as follows.

Each traversal from the root to a leaf node uses the second protocol. If a node in this traversal is full, we retry the traversal using the first protocol to get exclusive access (write lock). Afterwards, we split the full node and rebalance the tree.

The combination of the two protocols allows *Kreon* to scale well with increasing the number of threads, within a single NUMA node. With multiple NUMA nodes, the lock of the root node becomes the bottleneck and limits scalability. Figure 7b shows that going from 16 threads (1 NUMA node) to 32 threads (2 NUMA nodes) does not provide any performance improvement. The bottleneck in this case is the atomic increment operation used for the read locks. Related work [20] has shown that even read locks limit scalability in NUMA servers.

To enable better scalability in multiple NUMA nodes, we provide an optimistic extension of Bayer's protocol presented in Section 2.2. Our extension is based on the observation that rebalance operations in the root node are not frequent.

Bayer's first and second protocol require the following properties regarding the root node: (1) A single thread can modify the root at any given time and (2) writers should not check a version of the root that is in a transient state.

We achieve the same properties for root with the three following mechanisms:

(1) *Root write lock*: This ensures that a single thread at any given time can modify the root node. Only the thread that modifies the root acquires this lock.
(2) *Root Copy-on-Write*: To avoid other writers accessing the root in a transient state we use Copy-On-Write at the root node when a modification takes place. This allows concurrent writers to always access the root in valid state.

(3) *Lamport counters*: This mechanism allows other concurrent writers to detect that root is in transient state due to modification and retry the operation.

It is important to notice that in the case of a single NUMA node, this mechanism incurs higher overhead compared to acquiring a read lock. On the other hand, this overhead is negligible as root rebalance operations are infrequent.

Finally, our protocol can be applied to other B-tree designs as well. The only requirement is to use a top-down approach to acquire locks (i.e. from root to leaves), similar to Foster B-tree [36] which additionally increases concurrency during leaf split operations.

3.3 Memory-Mapped I/O

Most key-value stores and other systems that handle data use explicit I/O to access storage devices or files with read/write system calls. In many cases, they also employ a user-space cache as part of the application to minimize accesses to storage devices and user-kernel crossings for performance purposes. The use of a user-space cache is important to avoid frequent system calls for lookup operations that need to occur for every data item, regardless if it eventually hits or misses. However, even the use of an application user-level cache incurs significant overhead in the common path [38, 39, 61].

The use of memory-mapped I/O in *Kreon* reduces CPU overhead related to the I/O cache in three ways: (a) It eliminates cache lookups for hits by using valid virtual page mappings. Memory-mapped I/O does not require cache lookups because virtual memory mappings distinguish data that are present in memory from data that are only located on the device. All device data are mapped to the application address space but only data that are present in memory have valid virtual memory mappings. Accesses to data that are not present in memory result in page faults that are then handled by *mmap*. Given that many operations in key-value stores, such as get operations with a Zipf distribution, complete from memory, *Kreon* avoids all related cache lookup overheads. (b) There is no need to copy data between user and kernel space when performing I/O. Pages used for data in memory are used directly to perform I/O to and from the storage devices. (c) There is no need to serialize/deserialize data between memory and the storage devices. Finally, memory-mapped I/O uses a single address space for both memory and storage, which eliminates the need for pointer translation between memory and storage address spaces and therefore, the need to serialize and deserialize data when transferring between the two address spaces.

3.3.1 Kreon's Memory-Mapped I/O. *Kreon* provides its own custom memory-mapped I/O path to address the shortcomings of *mmap* in Linux.

First, in *mmap* there is no explicit control over data eviction, as with an application-specific cache. Linux uses an LRU-based policy, which may evict useful pages, for instance, pages of L_0 instead of L_1 pages. L_0 has to reside in main memory to amortize write I/O operations. Linux *mmap* does not provide a mechanism to achieve this. A possible solution is to lock important pages with *mlock*. However, Linux does not allow a large number of pages to be locked by a single process because this affects other parts of the system.

Second, each write operation in an empty page is effectively translated to a read-modify-write because *mmap* does not have any information about the status (allocated or free) of the underlying disk page and the intended use. This results in excessive device I/O. Instead, if applications can inform *mmap* whether a page contains garbage and will be written entirely, *mmap* can map this page without reading it first from the device, eliminating unnecessary read traffic.

Third, *mmap* employs aggressive evictions based on memory usage and time elapsed since pages marked as dirty to free memory and avoid starving other system components. Mapping large portions of the application virtual address space creates pressure to the virtual memory subsystem

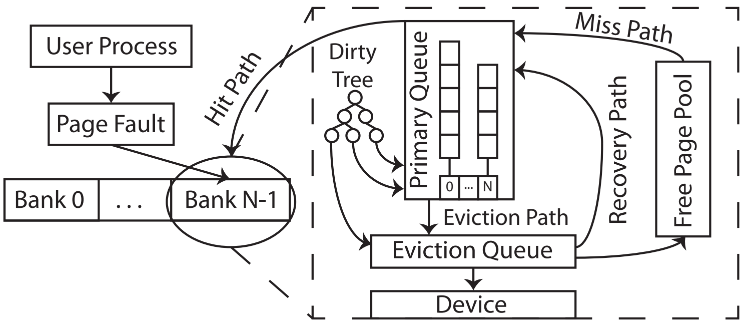


Fig. 4. The main structures of *kmmap*.

and results in unpredictable use of memory and bursty I/O. Furthermore, eager and uncoordinated evictions do not facilitate the creation of large I/Os through merging. Empirically, we often observe large intervals (of several 10s of seconds) where the system freezes while it performs I/O with *mmap* and applications do not make progress. Furthermore, we observe similar behaviour with *msync*. This unpredictability and large periods of inactivity are an important problem for key-value stores that serve data to online, user-facing applications.

To overcome these limitations, we implement a custom *mmap*, as a Linux kernel module, called *kmmap*. Figure 4 shows the overall design and data structures of *kmmap*.

Kmmap bypasses the Linux page cache and uses a priority-based FIFO replacement policy. As priority we define a small, per-page number (0 to 255). During memory pressure, a page with a higher priority is preferred for eviction. Priorities are kept only in memory and are set explicitly by *Kreon* with *ioctl* calls. Priorities are set as follows: *Kreon* assigns priority 0 to index nodes of L_0, 1 to index nodes of L_1, 2 to leaf nodes of L_1, and 3 to the log. L_0 fits in memory and it will not be evicted. Generally if we have more than two levels L_0 always uses priority 0 and the log maximum priority. We calculate the priority of level L_N as $(2 * N - 1)$ for index nodes and $(2 * N)$ for leaves.

To increase parallelism, *kmmap* organizes memory in independent banks, similar to DI-MMAP [28]. Pages are mapped to banks by hashing the page fault address. To place consecutive pages in the same bank, the page fault address is first shifted. Unlike DI-MMAP, *kmmap* uses fine-grain locking inside banks, which results in higher concurrency and eliminates periods of inactivity (long freezes).

When *Kreon* accesses a page (for read or write), that does not reside in main memory, a page fault occurs. On a page fault, *kmmap* retrieves a free page from an in-memory list (*Free Page Pool*), it reads the data from the device if required, and finally enqueues the page to the *Primary Queue* based on its priority. *kmmap* keeps a separate FIFO queue per priority inside the *Primary Queue*. In the case where the *Primary Queue* is full of pages, it dequeues a fixed number of entries for batching purposes, with preference to entries with higher priority. Then it unmaps them from the process address space and moves them into the *Eviction Queue*. The *Eviction Queue* is organized as an in-memory red-black tree structure, keeping keys sorted based on page offset at the device. For evictions, it traverses the *Eviction Queue* and merges consecutive pages to generate as large I/Os as possible. It keeps dirty pages that belong to the *Primary Queue* or the *Eviction Queue* in another in-memory red-black tree structure (*Dirty Tree*) sorted by their device offset. The *Dirty Tree* is used by *msync*, to avoid scanning unnecessary (clean) pages.

Kmmap compared to *mmap* keeps pages in memory for a longer period of time and does not evict them, unless there is a need to do so. This allows *Kreon* to generate larger I/Os during spill operations by merging more requests. When a spill is completed, *Kreon* sets the priority of pages from the previously spilled L_0 to 255 (smallest priority) so they get evicted as soon as possible.

To avoid unnecessary reads that occur when a new page is written in *Kreon*, *kmmap* detects and filters these read-before-write operations, whereas write and read-after-write operations are forwarded to the actual device. To achieve this, it uses an in-memory bitmap, which is initialized and updated by *Kreon* via a set of *ioctl* calls. The bitmap uses a bit per device block, so a 1 TB SSD requires 32 MB of memory for the bitmap.

Kmmap provides a non-blocking *msync* call that allows the system to continue operation while pages are written asynchronously to the devices. For this purpose we keep a timestamp for each page that indicates when it became dirty. To write dirty pages, we iterate the *Dirty Tree* and write only pages with timestamp older than the timestamp of *msync*. We use fine grain locking in *Dirty Tree* and we allow to add new dirty pages into it during *msync*. However, there can be pages that are already dirty and changed after *msync*, which should not be written. *Kreon* uses Copy-On-Write to ensure that after a commit dirty pages will not change again as we need to allocate new pages.

Finally, *Kreon* significantly reduces unpredictability with respect to memory management during system operation by limiting the maximum amount of memory it occupies throughout its operation. It uses a configuration parameter to calculate the size of L_0 in memory and based on this it preallocates all memory-mapped I/O structures.

3.4 Persistence

Kreon uses Copy-On-Write (CoW) [66] to maintain its state consistent and recoverable after failures. *Kreon*'s state includes the data section of each segment (metadata and data of the tree) and the allocator metadata. To persist a consistent version of its state *Kreon* provides a commit operation. This operation first writes the dirty (in-memory) data into the device and then switches atomically from the old state to the new state. More specifically, *Kreon* stores a pointer to the latest persistent state in the superblock. At the end of a commit operation, *Kreon* updates this pointer to the newly created persistent state which becomes immutable. In case of a failure, the new state that is not committed will be discarded during startup, resulting in a rollback to the last valid state.

In *Kreon* we use CoW for different purposes at L_0 and the rest of the levels. The index of all levels except L_0 is kept on the device and only brought to memory on demand. Therefore, typically, only a small part of these indexes is in memory. For these indexes, *Kreon* uses CoW to ensure consistency of the index on the device during failures. These levels are only written to the device during spills. Therefore, the only time when commits occur (besides L_0), is at the end of each spill operation.

L_0 is different and can always be recovered by replaying a subset of the key-value log. This subset is always the latest portion of the log and is easy to identify via markers placed in the log during the spill operation from L_0 to L_1. Therefore, after a failure, L_0 can be reconstructed. However, L_0 can grow significantly due to the large amount of memory available in modern servers. *Kreon* uses CoW to checkpoint L_0 to the device and to reduce recovery time. Therefore, *Kreon*'s commits of L_0 are not critical for recovery. L_0 checkpoints do not have to be very frequent. Infrequent L_0 commits do not lead to data loss because the L_0 index can be reconstructed through the replay of the key-value log. The log is written to the device more frequently, when a log segment (2 MB) becomes full.

Essentially, *Kreon* uses L_0 commits at a coarse granularity to improve recovery time, without however, a negative impact on the recovery point. The tradeoff introduced is that commits incur overhead during failure free operation. Overall, we expect that *Kreon* L_0 commits will be issued periodically at a time scale of minutes, which has a low impact on performance. Section 4.5 evaluates commit overhead in *Kreon*.

3.5 RDMA Client-Server Protocol

During the past decade network technology has evolved to provide link speeds up to 100 Gbps. Along with these advancements, the demand for high throughput and ultra-low latency has also grown in datacenter applications. However, TCP/IP protocol fails to deliver this network performance. As shown in previous works, TCP/IP incurs high CPU overhead [33, 55] and as a result few processing resources are left for applications [11]. This is because TCP/IP requires extensive computing power due to the its processing in the host CPU and it inherently incurs high overheads due to its streaming semantics.

On the contrary, RDMA protocol can meet those network requirements, since it provides low CPU overhead, ultra-low latency and high throughput. To achieve these, RDMA provides zero-copy transfers by allowing one computer to directly access the memory of a remote computer without involving the operating system at any host. Previous work [27, 43, 44, 57] has shown that RDMA-based protocols offer significant gains compared to TCP/IP for in-memory key-value stores.

In *Kreon* we implement an RDMA protocol for communication between clients and servers. In this work we investigate the portion of cycles a server devotes to network processing when using RDMA relative to the portion of cycles devoted to index manipulation and device I/O.

Previous work for in-memory, hash-based key-value stores has removed server involvement entirely by using RDMA read operations [27, 57, 75]. This is possible because they use a simple index, so clients can access data with a single remote read. However, *Kreon* and most persistent key-value stores use more complex index structures to access data that also support scans and requires index traversals. Thus, direct access from clients would result in several round-trip messages. For this reason, *Kreon* uses server-side processing for client requests. In particular, it uses a single RDMA-based round-trip message for each common data path operation (get, put, scan). *Kreon* uses RDMA writes for all messages, that allow arbitrary key and value sizes, unlike RDMA send messages that require a maximum fixed size [44]. Note that in our implementation, RDMA reads would provide worst performance than RDMA writes just because several RDMA reads should be posted to locate the key-value pairs remotely.

Kreon uses the following buffer management scheme for RDMA writes. RDMA operations need pre-registered memory regions in both the local and remote node to exchange data between two nodes. Nodes register two memory regions per connection: One for posting data to be sent to the remote peer and the other for receiving data from the remote peer. The receiving region mirrors the contents of the sending region in the remote peer. Both regions are split into blocks of 1 KB, with each receiving block being a mirror of a sending block. Each message uses one or more consecutive 1 KB mirrored blocks. The sender reserves mirrored blocks from its sending memory region, resulting indirectly in a reservation of the same mirrored blocks on the receiving memory region of the remote peer.

Regarding messages, each message is composed of a header and a payload. The header includes the request type (*get*, *put* or *scan*), operation ID, message size, ID of the region and number of operations included. The payload contains the key value pairs to insert (*put*), or the keys to lookup (*get* and *scan*) from client to server or the values found from server to client. Client inserts keys and values (if any) directly to the mirrored blocks, while server uses the mirrored blocks to issue the corresponding operation to *Kreon*, avoiding an extra memory copy.

To avoid interrupts, we use polling at the receive path for detecting arrival of new messages. Reservation of mirrored blocks is always done sequentially so messages arrive in consecutive blocks. Since our RDMA messages are variable size, we use two locations for polling, one for detecting arrival of the header and identifying message length and one for detecting arrival of the payload.

	Workload
A	50% reads, 50% updates
B	95% reads, 5% updates
C	100% reads
D	95% reads, 5% inserts
E	95% scans, 5% inserts
F	50% reads, 50% read-modify-write
G	100% scans

Table 1. Workloads evaluated with YCSB. All workloads use a query popularity that follows a Zipf distribution except for D that follows a latest distribution as defined by YCSB.

Note that RDMA requests follow the same path as local requests, for *Kreon* there is no difference between a local request or a RDMA request.

4 EXPERIMENTAL RESULTS

In this section we evaluate *Kreon* against RocksDB [30, 31]. Our goal is to examine the following aspects of *Kreon*:

(1) What is the efficiency in cycles/op achieved by *Kreon* compared to LSM-based key-value stores? Does higher efficiency come at the cost of worse absolute throughput or latency?
(2) How much does the new index design and memory-mapped I/O contribute to reducing overheads?
(3) How does *Kreon* improve I/O amplification? How much does it increase I/O randomness?
(4) How do the growth factor across levels and L_0 checkpoint interval affect performance?
(5) How much is the overhead of RDMA-based communication between clients and a server compared to I/O and index management?
(6) How much does *Kreon* improve the performance and efficiency in a production grade NoSQL system (MongoDB)?

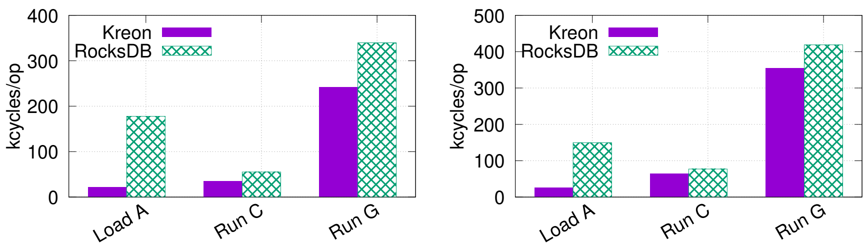
Next, we discuss our methodology and each aspect of *Kreon* in detail.

4.1 Methodology

Our testbed consists of a single server which runs the key-value store and the YCSB client. The server is equipped with two Intel(R) Xeon(R) CPU E5-2630 v3 CPUs running at 2.4 GHz, with 8 physical cores and 16 hyper-threads, for a total of 32 hyper-threads and with 256 GB DDR4 at 2400 MHz. It runs CentOS 7.3 with Linux kernel 4.4.44. During our evaluation we scale-down DRAM as required by different experiments. The server has six Samsung 850 PRO 256 GB SSDs, organized in a RAID-0 using Linux *md* and 1 MB chunk size. The systems are connected with Mellanox ConnectX-3 Pro 40 Gbps Ethernet cards through a 40 Gbps switch. In the case of MongoDB we use two separate clients. Each of them is equipped with two Intel(R) Xeon(R) Processor E5-2620 v2 CPUs running at 2.1 GHz with 6 physical cores and 12 hyper threads, for a total of 24 hyper-threads and with 128 GB DDR3. They also run CentOS 7.3 with Linux kernel 3.10. Clients access MongoDB server through TCP/IP MongoDB client driver. To generate enough load for the server we run 8 separate YCSB processes on each client, each of them with 8 threads.

We use RocksDB[1] v5.6.1, on top of *XFS* with disabled compression and jemalloc [29], as recommended. We configure RocksDB to use direct I/O because we evaluate experimentally that in our

[1]Options file: https://goo.gl/NJNLNr.



(a) Small dataset (b) Large dataset

Fig. 5. Efficiency of *Kreon* and RocksDB in cycles/op.

testbed results in better performance. Furthermore, we use RocksDB's user-space LRU cache, with 16 and 192 GB depending on the experiment.

Kreon is build from scratch in C. To remove JNI ovehreads in the Java version of YCSB, we use a C++ version of YCSB [65] with the recommended workloads proposed by YCSB [21, 22]. Table 1 summarizes these workloads. We add a new workload named *G* which is similar to *E* but consists only of scans. In all cases we use 128 YCSB threads for each client and 32 regions.

We emulate two datasets a small dataset that fits in memory and a large dataset that does not by using two different memory configurations for our system. In the small dataset we boot the server with 194 GB of memory, 192 GB for key-value store and 2 GB for the OS. To further stress I/O for the large dataset, we boot the server with 18 GB of memory, 16 GB for the key-value store and 2 GB for the OS. The dataset consists of 100M records and requires about 120 GB of storage. YCSB by default generates 10 columns for each key. We keep these 10 columns inside a single value. We use a 100M keys (recordcount and operationcount equals to 100M) * 10 columns which results in 1 billion columns.

In the small dataset, both the key-value log and the indexes fit in memory, so I/O is generated by commit operations. In the large dataset, neither the key-value log nor the indexes fit in memory and only L_0 is guaranteed to reside in memory. Therefore, the small dataset demonstrates more clearly overheads related to memory accesses whereas the large dataset stresses the I/O path.

We calculate efficiency in cycles/op as follows:

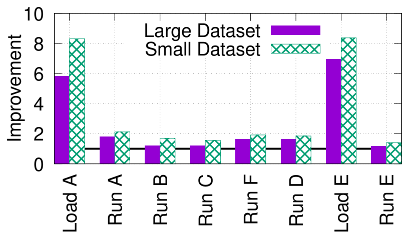
$$cycles/op = \frac{\frac{CPU\_utilization}{100} \times \frac{cycles}{s} \times cores}{\frac{average\_ops}{s}},$$

where $CPU\_utilization$ is the average of CPU utilization among all processors, excluding idle and I/O wait time, as given by *mpstat*. As $cycles/s$ we use the per-core clock frequency. $average\_ops/s$ is the throughput reported by YCSB, and $cores$ is the number of system cores including hyperthreads.

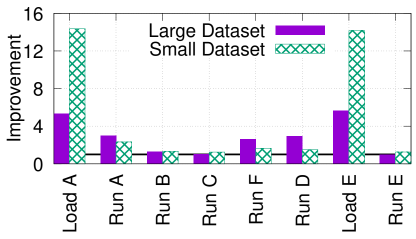
4.2 CPU Efficiency and Performance

We evaluate the efficiency of *Kreon* in terms of cycles/op required to complete each operation, excluding YCSB overhead. To exclude the overhead of the YCSB client, we profile the average cycles/op required by YCSB and we subtract this overhead from the overall value for both RocksDB and *Kreon*.

Figure 5 shows our overall results for *Kreon* and RocksDB. For the small dataset *Kreon* requires 8.3x, 1.56x, and 1.4x fewer cycles/op for *Load A*, *Run C*, and *Run G*, respectively. For the large dataset *Kreon* requires 5.82x, 1.2x, and 1.18x fewer cycles/op for *Load A*, *Run C*, and *Run G*, respectively. In

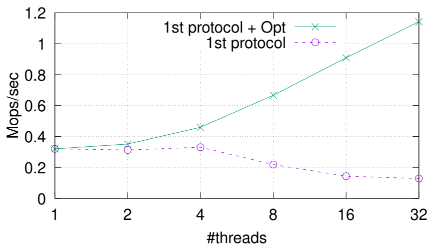


(a) Efficiency

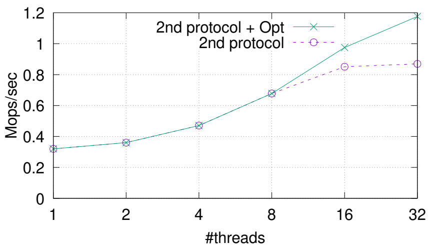


(b) Throughput

Fig. 6. Efficiency and throughput improvement of *Kreon* compared to RocksDB for all YCSB workloads.



(a) 1^{st} protocol



(b) 2^{nd} protocol

Fig. 7. Kreon throughput for Bayer's first (left) and second (right) protocols.

addition, for the small dataset and *Load A* we compare *Kreon* when using *kmmap* and when using vanilla *mmap*. Although we do not show these results for space purposes, using *kmmap*, *Kreon* achieves 1.47x fewer cycles/op compared to vanilla *mmap*, indicating the importance of proper and customized memory-mapped I/O for key value stores.

In terms of absolute numbers, we see that *Kreon* requires 21, 35, and 241 kcycles/op for each of *Load A*, *Run C*, and *Run G* for the small dataset and 25, 64, and 354 kcycles/op for each of *Load A*, *Run C*, and *Run G* for the large dataset.

We now show results from a complete run for all YCSB workloads. We run the workloads in the recommended sequence [21]: Load the database using the configuration file of workload A, run workloads A, B, C, F, and D in a row, delete the whole database, reload the database with the configuration file of workload E and finally run workload E.

For both the small and large dataset, Figure 6a shows the improvement in efficiency compared to RocksDB, whereas Figure 6b shows the improvement in throughput. Regarding efficiency, *Kreon* improves RocksDB efficiency, on average, by 3.4x and 2.68x, for the small and large dataset, respectively. Regarding throughput, the improvement in *Kreon* compared to RocksDB is, on average, 4.72x and 2.85x for the small and large datasets, respectively.

4.2.1 Scalability analysis. In this section, we evaluate the scalability of *Kreon* concurrency protocols described in Section 3.2.6. We show that our root optimization is essential to achieve a scalable performance in NUMA servers. In this case, we run *Load A* and we vary the number of threads from 1 to 32. We use the small dataset that fits in memory because we want to show the CPU synchronization overheads.

Figure 7a shows throughput scalability of Bayer's first protocol which acquires write locks in the whole path from the root to the leaves. The *"1st protocol"* curve shows Bayer's first protocol whereas the *"1st protocol + Opt"* curve uses same protocol and in addition the optimization for the root, as described in Section 3.2.6. We observe from the *"1st protocol"* curve that throughput drops after 4 threads because of the write lock that serializes operations in the root node. On the other hand, from the *" 1st protocol + Opt"* curve we observe that when we replace the write lock of the root with our root optimization throughput improves from 3× up to 10×. In this case we enable concurrency in the root node and inserts that do not conflict in the traversal to a leaf node proceed concurrently.

Figure 7b shows the same experiment with Bayer's second protocol which acquires read locks in the internal nodes and write lock only at the leaf. The *"2nd protocol"* curve is Bayer's second protocol whereas *"2nd protocol + Opt"* is the same protocol using our optimization for the root node. Figure 7b shows that Bayer's second protocol scales well within a single NUMA node (up to 16 threads). Using the second NUMA node (32 threads), *Kreon* fails to scale due to the root node read lock excessive traffic on the NUMA interconnect. With *"2nd protocol + Opt"*, the traffic on the NUMA interconnect decreases as we remove the single atomic operation from the root. This improves throughput by 66% using 32 threads. Using profiling and 32 threads we see that our mechanism in the root node is not the bottleneck. In this case, the performance is limited by the log lock, which writers use to append atomically. This lock takes about 50% of the execution time.

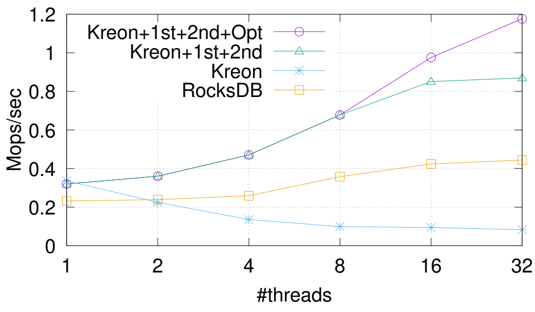


Fig. 8. Bayer's protocols scalability compared to Kreon and RocksDB.

Figure 8 shows the scalability for *RocksDB* and three versions of Kreon: *Kreon* that uses a single write lock, *"Kreon+1st+2nd"* that uses Bayer's second concurrent protocol without the root optimization, and *"Kreon+1st+2nd+Opt"* that uses Bayer's second protocol with the root optimization. We see that *"Kreon+1st+2nd+Opt"* scales better compared to *"Kreon+1st+2nd"* up to 32 threads. *Kreon* with a single lock does not scale with increasing the number of threads. Finally, using 32 threads *"Kreon+1st+2nd+Opt"* achieves 2.65× more throughput compared to *RocksDB*.

4.2.2 Latency analysis. First, we examine the average latency per operation for the small dataset. For *Load A*, RocksDB achieves 1162 μs/op, *Kreon* with vanilla *mmap* achieves 346 μs/op, and *Kreon* with *kmmap* achieves 72 μs/op. This shows that *kmmap* provides significant reduction in latencies compared to vanilla *mmap*. For *Run C*, RocksDB achieves 174 μs/op, *Kreon* with vanilla *mmap* achieves 119 μs/op, and *Kreon* with *kmmap* achieves 109 μs/op. Generally, *Kreon* with *kmmap* achieves 16.1x and 1.5x lower latency on average for *Load A* and *Run C* compared to RocksDB. For the large dataset and *Load A*, RocksDB achieves 1443 μs/op, *Kreon* with vanilla *mmap* achieves 479 μs/op, and *Kreon* with *kmmap* achieves 155 μs/op. For *Run C*, RocksDB achieves 182 μs/op,

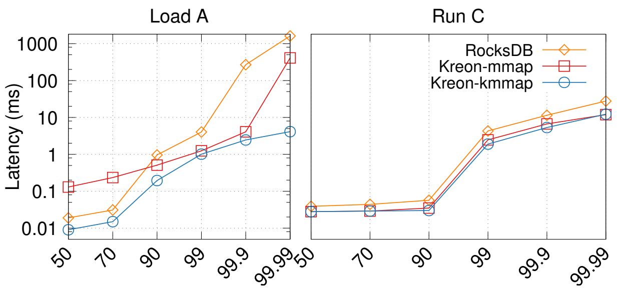


Fig. 9. Tail latency for Load A and Run C for RocksDB, *Kreon* with vanilla *mmap*, and *Kreon* with *kmmap* using the small dataset.

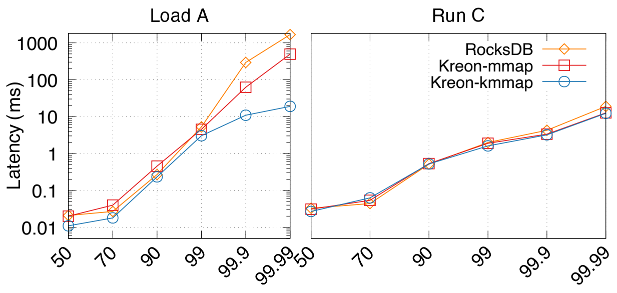
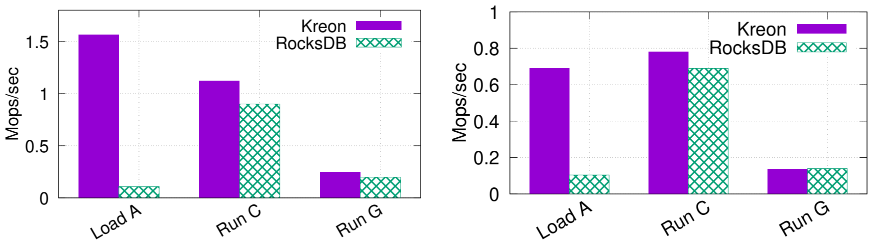


Fig. 10. Tail latency for Load A and Run C for RocksDB, *Kreon* with vanilla *mmap*, and *Kreon* with *kmmap* using the large dataset.

Kreon with vanilla *mmap* achieves 172 μs/op, and *Kreon* with *kmmap* achieves 170 μs/op. We see that with the large dataset, *Kreon* provides similar improvements as the small dataset.

Figure 9 shows the tail latency for *Kreon* using both *kmmap* and vanilla *mmap* and RocksDB with the small dataset. For *Load A*, for 99.99% of requests, *Kreon* with *kmmap* achieves 393x lower latency compared to RocksDB. Furthermore, *kmmap* results in 99x lower latency compared to vanilla *mmap*. In our design we remove blocking for inserts during *msync* and during spilling of L_0. Unlike *Kreon*, RocksDB blocks inserts during compaction operations for longer periods. For *Run C*, *Kreon* results in almost the same latency with and without *kmmap* and about 2x better than RocksDB. This is because in a read-only workload most overheads come from the data structure, as we use a dataset that fits in memory and removes the need for I/O. In the case of RocksDB this overhead includes also a cache lookup while in *Kreon* it only accesses already mapped memory. The use of *mmap* and *kmmap* results in almost the same performance as this experiment does not stress memory-mapped I/O path.

Figure 10 shows the tail latency for *Kreon* using both *kmmap* and vanilla *mmap* and RocksDB and with large dataset. Using *Load A*, for 99.99% of requests, *Kreon* with *kmmap* achieves 88x lower latency compared to RocksDB. Furthermore, *kmmap* results in 26x lower latency compared to vanilla *mmap*. For *Run C*, *Kreon* results in almost the same latency with and without *kmmap* and about 54% better than RocksDB. Using both *Load A* and *Run C* we see similar behaviour as in the small dataset. This shows that out approach provides better latency (both average and tail), regardless of the ratio cache to workload size.



(a) Small dataset (b) Large dataset

Fig. 11. Throughput for *Kreon* and RocksDB in ops/s.

4.2.3 Very large dataset. To examine *Kreon*'s behavior with a very large dataset we run *Load A* using 6 billion keys with one column per key (key size of 30 bytes and value size of 100 bytes). For this experiment we use 192 GB of DRAM for both *Kreon* and RocksDB. *Kreon* reduces cycles/op by 8.75x, increases ops/s by 12.11x, reduces write volume by 4.25x, and read volume by 3.14x.

4.2.4 Absolute operation throughput. Next, we examine if *Kreon*'s increased efficiency in cycles/op comes at the expense of reduced absolute performance. This is important for understanding if *Kreon* trades device and host CPU efficiency in the right manner. For *Kreon* and RocksDB, Figure 11 shows the throughput (ops/s), achieved by YCSB. For the small dataset, *Kreon* achieves 14.35x, 1.24x, and 1.25x more ops/s for *Load A*, *Run C*, and *Run G*, respectively.

For the large dataset, *Kreon* achieves 5.33x and 1.05x more ops/s for *Load A* and *Run C*, respectively, than RocksDB. However, *Kreon* is 2% worse for *Run G*. In this case, both RocksDB and *Kreon* are limited by device throughput and this is the reason that both systems are comparable. On the other hand, *Kreon* results in much lower CPU utilization: on average *Kreon* has a utilization of 13.8% while RocksDB has a utilization of 39.5%. Therefore, *Kreon* is able to support more clients given an adequate number of storage devices.

For the small dataset and *Load A*, we compare *Kreon* with *kmmap* and with vanilla *mmap*. We see that *kmmap* improves throughput by 4.34x compared to vanilla *mmap*.

4.3 Execution Time Breakdown

In this section we examine the main components that contribute to overhead in *Kreon* and RocksDB. Our purpose is to identify what are the main sources of improvement in *Kreon* compared to RocksDB and what are the remaining sources of overhead.

We examine two workloads a write-intensive (Load A) and a read-intensive (Run C) using both the small and large datasets. We profile *Load A* and *Run C* workloads and we use stack traces from *perf* and Flamegraph [37] to identify where cycles are spent. We divide overhead in the following components: index operations (updates/traversals for put/get operations), caching, I/O, and compaction/spill. I/O refers to explicit I/O operations in RocksDB and memory-mapped I/O in *Kreon*. Caching refers to the cycles needed for cache lookups, fetching new data for misses and page evictions when the cache becomes full. RocksDB uses a user-space LRU cache whereas in *Kreon* cache resides in kernel-space as part of *kmmap*.

Table 2 shows the breakdown for the write-intensive *Load A* workload. The number of cycles used by the YCSB client is roughly the same in all cases. In the small workload, index manipulation incurs about 44% lower overhead in *Kreon* (~13K cycles/op in *Kreon* vs. 24K cycles/op in RocksDB). Caching overhead for the write-intensive workload is lower for the large dataset whereas for the

kcycles/ operation	Load A (16GB)			Load A (192GB)		
	RocksDB	Kreon	Impro vement	RocksDB	Kreon	Impro vement
index	24.15	13.46	44%	26.76	13.1	51%
cache	0.33	0.56	-69%	0.82	0.45	45%
I/O pfault	2.92	5.84	61%	1.66	2.61	80%
I/O syswrite	12.20	0		11.91	0	
compaction/spill	63.41	0.78	98%	60.87	0.64	98%
Total	103.1	20.64	79%	102.02	16.8	83%
YCSB	26.67	25.34	-	22.79	21.37	-

Table 2. Breakdown of cycles per operation for workload Load A (write only). Numbers are in kcycles.

kcycles/ operation	Run C (16GB)			Run C (192GB)		
	RocksDB	Kreon	Impro vement	RocksDB	Kreon	Impro vement
index	4.87	4.28	12.3%	25.59	10.29	59%
cache	8.61	0.41	95%	9.79	0.74	92%
I/O pfault	0.12	3.16	-6%	0.54	5.9	23%
I/O sysread	2.86	0		7.21	0	
Total	16.46	7.85	52%	43.13	16.93	60%
YCSB	13.9	12.11	-	54.04	53.11	-

Table 3. Breakdown of cycles per operation for workload Run C (read only). Numbers are in kcycles.

small dataset *Kreon* spends more 0.23 Kcycles/op. For I/O *Kreon* requires 61% fewer cycles. For compaction/spill *Kreon* dramatically reduces the cycles required per operation from 63.41K to 0.78K. In the large workload, index manipulation requires 51% fewer cycles in *Kreon* (from 26K to 13K) and for I/O 80% fewer cycles. Similarly to the small dataset, *Kreon* significantly reduces the number of cycles per operation for compaction/spill from 60.87K to 0.64K.

Table 3 shows the breakdown for the read-intensive workload (*Run C* benchmark). In the small dataset, index manipulation incurs 12% fewer cycles (from 4.87K in RocksDB to 4.28K in *Kreon*). Caching overhead is reduced by 95% (from 8.61K cycles/op in RocksDB to 0.41K cycles/op in *Kreon*) whereas I/O requires 6% more cycles in *Kreon*. In the large dataset, index manipulation overhead is reduced by 59% in *Kreon*, caching overhead by 92%, and I/O by 23%.

Overall, we see that *Kreon*'s design significantly reduces overheads for index manipulation, spills, and I/O. We also see that all proposed mechanisms for indexing, spills that involve only metadata, and memory-mapped I/O-based caching, have important contributions. Finally, we see that in *Kreon* the largest number of cycles is consumed by index manipulation (up to 13K cycles/op) both for both datasets in both workloads and secondarily by page faults (up to 5.9K cycles/op).

4.4 I/O Amplification and Randomness

In this section we evaluate how *Kreon* reduces amplification at the expense of reduced I/O size and increased I/O randomness. To reduce amplification, *Kreon* generates by design smaller and more

	Load A	Run C	Run G
RocksDB-Read	669	138	296
Kreon-Read	112	127	1237
RocksDB-Write	869	0	8
Kreon-Write	221	0	139

Table 4. Total I/O volume (in GB) for Load A, Run C, and Run G using the large dataset.

	R_t	R_r	R_w
RocksDB	0.001780	0.003878	0.000112
Kreon	0.009851	0.033648	0.000325

Table 5. I/O randomness using the large dataset and *Load A*. The higher the value of R, the more random the I/O pattern.

random I/Os compared to RocksDB and traditional LSM-Trees. We measure the average request size for *Load A* using the large dataset. For writes, *Kreon* has an average request size of 94 KB compared to 333.2 KB for RocksDB. However, even at 94 KB, most SSDs exhibit high throughput with a large queue depth (Figure 1). For reads, *Kreon* produces 4 KB I/Os, compared to 126 KB for RocksDB. Because of compactions, RocksDB reads large chunks of data in order to merge them. This results in a large request size but it also results in high read amplification, 4.8x more data compared to *Kreon*.

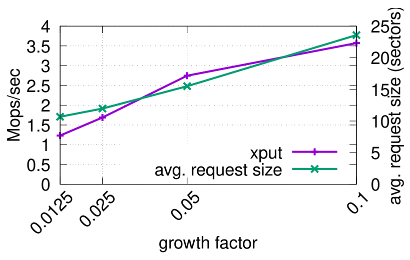
Table 4 shows the total amount of traffic to the device using the large dataset. We see that for *Load A Kreon* reduces both read traffic by 5.9x and write traffic by 3.9x, while the total traffic reduction is 4.6x. *Kreon* reads 1.08x less data for *Run C*. On the other hand, *Kreon* reads 4.1x more data for *Run G*, due to data re-organization. This cost is related only to scans and for leaves that are not re-organized. On the other hand, in RocksDB data reorganization takes place in every compaction.

To examine randomness, we implement a lightweight I/O tracer as a stackable block device in the Linux kernel that keeps the device offset and size for *bios* issued to the underlying device. The tracer stores this information to a ramdisk to reduce overhead and avoid interfering with the key-value store I/O pattern. Tracing reduces average throughput of YCSB by about 10%. We analyze traces after each experiment and calculate a metric for I/O randomness based on the distance and size of successive *bios*, as follows:

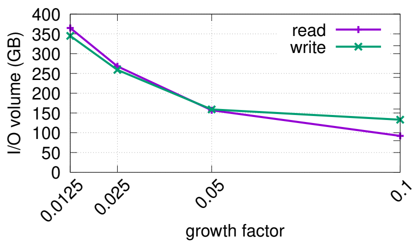
$$R = \frac{\sum_{i=0}^{nb-1} |bs[i+1].off - (bs[i].off + bs[i].size)| + bs[i].size}{device\_size\_in\_pages * \sum_{i=0}^{nb-1} bs[i].size},$$

where *bs* is the array that contains bio information and *nb* its length. R is the randomness metric and takes values between [0,1]. The larger R is, the more random the I/O pattern. Finally, we compute three versions of R, one for all *bios* (R_t), one for reads (R_r), and one for writes (R_w).

Table 5 shows our results for *Kreon* and RocksDB. For calibration purposes, we run *fio* with queue depth of 1 and block size of 4 KB: a sequential pattern is 0 and a random pattern is close to



(a) xput & avg. request size



(b) I/O volume

Fig. 12. Results with varying growth factor from 1.25% to 10% (x-axis) using the large dataset.

0.33. *Kreon* produces overall about 5.53x more random I/O patterns than RocksDB. Reads exhibit a larger difference in randomness, about 10x, because *Kreon* moves data between levels at smaller granularity than RocksDB. For writes, *Kreon* exhibits a 3x more random pattern.

Overall, during inserts, *Kreon* reduces write traffic by 2.8x and read traffic by 4.8x. In both cases, queue depth is about 30 on average. Figure 1 shows that, at this queue depth, commodity SSDs achieve their maximum throughput with at 32 KB requests, so *Kreon*'s 94 KB write requests result in little or no loss of device efficiency, while there is a 2.8x gain from reduced write traffic. For read traffic, *Kreon*'s 4K requests result in a small percentage drop of SSD throughput at a queue depth of 32, but at a 4.8x gain in traffic. Therefore, *Kreon* properly trades randomness and request size for amplification. The calculation is somewhat different for our NVMe devices, but still favorable to *Kreon*.

Finally, *Kreon* achieves an average read throughput of 123 MB/s and an average write throughput of 743 MB/s at an average queue depth of 21.2. On the other hand, RocksDB achieves 707 MB/s for reads and 889 MB/s for writes at an average queue size of 26.2. In both cases queue depth is large enough for devices to operate at high throughput, although *Kreon* exhibits lower throughput for reads due to the smaller request sizes it generates. This loss of device efficiency is compensated by the reduced amplification (by 4.6x) and the reduced CPU overhead, eventually resulting in higher performance and data serving density.

4.5 Growth Factor and Commit Interval

An important parameter for key value stores that use multi-level indexes is the ratio of the size between two successive levels (growth factor). The growth factor in *Kreon* represents the amount of buffering that happens for inserts in one level before keys are spilled to the next level. This affects how effectively I/Os are amortized across several inserts and reduces write amplification.

Figure 12 shows *Load A* with varying growth factor using the large dataset. A growth factor of 0.1 means that L_1 is 10x larger than L_0 and therefore L_0 can buffer about 10% of the keys in L_1. Figure 12b shows that a growth factor between 0.05 and 0.1 is appropriate, meaning that each level should buffer between 5-10% of the next level. A smaller growth factor results in significant increase in traffic and reduces device efficiency. Increasing the growth factor beyond 0.1 reduces traffic further, however, this also requires more memory for L_0. Figure 12a (right y-axis) shows that average request size increases as buffering increases and combined with the reduced traffic, results in increasing throughput (ops/s), as shown in Figure 12a (left y-axis).

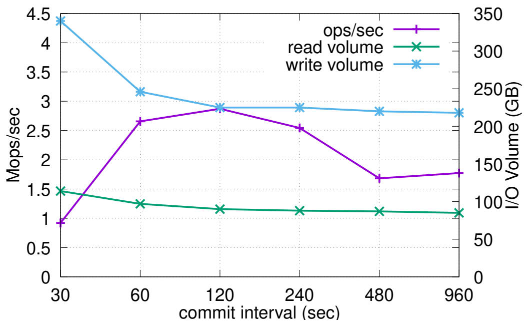


Fig. 13. Results with varying the commit interval (x-axis) for *Load A* and the large dataset.

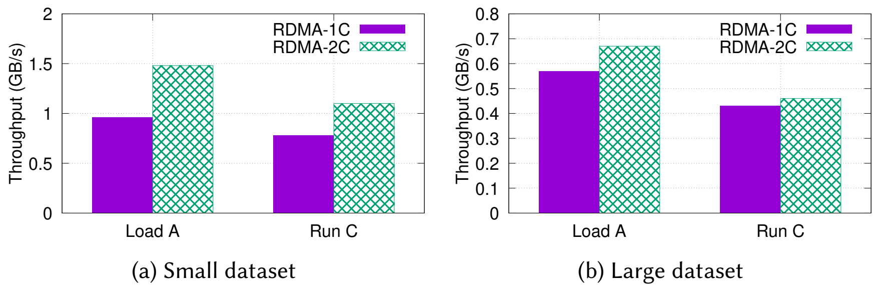


Fig. 14. Link throughput achieved by *Kreon*'s RDMA protocols with one and two clients for the small and large datasets.

Figure 13 shows how the commit interval for L_0 affects ops/s, read volume, and write volume in *Kreon*. For *Run C* the commit interval does not affect any of the metrics, therefore, we examine only *Load A* with the large dataset.

Increasing the commit interval decreases the total amount of data read and written to the device. This is due to Copy-on-Write. For each commit we create a read-only version of our tree, thus an insert has to allocate new nodes and copy data from the immutable copy. Additionally, we see that commit intervals longer than 120s have a small impact for read and write volume.

For throughput, a small commit interval results in larger read and write volume which reduces performance. Interestingly, a value larger than 240 seconds reduces throughput significantly as well. This is due to the behavior of *msync*. In *kmmap*, *msync* is optimized to generate many large and asynchronous I/Os from all dirty pages, which means that it is more efficient compared to the eviction path *mmap* where we evict less amount of data. Overall, we see that a good value for the commit interval is about 2 minutes, which we use in all our other experiments.

4.6 RDMA Communication Overhead

Since key-value stores typically serve network clients, we are interested in examining the relative overhead of RDMA-based communication compared to I/O and index management in *Kreon*. Figure 14 shows the link throughput achieved by *Kreon*'s protocol. We see that with two clients the throughput achieved is about 1.5 GB/s for the small dataset. Other systems [57] achieve similar link throughput with RDMA.

	Small 1C		Large 1C		Small 2C
	LoadA	**RunC**	**LoadA**	**RunC**	**LoadA**
Index	27.29	14.19	16.35	7.69	27.72
IO	10.44	12.64	15.49	14.87	19.70
RDMA	1.75	1.77	1.22	0.89	2.17
Polling	8.96	9.82	11.01	11.03	4.30
Memory	4.13	0.07	2.80	0.04	5.16
Util.	59.11	45.20	52.02	38.45	70.33

Table 6. Percentage of CPU used in each component of *Kreon*.

Next, we use `oprofile` to obtain a breakdown of CPU utilization for the main components of *Kreon*:

- **Index** represents the cost of index-related operations, except device I/O.
- **IO** represents the cost of I/O via *kmmap*.
- **RDMA** represents communication cost, including the issue and receive paths.
- **Polling** represents the CPU time spend in RDMA threads polling for messages.
- **Memory** represents the cost of memory copies used for index manipulation and RDMA-purposes.

Table 6 shows the overhead for each component, as percentage of the CPU used by the server for each workload, *Load A* and *Run C*, with the small and large datasets, and for both one and two clients. For *Load A*, we see that generally index processing dominates and is between 16-27% followed by device I/O, which is between 10-20%. RDMA processing overhead is about 2%. Also, memory copies in *Kreon* occur only for secondary uses in general and are below 5%. For *Run C*, index processing is less important, between 7-14%, device I/O importance increases and is between 12-14%, while RDMA percentage remains low and below 1.7%.

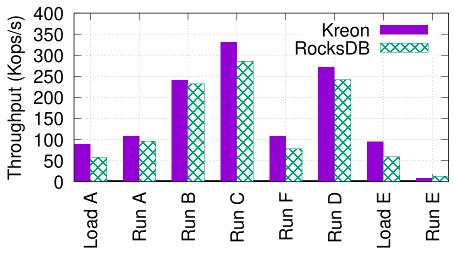
Polling for network messages takes between 4-11% of CPU utilization. Although this is a relatively large percentage, it is due to the fact that the server is not saturated, but rather limited by device I/O throughput. At higher utilization, the percentage spent in polling will be reduced. Nevertheless, these numbers show that polling strategies currently employed widely in RDMA protocols [27, 44, 45, 57] need to consider adaptive approaches to improve server efficiency.

Finally, server CPU utilization for the experiments of Figure 14 is between 38-70%. Saturating server CPU will increase link throughput to at most 2 GB/s. Thus, a 40Gbps link roughly can serve up to 64 cores (hyper-threads). Overall, we find that for persistent key-value stores, RDMA processing cost is relatively low, polling for messages requires adaptive approaches, and a 40 Gbps link is able to serve about 64 cores with *Kreon*.

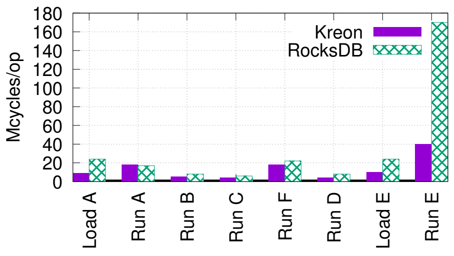
4.7 Integration with MongoDB

In this section, we quantify the benefits in performance and efficiency of *Kreon* in a production grade NoSQL system. For this reason we use MongoDB [18], a state-of-the-art general purpose, document-based database. MongoDB offers an API for developers to use custom storage engines. Towards this direction, MongoRocks [58] provides a layer that enables the use of RocksDB as a storage engine of MongoDB. We also use *Kreon* as a storage engine of MongoDB. To achieve this, we modify MongoRocks to use *Kreon* instead of RocksDB. For a fair comparison we disable

RocksDB's Bloom Filters and scan reorganization in *Kreon*. Bloom filters are not yet supported in *Kreon*.



(a) Throughput



(b) Efficiency

Fig. 15. Throughput and efficiency comparison of Kreon and RocksDB in MongoDB.

Figure 15a shows the throughput for each YCSB workload, using *Kreon* and RocksDB as storage engines. We observe that *Kreon*, improves throughput from 1.04× up to 1.2× for all workloads except *Run E*, where we have about 30% lower performance. This is because we disable scan reorganization in *Kreon* and we introduce random I/Os for the scans. Figure 15b shows the efficiency in terms of cycles/op for the same workloads. *Kreon* requires from 0.96× up to 4.26× less cycles/op across all workloads.

These results show that even in a complicated production grade NoSQL system, *Kreon* provides performance and efficiency benefits. On the other hand, they are less pronounced compared to our single node evaluation as MongoDB contains significant subsystems like query engine that affect performance.

5 RELATED WORK

Related work to *Kreon* falls in the following categories:

5.1 LSM-Tree based key-value stores taxonomy and optimizations

We identify the following three dimensions in the design space of LSM-Tree key-value stores that affect I/O amplification and CPU efficiency: (1) size and placement of SSTs, (2) logical level organization, and (3) value location. In Table 7, we present a taxonomy of existing systems based on these dimensions. These systems, to some extend, have tried to take advantage of device properties and improve performance.

Size and placement of SSTs: In an LSM-Tree key-value store levels are physically organized on the device in units named Sorted String Tables (SSTs). Their size is typically large (order of MBs) because *large SSTs* guarantee maximum device throughput, eliminating the effects of the I/O pattern (sequential or random) and metadata I/Os, as metadata are small and fit in memory. Equivalent, *small and sequentially* placed SSTs on the device [68] can achieve the same properties of maximum device throughput. This results in high I/O amplification but improves read performance at the expense of maintaining more metadata. Emerging device technologies allow using *small SSTs with random placement* which introduces randomness but has the potential to reduce I/O amplification [62].

key-value Stores	**SST size, placement**	**Organization**	**Value placement**
LSM[60], RocksDB[31],Locs[73], Dostoevsky[24], Triad[5], Mutant[77], bLSM[68], Silk[6], cLSM[32], VT-tree [69]	Large	Full	In-place
Atlas[48], WiscKey[54], HashKV[14]	Large	Full	Log
Jungle[1]	Large	Partial	Log
LSM-trie[76], Monkey[23], SifrDB[56], Novelsm[46], PebblesDB[64]	Large	Partial	In-place
Kreon[62]	Small	Full	Log
B^{ϵ}–Tree[10]	Small	Full	In-place

Table 7. Taxonomy of the main approaches to design key-value stores in three dimensions.

This approach is suitable for devices where random I/O throughput degrades gracefully compared to sequential I/O throughput.

Logical level organization: Keys in each level are logically organized either *fully* or *partially*. Full organization keeps the key space in fully sorted, non-overlapping SSTs. Full organization is usually done with leveling compaction [5, 14, 24, 31, 32, 48, 54, 60, 73, 77]. However, B-tree indexes have also been used to either optimize reads and scans [68] or reduce amplification [62]. Partial organization introduced in [40] maintains the key space in overlapping units, e.g. in the form of tiering compaction [23, 46, 56, 64, 76] which reduces merge amplification at the cost of reduced read and scan performance.

Value location: Finally, values can be placed either *in-place* with keys or in a separate *value log*. Typically, values are stored in-place because this results in optimal scan behavior at the expense of increasing amplification due to value movement during merge operations. Previous work has proposed techniques [14, 48, 54, 61, 62] that store values in a log, reducing amplification significantly, relying on modern devices to alleviate the impact on scan performance.

In addition to the basic three dimensions, key-value stores employ a set of various techniques to optimize for different aspects of system operation. These include tail latency or targeted optimizations for specific workloads (e.g updates). Next, we present a set of representative techniques.

bLSM [68], that targets HDDs, uses a B-tree index per level and bloom filters to enable efficient look-up operations. *Kreon* shares the idea of a B-tree index per level but keeps an index only for the metadata and it does not fully rewrite levels during spills trading I/O randomness for CPU efficiency. bLSM also introduces gear scheduling to bound write latency. Gear scheduling is a progress-based compaction scheduler that throttles compactions in the lower levels of the LSM-Tree. This scheduler is able to prioritize compactions taking place in the higher levels of the LSM-Tree, close to the in memory component improving tail latency of client applications. Silk [6] similar to bLSM tackles the same problem by introducing progress based compaction. In addition to bLSM, Silk performs compactions during off peak periods to reduce the probability of heavy compactions during bursty client activity. With this approach it trades increased I/O amplification, since it does not merge adjacent levels that necessarily grow by a constant factor f [7, 60], for bounding tail latency. FD-tree [52] is an LSM-Tree for flash devices, that replaces bloom filters, saving their corresponding memory budget, with fractional cascading [15] to speed up look up operations. VT-tree [69] tries to reduce I/O amplification merging only the actual overlapping parts between SSTs. In particular, instead of blindly performing a merge sort operation between a set of SSTs of L_i and L_{i+1} it identifies which parts are non-overlapping and it performs merge sort only for the overlapping parts. These techniques are orthogonal to *Kreon* and it can benefit from them.

LSM-trie [76] identifies as the main source of I/O amplification during the compaction process between two levels L_i and L_{i+1} the amount of data read and written from L_{i+1}. This is because L_{i+1} is f times larger than L_i and the compaction process always needs to read and write L_i to merge it with L_{i+1}. To reduce the data read and written from L_{i+1} it divides it into sub-levels and place keys in SSTs according to their key hash. Then it uses bits of the hash to select a part of the sublevel of L_{i+1} that it merge sorts with the SST of L_i. This optimization trades range queries in favor of reduced amplification. *Kreon* shares the same goal of reducing I/O amplification by using a value log and small SSTs but also supports range queries.

Atlas [48] is a key-value store that aims to improve data-serving density and data replica space efficiency. To achieve these, Atlas employs a LSM–based approach and separates keys from values to avoid moving values during compactions. Similarly, WiscKey [54] proposes the separation of keys and values to reduce write amplification. It stores values in a data log and keeps a LSM index for the keys. Furthermore, it implements a prefetching mechanism for speeding up range queries because values are written randomly on the device. Jungle [1] is an LSM-Tree key-value store optimized for updates. It uses a value log and organizes its levels using tiering. In particular, each level is organized as a forest of B-trees with overlapping key ranges. This organization reduces I/O amplification [7] but hurts look up performance. This is because each look up should check in the worst case all B-trees within a level. However, this trade off is a good fit for Jungle since it targets update heavy workloads, where the number of distinct keys grow slow.

PebblesDB [64] identifies as the main problem of write amplification in the LSM-Tree the repeated merges of files at each level during compaction. To fix this, it keeps overlapping sorted files at each level instead of non-overlapping. However, this approach adds overhead in the read path since multiple files need to be checked instead of a single. To improve this, PebblesDB introduces guards which act as a coarse grain index per level inspired by skip lists. *Kreon* shares the idea of using an index per level with the difference that in *Kreon* case is full. Furthermore, it uses memory-mapped I/O, keeps both keys and values on a separate log, and executes spill operations only on pointers to keys and values.

5.2 Other write optimized data structures

TokuDB [72] implements at its core a B$^\epsilon$–Tree structure. It keeps a global B-tree index in which it associates a small buffer per B-tree node. Buffers are relatively small so it keeps them unsorted and scans them during look-up queries. When a buffer fills it is spilled to its N children, where N is the fan out of the B-tree. Tucana [61] uses a B$^\epsilon$–Tree which buffers keys only at the last level of the tree and relies on a ratio of memory/data to operate efficiently. *Kreon* keeps a buffer per level in order to achieve better batching and is able to server larger datasets with smaller memory/data ratio.

KVell [50] is an efficient log structured key-value store designed for fast storage devices. It uses a value log and a single level B-tree index in which it stores metadata (pointers) to the actual key-value pairs. Furthermore, it uses asynchronous IO (io_uring [4]) and batching to perform efficient I/O with the devices. *Kreon* shares the same efficiency goals for fast storage devices with KVell but it uses memory-mapped I/O. This eliminates the need to constantly perform look-up operations about the position of a device block in DRAM even in the case of hits. This can save up to 30% [38] CPU overhead when the dataset fits in memory. Furthermore, *Kreon* uses an LSM-Tree structure which allows its index to grow efficiently beyond DRAM limits without the known performance issues of a B-tree index structure [35].

5.3 Memory-mapped I/O

DI-MMAP [28] proposes an alternative FIFO based replacement policy that targets data-intensive HPC applications. *kmmap* shares the same goals as DI-MMAP and introduces priorities for pages in memory. This gives applications fine grain control similar to user-space application specific caches. FastMap [63] optimizes Linux memory-mapped I/O path for scalability with increasing the number of threads. The proposed optimizations are orthogonal to the priorities of *kmmap*. Authors in [70] optimize the free page reclamation procedure and make use of extended vectored I/O to reduce the overhead of write operations. Finally, in [19] the authors propose techniques that reduce the overhead of page faults and page-table construction. These techniques are orthogonal to our design and they can be used in *Kreon* as well.

5.4 RDMA-based communication for data serving

There are two basic design choices for RDMA based systems: (1) The use of the appropriate RDMA operation (one-sided/two-sided) and (2) the type of queue pairs (reliable/unreliable) used for the RDMA connections. Previous work [44, 45] has analyzed different RDMA operations and has shown that one-sided RDMA writes provide the best performance. Furthermore, systems such as HERD [44], which is a hash-based in memory key-value store, show that reliable queue pair performance is almost identical with the use of unreliable. *Kreon* uses reliable connections that reduce protocol complexity and examines their relative overhead in persistent key-value stores. Also in *Kreon*, we use one-sided RDMA writes for efficiency.

Hash-based key-value stores, such as Pilaf [57], FaRM [27] and DrTM [75] try to remove server-side processing for get operations by using exclusively RDMA reads. For instance, Pilaf [57] uses solely one-sided RDMA reads to implement client-lookup operations. Pilaf implements gets transparent to the server since clients perform RDMA reads over multiple round trips to directly fetch data from the server's memory. On the contrary, it uses verb messages to implement put operations that are sent by clients to the server. Another example is FaRM [27] that uses one-sided RDMA reads to access data directly but it also uses RDMA writes to implement a fast message passing primitive. However, this results in multiple round trip messages for get operations. For put operations, they use a single round trip message with server involvement to avoid write-write races, however still need to deal with read-write races (gets in the presence of concurrent puts). *Kreon*, similar to most persistent key-value stores, uses a persistent index. Consequently, direct access from clients with RDMA reads would result in several round trip messages and possible synchronization between clients across the network. Therefore, *Kreon* uses server-side processing for client requests, and uses RDMA write operations that reduces the number of round trip messages.

Other implementations also involve request processing. For instance, RFP [71] is an RDMA-based RPC paradigm in which clients use RDMA writes to send requests, and clients fetch results from server's memory remotely by using RDMA reads. Jakiro an in-memory key-value store validates the effectiveness of RFP. HydraDB [74] is an in-memory key-value middleware that is presented to users as a distributed hash table and to ensure high availability. They use a message passing mechanism based on RDMA Write for put operations and they leverage RDMA Read for get operations. KV-Direct [51] is an in-memory key-value system that leverages programmable NICs in data centers. KV-Direct extends the RDMA primitives from memory operations to key-value operations. KV-Direct deals with the consistency and synchronization issues at server-side, thus removes computation overhead in client and reduces network traffic. FlatStore [17] is a persistent memory key-value storage engine that also uses RDMA writes to send both request and response messages between clients and servers.

6 CONCLUSIONS

In this paper, we design *Kreon*, a persistent key-value store based on LSM-Trees that uses an index within each level to eliminate the need for sorting large segments and uses a custom memory-mapped I/O path to reduce the cost of I/O. Compared to RocksDB, *Kreon* reduces CPU overhead by up to 8.3x, I/O amplification by up to 4.6x at the expense of increasing randomness of I/Os. Both index organization and memory-mapped I/O contribute significantly to the reduction of CPU overhead, while index manipulation and page faults emerge as the main components of per operation cost in *Kreon*.

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