Observations on Porting In-memory KV stores to Persistent Memory

Brian Choi  
*Johns Hopkins University*  
Parv Saxena  
*Johns Hopkins University*  
Ryan Huang  
*Johns Hopkins University*

Randal Burns  
*Johns Hopkins University*

Abstract

Systems that require high-throughput and fault tolerance, such as key-value stores and databases, are looking to persistent memory to combine the performance of in-memory systems with the data-consistent fault-tolerance of non-volatile stores. Persistent memory devices provide fast byte-addressable access to non-volatile memory.

We analyze the design space when integrating persistent memory into in-memory key value stores and quantify performance tradeoffs between throughput, latency, and recovery time. Previous works have explored many design choices, but did not quantify the tradeoffs. We implement persistent memory support in Redis and Memcached, adapting the data structures of each to work in two modes: (1) with all data in persistent memory and (2) a hybrid mode that uses persistent memory for key/value data and non-volatile memory for indexing and metadata. Our experience reveals three actionable design principles that hold in Redis and Memcached, despite their very different implementations. We conclude that the hybrid design increases throughput and decreases latency at a minor cost in recovery time and code complexity.

1 Introduction

Persistent memory (PM) has emerged as a new class of storage technology, filling the gap between DRAM and SSDs. PM devices can be placed alongside DRAM on the processor memory bus to enable byte-addressable memory accesses, with latency comparable but slower (2–3 × for loads [19]) than DRAM, and 10–100 × faster than state-of-the-art NAND flash [5]. Unlike volatile DRAM, data stored in persistent memory will survive reboot and power loss. With Intel Optane DC Persistent Memory, the first PM product, being released recently [6], many developers are looking to take advantage of persistent memory when building their applications. For in-memory key-value stores like Redis, it adds more efficient large capacity deployments and persistence options [1]. For non-volatile stores like Cassandra, it offers improved performance when compared with SSDs [3].

The many efforts to integrate persistent memory into existing storage systems have lead to a confusing array of design alternatives. Systems choose from among moving a volatile in-memory system to persistent memory, replacing SSDs with persistent memory in a storage hierarchy, using write-ahead logging principles to coordinate volatile and non-volatile memory, or decomposing the system into volatile and persistent data and data structures. All choices have consequences on latency, recovery time, and system complexity. Table 1 categorizes existing work based on how they use persistent memory. No clear guidelines exist that define and quantify the trade-offs accompanying different design choices.

In response, we provide an extensive measurement of different high-level system designs in order to inform developers and the research community about these trade-offs. Our analysis focuses on designs that integrate persistent memory into existing in-memory key-value stores in order to provide data-consistent crash recovery. This approach is popular, because it is incremental, involves small code changes, and allows high-throughput systems to add fault tolerance. We examine three major design decisions that developers have to make when porting their systems to persistent memory: (1) What data structures should be persistent and what data structures should be volatile? (2) What should the granularity of persistence be? (3) What PM primitives and interfaces to use? We then study how these design decisions directly effect six system properties, including operational throughput and latency, tail latency, recovery time, exposure to data loss, scalability and system complexity.

We choose two popular in-memory key-value stores, Redis and Memcached, as our subject. As there are already multiple existing works [16, 22, 23, 25, 28], our initial attempt was to leverage these implementations and compare them. However, these systems encode many decisions regarding one system property; they are incomplete or incomparable to evaluate by other properties. For example, many implementations focus on the operational performance aspect and are not fully recoverable upon restart. We were also unable to gain the source code for several published works.
Therefore, we decide to implement two different and comparable high-level systems designs in both Redis and Memcached. The first design is fully persistent because all volatile data structures are maintained in persistent memory. This eliminates most recovery work at the cost of additional latency when writing to or extending the hash table. The second hybrid design places key-value data in persistent memory and keeps the hash table indexing structure in volatile memory. During recovery, the hash table must be reconstructed from the keys and values. By implementing these four versions, we are able to isolate and compare the effect on individual design choice. We show that our conclusions hold across these very different implementations.

We summarize three actionable design principles for porting volatile key/value stores to persistent memory:

- A hybrid design nearly doubles operational throughput at the cost of an increased time to recovery that varies by system from minor in Memcached to major in Redis. System designers have a nuanced choice between operational performance and recovery.
- Allocating data in large chunks reduces latency by amortizing allocation costs and increases recovery performance.
- Full featured persistent memory libraries ease development and lead to simple implementations.

2 Background

PM technologies like 3D XPoint and ReRAM promise to provide byte-addressable accesses with low latency, unlike SSDs and disks that perform I/O at a block-granularity. After years of anticipation, the Intel Optane DC Persistent Memory product became publicly available in April 2019. Optane DC offers two operation modes [18]. The Memory Mode transparently integrates the device into the memory hierarchy so that applications perceive the device as a large pool of main memory. The advantage is that no application changes are required. But the data is not durable upon power loss. In the App Direct Mode, applications are aware of the PM, and data written to the PM can be persisted. But applications need to be modified to access the persistent memory region via a PM-aware file system or loads/stores.

It is expected that PM devices like Optane DC (particularly its App Direct Mode) would not only enable a rising number of new PM storage systems but also motivate developers of existing (legacy) in-memory applications to modify their applications to build efficient persistence. We focus on the latter “porting” scenario. A representative class of applications is existing in-memory key-value stores. At present, in-memory key-value stores support persistence through either periodic snapshots, which can lose significant data, or costly logging.

Porting existing in-memory key-value stores to PM, however, has complexities that arise from hardware characteristics. First, PM has much higher write latency [32] and lower write bandwidth [19] compared to DRAM. It is thus not feasible to port all volatile data that involves frequent writes or updates to persistent memory. This suggests that developers have to make careful decisions to selectively persist data structures. Second, PM requires the proper use of flushes, fences, and transactions to ensure data consistency. Developers need to explicitly flush cache lines using instructions like clwb because writes to the PM device may be cached. Besides flush, sfence is necessary because the compiler or memory controller may reorder writes. While the PM device guarantees failure atomicity in 8-byte units, larger writes could lead to inconsistent data in the event of failure, which should be avoided with transactions. All of these mechanisms introduce significant performance overhead [10, 12, 30] that must be considered when porting a key-value store.

Redis: Redis is one of the most popular key value stores [2] and used as an in-memory cache or as a database. Redis stores data in main memory for fast access and implements an extendable hash table indexing structure for efficient lookups. Redis extends the key/value model to support a large number of data structures, such as string, hashmaps, sets, and lists. Notably, Redis is a single threaded service, which eliminates the need for locks and synchronization. Redis supports the RDB feature that takes periodic snapshots of the dataset either after a period of time or after a number of keys have been modified. It also provides the AOF persistence option in which Redis logs every write operation and replays the log on startup.

Memcached: Memcached is another popular key value store used primarily as a cache. Similar to Redis, Memcached keeps key value data in memory indexed by an extendible hash table. Memcached does not have built-in persistence, but there are extensions. Memcached differs from Redis in several important ways. First, it uses a slab allocation organized by data size to amortize allocation across many objects. Second, Memcached supports multithreading and uses locks to synchronize concurrent access to data structures. Third, Memcached does not have complete persistence options like Redis does yet [7].
3 Related Work

The integration of PM into storage services, particularly key-value (KV) stores, has received much attention in recent years. In this Section, we describe the landscape of persistent memory key/value stores. We put these systems into four main categories based on their persistence designs: Fully Persistent, Hybrid, Mixed Indexing and Data, and Checkpointing and Logging. We further split these works into 2 sub-classes: a KV store newly designed for PM from ground up or a modification of an existing in-memory KV store to support PM. Table 1 shows the taxonomy.

Fully Persistent: These systems choose to maintain all indexing structures and key-value data inside persistent memory. This is the simplest design. However, extensive writes incur the additional latency of PM. As a result, newly designed persistent KV stores focus on reducing the number of writes to their indexing structure (caused by actions such as hash table resizing, tree node splitting) with various optimization techniques including level hashing [36], sorted node organizations [9] and indirection [10, 26]. In addition, they can customize the recovery process using unique data structures [26] to reduce the number of flushes. Other newly designed fully persistent systems use B+-trees for indexing. They make optimizations to minimize writes, such as keeping nodes unsorted and merging tree nodes [11].

Our fully persistent implementations follow works that modify existing KV stores [23, 25]. These systems are designed for DRAM-based architecture and feature fewer write optimizations. Debnath et al. [15] study how different DRAM-based hashing schemes perform when directly ported to PM with few optimizations. In WHISPER’s fully persistent port of Memcached [25], they allocate the hashtable in persistent memory segments and surround all accesses to persistent memory in durable transactions. In Oracle’s implementation of persistent Memcached, they started with a hybrid design, but converge on a fully persistent design when they realized that recovery without persisting related data structures, such as the slabs and LRU, proved to be difficult. [23]

Hybrid: Other persistent KV stores choose to keep their indexing structure in volatile memory and their key-value data inside PM, which we refer to as hybrid. The benefit is that writes to the index, including extending and reorganizing indices, occur in memory at lower latencies. Some hybrid KV stores do not implement recovery logic, focusing on performance evaluation or using PM to increase capacity. WHISPER’s Redis [29] and Intel’s PMEM Redis [16] replace volatile key-value data allocations with persistent allocations and add basic query support. NVMCached [33] trades data loss for performance (reduced flushes) and stores the checksums of KV data in a persistent data structure called a “zone” to allow verifying data integrity upon restart. Those systems that do support recovery need to properly recover indexes, which are volatile and not crash consistent. Without a persisted indexing structure, Hybrid KV-stores need a way to access their persistent data upon restart in an organized manner. Strategies include allocating ranges in segments [21] and using auxiliary data structures such as persistent slabs [22]. Our Hybrid implementation leverages the fact that the PMDK allocator keeps track of all persistent memory allocations and uses its exposed iterator interface to reconstruct hash table upon restart.

Mixed Indexing and Data: These systems maintain data and/or indexes in the mixture of volatile and persistent memory [8, 20, 27, 34]. For example, some systems split indexes so that some parts of the index are in volatile memory and other parts of it are in persistent memory. This differs from the hybrid design as hybrid is purely volatile indexing and purely persistent data. A common case keeps the leaf nodes of a B+-tree in persistent memory and the interior nodes in volatile memory [27]. PapyrusKV [20] stores local MemTables (in-memory data structure that stores KV pairs) in volatile memory and SSTables (Sorted String Table, which stores immutable KV Pairs after MemTables have reached max capacity) in PM as a form of indirection to increase performance in a distributed setting. HiKV [34] keeps a hash index in volatile memory for high-frequency updates and a B+-Tree index in persistent memory. Echo [8] is a PM KV store that has threads store data in local hashable stores before being added to a queue to be added to a global persistent store. Redis Lab’s Redis on Flash [4] stores its keys, dictionary, and hot values inside DRAM while storing its warm values on SSDs. Crash recovery in Redis-on-Flash relies on Redis’ disk-based snapshots. PMEM-Redis [28] places values in persistent memory that are larger than an PM threshold size while keeping smaller values in memory. NVTree [35] is a B+-Tree that only enforces consistency on leaf nodes (critical data) and does not guarantee consistency for inner nodes, but keeps nodes in PM.

Checkpointing and Logging: These systems keep all data in volatile memory but maintain a replication medium in persistent memory. In-memory KV stores, such as Redis, use checkpointing and logging to have some form of persistence. Placing the logging file or snapshot in persistent memory improves performance, because writes to persistent memory have much smaller latencies than writes to disk or SSDs. Bullet [17] uses Cross-Referencing Logs that record both the key-value data and ordering dependencies among records to allow proper recovery. libpmemlog-AOF-Redis [24] supports recovery using a persistent Append-Only File that logs every write operation and replays them upon restart.

4 Motivation and Scope of Investigation

Our taxonomy in Table 1 demonstrates that there exist a variety of design choices for KV stores with persistent memory.
It also shows that there is no consensus about how to design such systems. It is crucial to understand the trade-offs implied by different designs. Thus we further organize these related work based on the system properties that are evaluated as shown in Table 2. We can see that almost all systems measure regular performance (throughput and latency) and many also evaluate scalability. However, other properties such as recovery performance, tail latency, data loss are much less often examined. These properties are as important for a real-world persistent-memory KV store operating in production.

Moreover, while many KV stores have been built from the ground up and customized for persistent memory such as uDepot [21] and CCEH [26], it is increasingly common for developers to add persistent memory support to an existing in-memory KV store. We refer to this process as porting. Porting builds on the battle-tested maturity of the existing system, inherits its operational properties, minimizes code complexity, and eases adoption. Porting also presents unique challenges in properly integrating the modifications with existing code that is originally designed for DRAM. Unfortunately, as Table 2 shows, porting is not well explored in current literature.

In this work, we aim to shed some light on the aforementioned gap by comparing the design choices of porting an in-memory KV store to persistent memory, and comprehensively quantifying the trade-offs of these choices. We focused our efforts on fully persistent and hybrid systems because these techniques both (1) take advantage of the byte-addressable properties of persistent memory and (2) can be used to add recoverability to existing systems. Mixed systems are interesting and complex and typically require an entire re-design.

A closely related work examines the difficulties in porting Memcached to persistent memory [23]. They cover many salient points in the design of a ported key/value systems, such as tracking persistent and non-persistent object interactions, the necessity of using failure-atomic transactions, and the difficulty in deciding which data structures to persist. Their treatment is limited to Memcached and the fully persistent design only. Their evaluation also focuses on regular performance and scalability (recovery is mentioned to be “instantaneous” but not quantitatively evaluated).

## 5 Design

We present two designs for porting Redis and Memcached to use PM for fault-tolerance. The first, hybrid design stores all key-value data in PM and maintains indexing structures in volatile memory. The second, fully persistent maintains all data structures in PM, including all indexing and bookkeeping structures. All other aspects of the two designs are made similar in order to isolate and highlight the effects of this fundamental difference. For example, both use the same PM programming primitives. The designs are also minimal. We inherit as much as we can from the original implementation in an attempt to preserve the properties of the original systems.

We consider and later evaluate (Section 6) a number of properties: (1) operational throughput: the performance while executing GET/SET/UPDATE/DELETE queries; (2) recoverability: if the system can properly recover the data with consistency and minimal loss; (3) recovery performance: how fast the systems can recover the persisted data and reconstruct in-memory structures from it upon restart to continue operations; (4) tail latency: performance influenced by data structure reorganizations, background tasks etc.; (5) concurrency effect: would the ported systems handle concurrency properly as before and scale; (6) development effort: the extensiveness and difficulty of making the modifications to the system.

### 5.1 Challenges and Design Trajectory

A key challenge in both designs was determining which data structures to persist. Making one data structure nonvolatile
can create a large number of dependencies. Other variables that are referred to either (1) may be made persistent as well; (2) may be kept volatile and need to be recovered on restart. For example, when persisting Memcached’s hashtable, we also had to persist the internal slab pointers that Memcached uses to track allocations. We also had to persist global variables that contain system metadata, such as the hash power and hashsize. However, one needs to be careful not to persist any unnecessary data structures or variables, because persistent memory writes reduce performance. Our strategy was to first choose a primary data structure to persist and then trace all of its internal variables to see if they also needed to be persisted or could be recovered. After this, we used testing and static analysis to determine that the state was either persistent or correctly recovered on restart, and then repeat the process.

It turns out that the two choices lead by induction to our two designs. When you decide to persist dependent variables, you create further dependencies that also need to be persistent. When you decide to recover a data structure instead, its dependencies must also be recovered. We do notice that even in the fully persistent implementation, we keep as many variables volatile as possible, e.g. cache state, for performance reasons. The choice of what to persist was much deeper and more complex than we expected.

Another challenge is to recover persistent pointers, because persistent memory regions are mapped into different addresses on each system instantiation. The first option is to change all pointer references in the code to address memory using a persistent memory offset. The other option is to update/rewrite all pointers during recovery. Systems like Memcached that rely on a slab allocator already use compound pointers and translate more easily to persistent memory.

5.2 PMDK Library

Unlike many related work that use the low-level clwb and sflush instructions to program persistent memory, our implementation uses Intel’s Persistent Memory Development Kit (PMDK). PMDK provides a set of libraries with high-level programming constructs and APIs for developers to use. The libraries build on the DAX (direct access) support from the OS that allows applications to use accesses persistent memory device as memory mapped files. We chose this library persistence programming model for two main reasons. First, the PMDK APIs are simple to use and greatly ease the porting efforts as one does not need to reason about persistence at the cache line granularity. Second, cache line flush and fence alone are not enough to ensure recoverability. In existing KV stores, handling a single request like INSERT typically involves modifying multiple data structures across a series of complex operations. These modifications need to be atomic.

Particularly, we leverage PMDK’s libpmemobj library which provides a transactional object store for persistent memory management to ensure proper data consistency within the persistent memory mapped file. Developers define the transaction region and call the libpmemobj’s transactional functions (pmemobj_tx_alloc, pmemobj_tx_add_range, etc.). Transactions can be nested. Writes within the transaction will be flushed at the end of the transaction. In the case of an unexpected crash, libpmemobj uses an undo log to properly undo all persistent changes that had occurred within transactions.

5.3 Fully Persistent Redis

Fully Persistent Redis ports Redis’ data and indexes in persistent memory in order to minimize interactions between volatile and nonvolatile data. We replace all relevant volatile allocations with libpmemobj’s persistent alloc function. These include the Simple Dynamic String (sds), Redis Object (robj), Dictionary Entry (dictEntry), and the hashtable (dict, ddictht, and bucket). Figure 1 shows the hierarchy of data structures and indicates that they are all placed in persistent memory.

Although placing hashtables in persistent memory streamlines the recovery process, we still need to remap all persistent pointers. Recovery requires reattaching the persistent hash tables. Upon application start, the libpmemobj library creates or opens a memory mapped file, called a pool, that contains a root virtual address. A new memory mapped address will be assigned for the root, effectively displacing all the previously saved direct, persistent pointers. Thus, all Redis’ hashtables and datastructures are virtual addresses with respect to the last system startup and become invalid when the system is restarted. To make these pointers valid, we keep track of the old address where the persistent memory device was mmapped, and use the address translation with respect to the following formula: new_pointer = old_pointer - old_mmap_address + new_mmap_address. Using this formula, we walk through the hashtables and reconstruct all the pointers. During a restart, Fully Persistent Redis iterates over a hashtable entry and validates all of its pointers to key value data before reconstructing the “next” hashtable entry pointer and moving on to that entry. Figure 2 shows that the base Hashable offset, the base entry of HT[0]’s offset, the base entry of HT[1]’s offset and the old memory mapped address are all stored contiguously at the root of the persistent file.
and are updated whenever they are modified during Redis’ operational time.

One way of circumventing this issue is to modify all of Redis’ data structures to just use offsets rather than pointers. In this manner, you no longer have to reconstruct pointers every time you restart as your offsets remain constant. However, this requires significant coding effort as you have to replace every single pointer and pointer reference with offsets and offset memory access helper functions respectively.

As a whole, Fully Persistent Redis drastically improves Redis’ recovery performance at the cost of operational latency. Fully Persistent Redis slows hashtable modifications and accesses owing to persistent memory’s larger write latency. The main drop in performance occurs when the system resizes the hashtable as the key-value items grow. Another problem that we encountered with Fully Persistent Redis was the fact that we had to make the random hashseed for Redis’ hash function constant across multiple runs of Redis so that the hash function is stable across restarts.

5.4 Hybrid Redis

Hybrid Redis maintains the indexing hashtables (dict, dictht) in volatile memory and only stores key-value data (robj and sds) inside persistent memory (Figure 1). By making the bare minimum amount of data and metatdata persistent, Hybrid Redis greatly reduces the number of writes and allocations to persistent memory and thus improves the operational performance. This improvement comes at the expense of a longer and more complex recovery.

For recovery, Hybrid Redis iterates over persistent key and value data and rebuilds the volatile hashtables. The challenge is to determine how to restore all the data across restarts without the aid of a persistent hashtable. On restart, the robj and sds data are available in persistent memory at new addresses. But the hashtable and dictEntry’s are empty. We initially tried to use a new auxiliary data structure called bookKeeper to track allocations of key-value data. However, this approach subverts the design, because it makes additional writes to persistent memory on every allocation. These maintenance costs cancels out the benefit of the hybrid design.

We then determined that PMDK tracks allocated objects and we can use this record to iterate over allocations to discover key value data on restart. The libpmemobj maintains a linked list structure that tracks persistently allocated data across restarts. libpmemobj’s allocator also allows one to tag an allocation with a type enumeration (typenum). Redis allocates individual keys and values. Hybrid Redis makes these allocations in persistent memory and tags them with the object type (key robj, key sds, val robj, val sds) (Figure 3).

We augment the Redis robj data structure to contain recovery information for a key-value pair. Because there are no guarantees on a fixed order for allocations, we modified the robj structure to contain all of the addresses for key value data that is necessary for reconstructing the key value pair upon restart. Figure 4 shows the added fields that record the persistent memory offsets from the base. On restart, we use the allocator link list to identify key objects and then use the offsets in each key to locate the related key data and value object and data. The discovered object is inserted into the hashtable. After traversing all allocated objects, the hashtable is reconstructed so that it indexes same contents as it did before shutdown or failure.
5.5 Fully Persistent Memcached

For the most part, Fully Persistent Memcached follows the same design principles as Fully Persistent Redis. We maintain the hashtable, all linked lists, and key-value data structures inside persistent memory (Figure 5) in order to ease recovery at the expense of reduced operational performance.

The major difference is that memcached uses a slab allocator so that we allocate and manage key-value data on a slab by slab basis rather than at a fine granularity. Memcached allocates chunks of varying size. Variable length data is placed contiguously in the appropriate slab until Memcached has to allocate a new slab. To access the key and value strings inside of slabs, Memcached uses a set of mathematical macros that calculate the address of the strings using the offsets from the given item pointer. We make the allocated item slabs persistent in Fully Persistent Memcached. This differs from Redis where we persist individual key and value objects. This improves the performance of Memcached when compared with its persistent Redis variants, because it amortizes the cost of allocation over multiple key-value pairs.

The recovery process in Memcached follow that of Redis, but is slower in practice because Memcached uses more pointers for the same number of key/value pairs. Similar to Redis, we validate every pointer on restart. However, in addition to the hashtable and key-value object pointers, Memcached has a slabclass linked list and caching data structures. We split the recovery process into two portions. First, we walk the slabclass array of slab pointers, validating each item in every slab individually. Then, we walk through the hashtable pointers and validating the pointers for each item entry.

5.6 Hybrid Memcached

Hybrid Memcached maintains indexes and cache data structures in volatile memory and stores key-value data in persistently allocated slabs, following the slab allocation schema of Memcached. In Hybrid Memcached, the old slab data structures are still volatile (Figure 5). However, the key and value data are now stored in the persistent slab. This persistent slab contains the minimum amount of information to reconstruct its key/value pairs upon restart, including key data, value data, and corresponding metadata. Recovery reads all the slabs to rebuild slabclass and then recovers all keys and values in the slabs to repopulate the hashtable and cache. To accomplish this, we modify the item class and addressing macros to refer to keys and values as a base address and offset (Figure 6).

5.7 Dealing with Concurrency

Since Redis is single-threaded, in our porting of Redis, we did not specially handle concurrency. But in porting Memcached, we have to consider its multithreading designs. If we access shared objects in a persistent transaction, acquiring a lock may be necessary (as PMDK transaction itself does not provide isolation). Fortunately, the original Memcached has properly synchronized its slab allocations and item modifications. So we need not add much additional synchronization code. We used locks mainly when we are modifying the global offsets that we added to save in the persistent items. Without these locks, we would experience race conditions that affect recoverability. We also prevent the added locks from affecting scalability by keeping the critical sections small (computing the new offsets and saving to a local variable) and performing persistent I/O outside the critical section.

6 Evaluation

We evaluate the systems with the goals of comparing the hybrid and fully-persistent designs for both Redis and Memcached and examining six main measures (Section 5): operational throughput and latency, tail latency, recoverability, recovery performance, concurrency effect, and development effort. We also compare our implementations with the original implementation and several open-source porting efforts.

We run a custom benchmark that isolates the overhead of persistent memory and hashtable reorganization during bulk insertions. We also run YCSB [13] benchmarks to characterize system performance under various workloads: A (50/50 Reads and Writes), B (95/5 Reads and Writes), C (Read Only),

```c
typedef struct _stritem {
  void *base_addr;
  uint64_t offset;
  ...
  struct _stritem *h_next;
  rel_time_t time;
  ...
  union {
    uint64_t cas;
    char end;
  }
  data[];
} item;
```

Figure 6: Hybrid Memcached item structure modifications.
Table 3: Measure latencies of the DRAM and Intel Optane DC persistent memory in our server.

|          | Sequential Read | Random Read | Write |
|----------|-----------------|-------------|-------|
| DRAM     | 81.4 ns         | 83.2 ns     | 157.7 ns |
| PMEM     | 179.0 ns        | 317.6 ns    | 160.4 ns |

Operational Throughput and Latency: Figure 7a shows the aggregate throughput for the Redis group. The persistent versions reduce throughput from 450,000 operations per second to below 150,000, incurring a degradation of 3.6×. This slowdown is because the persistent variants of Redis must write multiple offsets within a transaction, which incurs logging overhead and the cost of flushing writes to persistent memory when transactions commit. Hybrid Redis is 1.8× faster than Fully Persistent Redis because it updates the hashtable in DRAM rather than persistent memory. In terms of average latency, Hybrid Redis is 2.2× better than Fully Persistent Redis as shown in Figure 7b.

Results for Memcached in Figure 7c and Figure 7d follow the same pattern as Redis: Hybrid Memcached is 1.45× better than Fully Persistent Memcached in overall throughput and 7× better in average latency. But compared to Redis, Memcached incurs much less overhead for persistent memory. Hybrid Memcached is only 18% slower than the base implementation in DRAM. We attribute the significant reduction in performance loss to Memcached’s slab allocation amortizing allocation costs across multiple keys, which significantly reduces the persistent object allocations.

Reorganization Overhead: We further analyze the throughput results and find that hash table reorganization contributes to Hybrid designs’ performance advantage. Figure 8 shows the time-series throughput results for only the first 100,000 writes from the same insertion experiment (the remaining writes have similar trends). We can see that significant drops in throughputs at regular intervals (at a power of two writes, 16K, 32K, etc.). These drops are due to hash table re-organizations. Interestingly, Fully Persistent Redis incurs more overhead (73%) during reorganization than Hybrid Redis (15%). In Hybrid Redis the drop is lower because the writes to persistent memory of the main workload dominate the writes to reorganize the hashtable in DRAM.

For Memcached, as Figure 9 shows, the trend is similar to Redis: the drops in throughput due to hash table reorganization are 7% for Hybrid Memcached and 19% for Fully Persistent Memcached. However, Memcached’s overall drops and drop differences are smaller than Redis’. Memcached allocates new hashtables in slabs, which accounts for the better reorganization performance.
Table 4: Percentile Latencies of Persistent Redis.

| Percentile | Base | Base+RDB | Fully Persistent | Hybrid |
|------------|------|----------|------------------|--------|
| 50         | 1 µs | 1 µs     | 8 µs             | 6 µs   |
| 90         | 1 µs | 1 µs     | 32 µs            | 8 µs   |
| 99         | 2 µs | 1 µs     | 41 µs            | 10 µs  |
| 99.9       | 3 µs | 3 µs     | 64 µs            | 18 µs  |
| 99.99      | 16 µs| 14 µs    | 624 µs           | 528 µs |

We conclude that a Hybrid design has both higher performance, about twice the throughput for Redis, and much more stable performance than a Fully Persistent design. Hashtable reorganization in persistent memory leads to substantial throughput drops, which we will further describe in our analysis of tail latency.

**Snapshot Overhead:** We quickly address the standard alternative for persistent storage in Redis, which we will use as a point of comparison for throughput and tail latency. When users enable the RDB feature of Redis, Redis takes periodical snapshots to non-volatile storage. This does not protect against data loss in the event of failure, but it often used by applications with weak consistency requirements. Figure 10 shows the same workload in Redis with and without snapshots. Both systems run at close to the same throughput except for the singular operations that occur at snapshot boundaries.

### 6.2 Tail Latency

Tail latency is important for applications to meet Service Level Agreements (SLAs) [14]. We measure tail latency in the same insertion benchmark experiment with 50M keys. Table 4 show the latency percentiles for Redis. Both persistent designs have significantly worse (8 × at 90th percentile) tail latencies compared to the base design. Hybrid Redis’ tail latency at 90th percentile is 4 × better than Fully Persistent Redis, which is attributable to its better performance under reorganizations. At the 99.99th percentile, the tail latencies have massive increase. We believe these are due to a few persistent memory operations (transactions) being slow. For the Redis RDB design, we see a dramatic throughput drop in Figure 10 during snapshot operations. But we do not see the effect on tail latencies at the 99.99% level, because the small number of snapshot operations during 50M insertions. Only at the 99.999% level do we see the slowdown. The tail latencies of Memcached designs follow the same trend as Redis: the Hybrid Memcached’s tail latency at 90% is 7 × better than Fully Persistent Memcached.

Figures 11 and 12 show the full latency distributions. In Redis, the Fully Persistent distribution is bi-modal with a second peak occurring half a magnitude higher than the Hybrid distribution’s peak. In Memcached, the Fully Persistent distribution’s peak occurs a magnitude higher than the Hybrid distribution’s peak. The Redis histogram verifies that a few outlier operations take an order of magnitude more time.

### 6.3 YCSB Workloads

The YCSB benchmarks verify the performance gap between volatile and persistent memory and the operational throughput differences between Fully-persistent and Hybrid variants, showing that results apply to a variety of mixed workloads. Figures 13 and 14 show the results of the benchmarks for workloads A-D and F; workload E relies on range functionality and does not apply. These benchmarks were run with 8 clients to achieve stable and high performance. The performance differences between Fully Persistent and Hybrid varies between 10 and 40%, which is less than in the insertion benchmarks. These workloads include a mix of reads and writes where reads do not have transaction or allocation overheads. These workloads also do not grow the databases, so that they do not trigger resizing of the hashtables.

**Scalability:** Figures 15 and 16 show how the Redis and Memcached designs scale as the YCSB client threads increase. We can see that our ported designs preserve the scalability characteristics of the base systems. The Hybrid and Fully Persistent designs have similar behavior when increasing the client threads. In Redis, they both hit the scalability bottleneck with 4 threads while the base Redis stops scaling at 6 threads. We suspect this is in part due to contention in the CPU. For Memcached, all three designs scale to 16 threads, demonstrating its multithreading advantage.

### 6.4 Recovery Performance

In this experiment, we insert a variable number of keys (100K to 10M), shutdown and restart the system, and measure the time to recover the system as a function of the size of the key-value store. The recovery process revalidates pointers and reattaches persistent memory allocations and rebuilds volatile data structures as necessary. The recovery finish point is when the system properly restores all the key-values it persisted before the shutdown or failure.

Figure 17 shows that the recovery time of all variants increases linearly in the size of the keyspace and that Hybrid Redis takes around 20–25 × as long to recover as does Fully Persistent Redis. With 10 million keys, Hybrid Redis takes 28.5 seconds to recover all the data, whereas Fully Persistent Redis only takes 4 seconds—a 7 × difference. Fully Persistent Redis recovers in a single pass over the memory space to rewrite pointers. Hybrid Redis has to (1) iterate through the PMDK list of allocation pointer and (2) reinsert all keys.
into the hashtable to recover the pointers. We break down the recovery time of Hybrid Redis by the two steps. Figure 17 shows that the majority of the recovery time comes from the libpmemobj iteration.

Recovery in Memcached shows different structure with Hybrid Memcached recovering nearly as fast as Fully Persistent Memcached (Figure 18). Rebuilding the hash table ends up being much faster as there are no new memory allocations. The hash table pointers are updated in place in the persistent items. Recovery of both variants is substantially slower than Fully Persistent Redis. In Fully Persistent Memcached, there is more recovery work to do because there are more pointers for Memcached more complex data structures.

We note that the differences in the design of Redis and Memcached may lead to different decisions when choosing between Hybrid and Fully Persistent Designs. Redis has much larger overheads for recovery in the Hybrid design to realize a comparable increase in operational throughput.

6.5 Data Loss

In order to ensure that our systems were crash consistent we used transactions over each single key operation. This way we can make sure that no more than 1 key value pair is lost upon system failure. However, with volatile systems that rely on less consistent persistence options such as Base Redis’ RDB feature, we saw a much larger data loss. We set Base Redis w/ RDB to snapshot its state to disk every 3 seconds. We crash the system at set intervals of 2.5, 5, 10 and 15 seconds. With a transactional interface, Fully Persistent Redis and Hybrid Redis were able to show only 1 key value pair loss while Base Redis with RDB suffered heavier losses: it lost 306,752 (all items), 797,239, 687,864, 853,219 key-value pairs respectively under the four crash points.

Table 7 shows the modifications in lines of code we made to the base systems. We meet our goal in making our changes small and less disruptive. We touched more lines of code with the Fully Persistent designs. This is in main part due to the sheer amount of data structures and corresponding functions that we had to convert to persistent memory.

In terms of complexity, in developing Fully Persistent implementations, we have to be diligent in tracking data dependencies among the inter-related data structures. With a large codebase, it is easy to miss making some dependent variables persistent and introduce partial inconsistency bugs. We had to iteratively make the design correct.

The main porting challenge that came from the Hybrid Design was finding a way of organizing persistent data across restart without an indexing structure. If we had implemented this with an auxiliary data structure we would have experienced much more SLOC as maintaining such a structure is not simple. However, by leveraging pmdk’s allocator linked list, we were able to reduce the amount of effort.

6.6 Porting Efforts

Table 7 shows the modifications in lines of code we made to the base systems. We meet our goal in making our changes small and less disruptive. We touched more lines of code with the Fully Persistent designs. This is in main part due to the sheer amount of data structures and corresponding functions that we had to convert to persistent memory.

In terms of complexity, in developing Fully Persistent implementations, we have to be diligent in tracking data dependencies among the inter-related data structures. With a large codebase, it is easy to miss making some dependent variables persistent and introduce partial inconsistency bugs. We had to iteratively make the design correct.

The main porting challenge that came from the Hybrid Design was finding a way of organizing persistent data across restart without an indexing structure. If we had implemented this with an auxiliary data structure we would have experienced much more SLOC as maintaining such a structure is not simple. However, by leveraging pmdk’s allocator linked list, we were able to reduce the amount of effort.
We compare our ported designs with several open source PM ports of Redis and Memcached. Table 6 shows the average throughputs. PMEM-Redis [28] writes values to persistent memory that are larger than an NVM threshold size while keeping smaller values in volatile memory (Section 3). Not surprisingly, this design is faster than both of our Redis implementations. Its better performance comes at a cost of severe data loss, whereas our implementations lose at most 1 key-value pair. Similarly, libpmemlog-AOF [24] uses a persistent AOF for recovery allowing its system to be slightly faster than our Hybrid Redis implementation. From a recovery standpoint, our Fully Persistent Redis outperformed libpmemlog-AOF and PMEM-Redis by over 3x while our Hybrid Redis was around 40-50% slower. Lenovo’s Memcached implementation [22] shows throughput 17% better than our Fully Persistent Memcached but 24.4% slower than our Hybrid Memcached implementation due to their implementation choosing to persist entire items to their persistent slabs.

Table 7 shows the modifications in the related work. Our Memcached modifications are smaller than Lenovo’s. This is mainly because Lenovo’s pmemcached is using the low-level PMDK interfaces such as pmem_flush and pmem_persist. To ensure atomicity, it has to add additional sanity check fields into the persistent data structures, such as checksums, validity bit and linked flag. Upon restart, it will examine and discard potentially inconsistent data. We use the transaction interfaces of PMDK, which significantly simplify our modifications. We also notice that, due to the lack of failure-atomic transactions, even with the sanity checks, the Lenovo pmemcached can still incur partial inconsistencies when there is a untimely crash: e.g., the time field of an item.

## 6.7 Comparison with Other PMEM Redis and Memcached

We compare our ported designs with several open source PM ports of Redis and Memcached. Table 6 shows the average throughputs. PMEM-Redis [28] writes values to persistent memory that are larger than an NVM threshold size while keeping smaller values in volatile memory (Section 3). Not surprisingly, this design is faster than both of our Redis implementations. Its better performance comes at a cost of severe data loss, whereas our implementations lose at most 1 key-value pair. Similarly, libpmemlog-AOF [24] uses a persistent AOF for recovery allowing its system to be slightly faster than our Hybrid Redis implementation. From a recovery standpoint, our Fully Persistent Redis outperformed libpmemlog-AOF and PMEM-Redis by over 3x while our Hybrid Redis was around 40-50% slower. Lenovo’s Memcached implementation [22] shows throughput 17% better than our Fully Persistent Memcached but 24.4% slower than our Hybrid Memcached implementation due to their implementation choosing to persist entire items to their persistent slabs.

Table 7 shows the modifications in the related work. Our Memcached modifications are smaller than Lenovo’s. This is mainly because Lenovo’s pmemcached is using the low-level PMDK interfaces such as pmem_flush and pmem_persist. To ensure atomicity, it has to add additional sanity check fields into the persistent data structures, such as checksums, validity bit and linked flag. Upon restart, it will examine and discard potentially inconsistent data. We use the transaction interfaces of PMDK, which significantly simplify our modifications. We also notice that, due to the lack of failure-atomic transactions, even with the sanity checks, the Lenovo pmemcached can still incur partial inconsistencies when there is a untimely crash: e.g., the time field of an item.

### 7 Discussions

Through the implementation of Hybrid and Fully Persistent versions of Redis and Memcached, we summarize three principles for porting volatile KV stores to persistent memory.

A **hybrid design is preferable**. Although keeping all relevant indexing structures persistent greatly speeds up the recovery, the Fully Persistent design suffers from significant performance overhead. For many modern KV stores that receive a large amount of requests, ensuring large operational throughput, quick turnaround time, and good tail latency is of utmost importance to users. Even though hybrid designs recover slower, its absolute recovery time is still compelling (for 10M keys, Hybrid Redis can recover in 28 seconds).

**Persistent data structures should be allocated in large chunks to amortize the increased latency of persistent memory.** One of the major differences between Redis and Memcached that heavily influenced the porting procedure to persistent memory was the differing allocation schemes (per-key/value-pair vs. slab allocation). Just as a designer should aim to reduce the number of writes in persistent memory, they should also aim to reduce the number of allocations in persistent memory due to its high cost and performance inefficiency. Having a per-key/value pair allocation scheme in a volatile KV store is still reasonable as the performance costs of volatile allocation are negligible and the complexity of managing larger allocations can be cumbersome. However, persistent allocations require writes to PM, which incurs a much larger performance cost than volatile writes.

**Full featured persistent memory libraries ease development and lead to simple implementations.** In order to have a method of reading persistent data upon restart, developers either have to maintain their own auxiliary persistent data structure or rely on their persistent memory library to recollect data. While some libraries might store persistent data contiguously and make any reads from persistent files inconsequential, other libraries such as PMDK may require one to make some modifications to keep track of persistent data addresses. Without relying on a persistent memory library, developers will have to manually create their own persistent data storage method or structure. These findings are directly taken from our observations when we maintained our own auxiliary data structure for Hybrid Redis. We found that creating our own data structure
was not only a significant development effort to maintain but was also difficult to keep efficient. As a result, we switched to using the PMDK allocator iterator for Hybrid Redis.

8 Conclusion

With the combination of our empirical evaluation and guiding principles, we were able to show that the hybrid design encapsulated the operational performance needs of storage systems while the fully persistent design optimizes the recovery performance of storage systems. Hybrid Redis demonstrated $2 \times$ better operational throughput and $4 \times$ better tail latency compared to Fully Persistent Redis. However, Fully Persistent Redis can recover 10 million keys $7 \times$ faster compared to Hybrid Redis. Hybrid Memcached had $1.45 \times$ better operational throughput and $7 \times$ better tail latency compared to Fully Persistent Memcached. Fully Persistent Memcached had 33% faster recovery than Hybrid Memcached. We also gathered an additional 3 actionable design principles to keep in mind when porting persistent KV Stores that carried over various systems. We conclude that when porting legacy systems to persistent memory, developers should consider the hybrid design, a combination of volatile and nonvolatile data structures, when prioritizing operational performance and the fully persistent design, keeping all data structures in nonvolatile memory, for recovery purposes.

References

[1] Break the cost and capacity barrier with intel optane dc persistent memory. https://www.intel.com/content/dam/www/public/us/en/documents/solution-briefs/redis-enterprise-brief.pdf. Accessed: 2019-09-17.

[2] Engines ranking. https://db-engines.com/en/ranking.

[3] Making NoSQL databases persistent-memory-aware: The Apache Cassandra example. https://software.intel.com/en-us/articles/making-nosql-databases-persistent-memory-aware-the-apache-cassandra-example. Accessed: 2019-09-17.

[4] Redis on flash. https://redislabs.com/redis-enterprise/technology/redis-on-flash/. Accessed: 2019-09-15.

[5] Ultra-low latency with Samsung Z-NAND SSD. https://www.samsung.com/semiconductor/global.semi.static/Ultra-Low_Latency_with_Samsung_Z-NAND_SSD-0.pdf.

[6] Intel announces broadest product portfolio for moving, storing and processing data. https://newsroom.intel.com/news-releases/intel-data-centric-launch, April 2019.

[7] Restartable cache pull request for Memcached. https://github.com/memcached/memcached/pull/342, 2019.

[8] K. A. Bailey, P. Hornyack, L. Ceze, S. D. Gribble, and H. M. Levy. Exploring storage class memory with key value stores. In Proceedings of the 1st Workshop on Interactions of NVM/FLASH with Operating Systems and Workloads, page 4. ACM, 2013.

[9] S. Chen, P. B. Gibbons, S. Nath, et al. Rethinking database algorithms for phase change memory. In Cidr, pages 21–31, 2011.

[10] S. Chen and Q. Jin. Persistent B+-trees in non-volatile main memory. Proc. VLDB Endow., 8(7):786–797, Feb. 2015.

[11] P. Chi, W.-C. Lee, and Y. Xie. Making B+-tree efficient in PCM-based main memory. In Proceedings of the 2014 International Symposium on Low Power Electronics and Design, ISLPED ’14, pages 69–74, La Jolla, California, USA, 2014.

[12] J. Condit, E. B. Nightingale, C. Frost, E. Ipek, B. Lee, D. Burger, and D. Coetzee. Better I/O through byte-addressable, persistent memory. In Proceedings of the ACM SIGOPS 22nd symposium on Operating systems principles, pages 133–146. ACM, 2009.

[13] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, and R. Sears. Benchmarking cloud serving systems with YCSB. In Proceedings of the 1st ACM Symposium on Cloud Computing, SoCC ’10, pages 143–154, Indianapolis, Indiana, USA, 2010.

[14] J. Dean and L. A. Barroso. The tail at scale. Commun. ACM, 56(2):74–80, Feb. 2013.

[15] B. Deb Nath, A. Haghdoost, A. Kadav, M. G. Khatib, and C. Ungureanu. Revisiting hash table design for phase change memory. In Proceedings of the 3rd Workshop on Interactions of NVM/FLASH with Operating Systems and Workloads, INFLOW ’15, pages 1:1–1:9, Monterey, California, 2015.

[16] K. Filipek. pmem redis. https://github.com/pmem/redis, 2019.

[17] Y. Huang, M. Pavlovic, V. J. Marathe, M. Seltzer, T. Harris, and S. Byan. Closing the performance gap between volatile and persistent key-value stores using cross-referencing logs. In Proceedings of the 2018 USENIX Conference on Usenix Annual Technical Conference, USENIX ATC ’18, pages 967–979, Boston, MA, USA, 2018.
[18] A. Ilkbahar. Intel Optane DC persistent memory operating modes explained. https://itepeernetwork.intel.com/intel-optane-dc-persistent-memory-operating-modes/, 2018.

[19] J. Izraelevitz, J. Yang, L. Zhang, J. Kim, X. Liu, A. Memaripour, Y. J. Soh, Z. Wang, Y. Xu, S. R. Dulloor, J. Zhao, and S. Swanson. Basic Performance Measurements of the Intel Optane DC Persistent Memory Module. arXiv e-prints, page arXiv:1903.05714, Mar 2019.

[20] J. Kim, S. Lee, and J. S. Vetter. PapyrusKV: A high-performance parallel key-value store for distributed NVM architectures. In Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis, SC ’17, pages 57:1–57:14, Denver, Colorado, 2017.

[21] K. Kourtis, N. Ioannou, and I. Koltsidas. Reaping the performance of fast NVMe storage with uDepot. In Proceedings of the 17th USENIX Conference on File and Storage Technologies, FAST’19, pages 1–15, Boston, MA, USA, 2019.

[22] Lenovo. memcached-pmem. https://github.com/lenovo/memcached-pmem, 2018.

[23] V. J. Marathe, M. Seltzer, S. Byan, and T. Harris. Persistent Memcached: Bringing legacy code to byte-addressable persistent memory. In Proceedings of the 9th USENIX Conference on Hot Topics in Storage and File Systems, HotStorage’17, pages 4–4, Santa Clara, CA, 2017.

[24] T. Menjo. libpmemlog-aof redis. https://github.com/tmenjo/redis/tree/libpmemlog-AOF, 2017.

[25] S. Nalli, S. Haria, M. D. Hill, M. M. Swift, H. Volos, and K. Keeton. An analysis of persistent memory use with whisper. In Proceedings of the Twenty-Second International Conference on Architectural Support for Programming Languages and Operating Systems, ASPLOS ’17, pages 135–148, Xi’an, China, 2017.

[26] M. Nam, H. Cha, Y. ri Choi, S. H. Noh, and B. Nam. Write-optimized dynamic hashing for persistent memory. In 17th USENIX Conference on File and Storage Technologies (FAST 19), pages 31–44. USENIX Association, 2019.

[27] I. Oukid, J. Lasperas, A. Nica, T. Willhalm, and W. Lehner. Fptree: A hybrid scm-dram persistent and concurrent b-tree for storage class memory. In Proceedings of the 2016 International Conference on Management of Data, SIGMOD ’16, pages 371–386, San Francisco, California, USA, 2016.

[28] g. PeifengSi, LynnaPan. pmem-redis. https://github.com/pmem/pmem-redis, 2018.

[29] Snalli. Redis pmem. https://github.com/snalli/redis, 2016.

[30] S. Venkataraman, N. Tolia, P. Ranganathan, and R. H. Campbell. Consistent and durable data structures for non-volatile byte-addressable memory. In Proceedings of the 9th USENIX Conference on File and Storage Technologies, FAST’11, pages 5–5, San Jose, California, 2011.

[31] V. Viswanathan. Intel memory latency checker. https://software.intel.com/en-us/articles/intel-memory-latency-checker, 2019.

[32] H. Volos, A. J. Tack, and M. M. Swift. Mnemosyne: Lightweight persistent memory. In Proceedings of the Sixteenth International Conference on Architectural Support for Programming Languages and Operating Systems, ASPLOS XVI, pages 91–104, Newport Beach, California, USA, 2011.

[33] X. Wu, F. Ni, L. Zhang, Y. Wang, Y. Ren, M. Hack, Z. Shao, and S. Jiang. NVMcached: An nvm-based key-value cache. In Proceedings of the 7th ACM SIGOPS Asia-Pacific Workshop on Systems, page 18. ACM, 2016.

[34] F. Xia, D. Jiang, J. Xiong, and N. Sun. HiKV: A hybrid index key-value store for dram-nvm memory systems. In Proceedings of the 2017 USENIX Conference on Usenix Annual Technical Conference, USENIX ATC ’17, pages 349–362, Santa Clara, CA, USA, 2017.

[35] J. Yang, Q. Wei, C. Chen, C. Wang, K. L. Yong, and B. He. Nv-tree: reducing consistency cost for nvm-based single level systems. In 13th {USENIX} Conference on File and Storage Technologies ({FAST} 15), pages 167–181, 2015.

[36] P. Zuo, Y. Hua, and J. Wu. Write-optimized and high-performance hashing index scheme for persistent memory. In Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation, OSDI’18, pages 461–476, Carlsbad, CA, USA, 2018.