Efficient Kernel Object Management for Tiered Memory Systems with KLOC

Sudarsun Kannan (Rutgers University), Yujie Ren (Rutgers University), Abhishek Bhattacharjee (Yale University)

Abstract

Software-controlled heterogeneous memory systems have the potential to improve performance, efficiency, and cost tradeoffs in emerging systems. Delivering on this promise requires efficient operating system (OS) mechanisms and policies for data management. Unfortunately, modern OSes do not support efficient tiering of data between heterogeneous memories. While this problem is known (and is being studied) for application-level data pages, the question of how best to tier OS kernel objects has largely been ignored.

We show that careful kernel object management is vital to the performance of software-controlled tiered memory systems. We find that the state-of-the-art OS page management research leaves considerable performance on the table by overlooking how best to tier, migrate, and manage kernel objects like inodes, dentry caches, journal blocks, network socket buffers, etc., associated with the filesystem and network stack. In response, we characterize hotness, reuse, and liveness properties of kernel objects to develop appropriate tiering/migration mechanisms and policies. We evaluate our proposal using a real-system emulation framework on large-scale workloads like RocksDB, Redis, Cassandra, and Spark, and achieve 1.4× to 4× higher throughput compared to prior art.

1 Introduction

Hardware heterogeneity is here. Vendors are coupling general-purpose CPUs with accelerators ranging from GPUs and FPGAs to domain-specific hardware for deep learning, signal processing, finite automata, and much more [10,11,32]. Memory systems are combining the best properties of emerging technologies optimized for latency, bandwidth, capacity, volatility, or cost. Researchers are already studying the benefits of die-stacked DRAM [9,29,44], while Intel’s Knight’s Landing uses high bandwidth multi-channel DRAM (MC-DRAM) alongside DDR4 memory to achieve both high bandwidth and high capacity [5]. Non-volatile 3D XPoint memories are now commercially available for database systems, and disaggregated memory is being touted as a promising solution to scale capacity for blade servers [40]. Next-generation systems will consist of heterogeneous compute nodes (CPU, GPU, or both) connected to multiple types of memory with different bandwidth, latency, and capacity properties.

To harness the promise of heterogeneity, software-controlled data management is necessary to ensure that as programs navigate different phases of execution, each with potentially distinct working sets, data is tiered appropriately. To optimize for performance, ideally the hottest data will be placed in the fastest memory node (in terms of latency or bandwidth) until that node is full, the next-hottest data will be filled into the second-fastest node up to its capacity, and so on. As a program executes, its data must be periodically assessed for hotness and re-organized to maximize performance. Doing this successfully requires effective OS policies and mechanisms to determine data reuse and control data migration.

Unfortunately, data hotness tracking and page migration in modern OSes have high overheads and are surprisingly inefficient. Recent studies address this in many ways, including support for transparent huge page migration [37], concurrent migration of multiple pages and symmetric exchange of pages [54], compiler- and MemIf-based frameworks [41,50] that determine data hotness via heap profiling, and machine learning to determine page hotness [38]. Other OS-based approaches [8,35] and hardware accelerated approaches [13,30,42,57] have been proposed. Although effective, these studies focus on application-level data and largely ignore the question of how best to tier kernel objects associated with I/O.

We show that ignoring kernel objects leaves considerable performance on the table and that carefully tiering, migrating, and managing kernel objects like inodes, dentry caches, journal blocks, network socket buffers, etc., is vital to overall system performance. We also show that by characterizing hotness, reuse, and liveness properties – that techniques previously proposed for application-level data tiering are a poor fit for kernel objects. This is because of three key differences between application-level pages and kernel objects. First, kernel objects are not mapped or owned by a specific application. Second, kernel objects can and are shared and reused across multiple tenants. Third, kernel objects are much shorter lived than application-level data. For these reasons, traditional hotness scanning and page migration techniques cannot simply be extended to kernel objects, which can neither be associated with a specific application nor are sufficiently long-lived to tolerate the latencies of state-of-the-art application-level page migration techniques [54].

In response, we introduce the concept of kernel-level object contexts (or KLOCs). Each KLOC encapsulates a set of kernel-level objects associated with entities like files, sockets, virtual device files etc. We build allocation, deallocation, page placement, and page migration mechanisms and policies for KLOCs, striking a compromise between tying kernel-level objects to application-level characteristics while also adapting to the unique reuse/lifetime characteristics of kernel-level objects. KLOC-based tiering allows the OS to associate applications...
and kernel-level objects (thereby tracking when, how, and why applications access kernel-level objects) while also understanding that kernel-objects can be shared across different applications (with different I/O behavior) and have shorter lifetimes than application-level data. KLOC-based tiering also permits kernel objects to leverage aspects of the file system and networking stacks that have already been optimized for performance (e.g., data prefetching for I/O, etc.).

To build KLOCs, we address several research challenges. Unlike coarser-grained application-level approaches based on NUMA-affinity, which generally tie data to particular memory sockets through large chunks of application lifetime, files and sockets can be rapidly spawned/killed and accessed/reused in a myriad ways (for example, RocksDB [2], creates and operates on hundreds of files through its lifetime). Some kernel objects (like file system journals) can be shared across multiple files (and applications). Finally, currently OSes lack support for kernel object migration entirely (kernel objects are managed by the OS’s slab allocator and remains in the location it was allocated through time). Even worse, building kernel object migration is a non-trivial effort – many kernel objects (like kernel buffer pages) have lifetimes that are so short (in tens of milliseconds), that the latency to migrate them between memory tiers and perform associated operations like TLB shootdowns [42, 43] can be prohibitively high.

To accurately gauge the benefits of KLOCs, we prototype our approach in the mainline Linux kernel v4.17. To determine the set of kernel objects per KLOC, we rely on application-level system calls to identify the files and sockets, virtual devices, etc., being accessed and the newly-allocated kernel objects (e.g., a dentry, cache page, packet/socket buffer) that are associated with. Each file, socket, and a virtual device has its own KLOC. We also associate kernel objects with CPUs in order to maintain information about CPU- and application-wide KLOC association. To track chains of kernel objects associated with KLOCs in an efficient manner, we implement a lightweight object map table within the kernel. This map is accessed by the OS to determine KLOCs associated with cold kernel objects so that they can be migrated to slow memory, and is designed to obviate the need for high-overhead page table scans to determine page hotness. We overcome this challenge by grouping kernel objects used by files and sockets to a large region of virtually contiguous pages. By doing this, and also then going beyond modern OSes and implementing support for kernel object migration, we enable good performance. To boost efficiency, we also exploit I/O stack optimizations like prefetching of file data and insertion of prefetched cache pages to faster memory (which is particularly beneficial for workloads with sequential I/O access patterns). Overall, we add 6K lines of code in the Linux kernel to implement these techniques, and make no changes to the hardware or applications.

We quantify the benefits of KLOCs by using a two-socket system to emulate a two-tier memory system with a fast and slow memory, similar to prior work [23, 26, 36, 54]. We perform end-to-end evaluations with RocksDB (a persistent key-value store), Redis (a network-intensive memory store), Cassandra (a distributed wide column store), and Spark (a distributed general-purpose cluster-computing framework), in addition to microbenchmarks like Filebench. Our performance gains of up to 1.4× and 4× respectively show the performance potential of KLOCs, and lay the groundwork for further exploration of kernel object tiering mechanisms and policies in the systems research community.

2 Background and Related Work

Advances in heterogeneous memory hardware have motivated the need for efficient management of memory resources that vary in capacity, speed, and cost. We first discuss hardware and software trends, followed by related work on techniques for memory heterogeneity management and their limitations.

2.1 Heterogeneous Memory Trends

Several heterogeneous memory technologies, such as non-volatile memory (NVM), Hybrid Memory Cube (HMC), and High Bandwidth Memory (HBM) will coexist with traditional DRAMs. On-chip memory such as stacked 3D-DRAM, Hybrid Memory Cube (HMC) and High Bandwidth Memory (HBM) [13, 42] are expected to provide 10× higher bandwidth and 1.5× lower latency, but provide 8-16× [7, 9, 12, 43] lower capacity compared to DRAM. Other technologies, like NVMs, offer 4-8× higher capacity compared to DRAMs but suffer from 2-3× higher read latency, 5× higher write latency, and 3-5× lower random access bandwidth compared to DRAM. Several file systems [15, 21, 52, 53] and user-level libraries [28, 49] have been proposed to exploit persistence, as have approaches to integrate them as virtual memory [22, 36]. Given the differences in bandwidth, latency, and capacity, heterogeneous memory systems will increase the complexity of the memory management software stack.

2.2 Managing Heterogeneous Tiered Memories

Hardware-level management. There have been several prior proposals to manage memory heterogeneity in the hardware. Batman modifies the memory controller to randomize data placement for increasing the cumulative DRAM and stacked 3D-DRAM bandwidth [13]. Meswani et al. [42] discuss extending the TLB and the memory controller with additional logic for identifying page hotness. To reduce page migration cost, Dong et al. [20] propose SSD FTL-like mapping of physical addresses dynamically [14]. Oskin et al. propose an architectural mechanism to selectively invalidate entries in the TLB for reducing the TLB shoot-downs during migrations [43]. Ramos et al. propose a hybrid design with hardware-driven page placement policy and the OS periodically updating its page tables using the information from the memory controller [46].
Software-level management. Several recent studies augment traditional OS approaches to track page hotness by scanning page tables to migrate application pages of different sizes [8, 24, 35, 38, 41, 43, 54]. These approaches extend work originally proposed by Denning [19] for disk swapping. Gupta et al. propose HeteroVisor [24], which uses page hotness tracking and migration techniques for virtualized datacenters, whereas Kannan et al. [35] propose on-demand data placement for virtualized datacenters. Yan et al. [54] propose techniques to accelerate page migration in heterogeneous memory systems by increasing parallelism. Lagar-Cavilla et al. [38] propose a combination of OS-level hotness scanning combined with machine learning for data placement across fast and slow memories. Many of these techniques extend the concept of NUMA-affinity to data pages. That is, they associate applications to particular memory sockets in order to accelerate memory access from CPUs that are physically closer.

While these approaches are beneficial for application-level data, kernel object management for heterogeneous memory remains unexplored and is in its infancy (for example, there is no support for kernel object migration in modern OSes).

### 3 Characterizing Reuse, Liveness, and Access Properties of Kernel-Level Objects

For optimal application performance in heterogeneous memory systems, placing not only application-level pages but also kernel pages to faster memory is critical. However, page placement of kernel pages (and objects) is not well studied. To understand the need for kernel object placement in heterogeneous memory systems, we next analyze real-world I/O-intensive applications.

#### 3.1 Experimental Methodology

Quantifying the performance of kernel object tiering requires a platform that permits end-to-end execution of large scale workloads (we use those summarized in Table 1) with full-system effects. Cycle-accurate simulators are too slow and lack the detail necessary to (easily and accurately) study kernel-level structures in the virtual memory, storage, and network subsystems [13, 20, 42]. Ideally, we would use a commercially-available heterogeneous memory platform with support for flexible tiering of kernel objects. Regrettably, there are no commercial platforms that can be configured to do this yet. For example, we considered Intel’s DC memory [4], which attaches a persistent Optane memory side-by-side with DRAM. Unfortunately, this system can currently only be configured such that the persistent memory is a direct-access file system accessible via custom user-level runtimes, or the DRAM is a direct-mapped L4 cache of the persistent memory. There is no way to configure the DC memory platform to make it entirely visible (or kernel objects visible) to the virtual memory sub-system, which is what we need for our studies.

Therefore, while we will revisit Intel’s DC platform in Section 6, and for now we use a two-socket memory system to emulate a two-level tiered memory in a manner that is similar to recent work [24, 26, 36, 43, 54]. These sockets have the architectural configuration described in Table 2. Like previous work [24, 26, 36], we emulate a fast memory on one of the sockets, and a slow memory on the other by applying thermal throttling to slow down the latter. The slow memory’s bandwidth and latency are configured by modifying the PCI-based thermal registers. The flexibility of this platform enables exploration of a generic software-controlled heterogeneous framework as we can vary capacities of the memory nodes, as well as their latency/bandwidth characteristics. For our studies, we vary capacity/bandwidth differences between the fast and slow memories from $2 \times 10$ to 16 $\times 10$. Furthermore, for some of our experiments, we controlled application/kernel page placement in the fast/slow memories by adding hooks in Linux’s memory management stack to redirect page allocations. All workloads are executed on the 20 CPUs of the node associated with fast memory. We will publicly release our kernel and tools so that they can be used by the community for follow-up studies.

### Table 1: Applications and workloads

| Application | Description | Resident Mem. Size |
|-------------|-------------|--------------------|
| RocksDB [2] | Facebook’s persistent key-value store based on log-structured merge tree; Workload: Widely-used DBbench [3] with 1M keys. | 8.4GB |
| Redis [6] | Network-intensive key-value store with support for persistence; uses Redis Bench, 4 millions ops., 75%/25% Set/Get distribution. | 14GB |
| Filebench [47] | File system benchmark; uses eight threads, 8GB per-thread, performing sequential and random reads. | 16.3GB |
| Cassandra [1] | Java-based NoSQL DB; run with YCSB [16] workload using eight threads, 50% read-write ratio. | 11GB |
| Spark [56] | Apache Spark; performs Terrasort on 20GB data using sixteen threads and uses Hadoop file system. | 32.1GB |

Table 2: System configurations.

| Experimental Environment | |
|--------------------------|--------------------------|
| Processors | 2.4 GHz Intel E5–2650v4 (Broadwell), 20 cores/socket, 2 threads/core |
| Cache | 512 KB L2, 25 MB LLC |
| Memory Sockets | Two 80 GB sockets configured as NUMA nodes, max bandwidth of |
| Storage | 512 GB NVMe with 1.2 GB and 412 MB sequential and random access bandwidth |
| OS | Debian Trusty — Linux v4.17.0 |
3.2 Experimental Results

Table 1 shows that we focus on large-scale workloads that are compute-, file-, and network-intensive in order to stress-test our approach. We also use Filebench, which is a mixed random write and read access workload. We structure our studies around the following questions:

How are kernel memory objects allocated and accessed?
Modern data center applications are known to be I/O intensive and expend considerable portions of their runtime within the kernel-level file system and networking stacks. For example, 40% of the runtime of RocksDB is spent within the file system code path. What is less well-known, however, is that these applications also allocate millions of memory pages for kernel objects that perform I/O caching, in-memory metadata and book-keeping structures (like radix trees for caches), journals and logs, as well as ingress and egress network socket buffers.

Figure 1a quantifies the number of pages allocated for different kernel objects. The data shows that all the workloads allocate many page cache pages and kernel buffers (using slab allocations via kmalloc). Filebench uses eight I/O threads to simultaneously write 4KB blocks to separate files. The write and read operation entails allocation of page cache (for writing data or bringing data from disk) as well as updates to system metadata structures, which involves allocating journals, radix tree, block driver buffers, etc. Consequently, both page cache and kernel metadata allocations increase significantly compared to user-level pages. In contrast, RocksDB updates hundreds of 4MB files with key-value data. Therefore, slab allocations for inodes, dentry caches, radix tree nodes (for the indexing cache), driver block I/O and journals are all frequent and contribute to 36% of the pages allocated to kernel objects. RocksDB and filebench use slab allocations via Hadoop file system (HDFS) to store and checkpoint data (RDDs [56]). Note that HDFS is run as a separate process. HDFS maintains user-level cache and periodically updates page cache (so less kernel buffer pages).

We also profile the frequency with which these different kernel objects are accessed in Figure 1b and the distribution of last-level cache misses in Figure 1c. Even though fewer kernel buffers are allocated (see Figure 1a), they are accessed more often than other kernel objects. To understand why, consider, for example, a file write in Filebench. The virtual file system (VFS) looks up the page cache radix tree, allocates a new page if the necessary, inserts the page into the radix tree, performs metadata/data journaling with logging, and finally, commits to storage. These steps are more memory-intensive than writing the data to the page cache. In fact, scaling the workload inputs leads to a sharp increase in LLC misses due to higher traffic to kernel buffers. Filebench’s spends 86% of execution time inside the OS, and hence, the memory accesses increase proportionately, compared to RocksDB (54%) and Redis (38%).

How does tiering of kernel objects impact performance?
To study the impact of kernel object placement in fast/slow memory, we configure the capacity of the fast memory so that it cannot fit all the application’s user-level and kernel-level pages. Our results, illustrated in Figure 2, assume that fast and slow memory are 5GB and 40GB respectively, and that slow memory has a bandwidth of 5GB/second, thereby emulating a 5× bandwidth difference between fast and slow memory. This is similar to recent work [24,35,42] and is representative of the bandwidth differences between HBM and NVM technologies relative to DRAM. In tandem, Figure 3 and Figure 4 show the impact of varying slow memory bandwidth and fast memory capacity. The App Slow + OS Slow bars show the worst-case scenario where all pages are placed in slower memory. App Slow + OS Fast shows the case where only the kernel pages are placed in fast memory. App Fast + OS Slow shows the case where only application-level pages are placed in fast memory, and App Fast + OS Fast shows an ideal case all pages fit in fast memory. The y-axis shows the normalized throughput.

Placing both application and kernel pages (App Slow + OS Slow) in slow memory degrades performance across all workloads. As shown in Figure 2, placing only kernel pages (App Slow + OS Fast) to limited-capacity fast memory does improve performance; for example, RocksDB and filebench improve by 1.58× and 2.8× respectively compared to App Slow + OS Slow. In real-world settings, one would not just place kernel pages in fast memory (but would also do so for application-pages as much as possible) but this experiment shows that even just tiering kernel objects appropriately impacts performance. For network (and storage) intensive Redis, placing kernel pages in fast memory boosts performance by 1.8× over App Slow + OS Slow. In Spark, we note a high contention between Spark compute pages (heap) and HDFS storage (kernel pages) for a limited-capacity fast memory. Only placing kernel pages in fast memory improves performance by 1.3×, mostly due to page cache placement in fast memory.

Finally, suppose we place application pages in fast memory but prevent kernel objects from being in fast memory. While Redis improves marginally, this is not the case for Filebench, which spends 86% of execution inside the OS.

Figure 3 and Figure 4 show the sensitivity of RocksDB (highly I/O and OS-intensive) and Spark (mostly compute-intensive with intermittent I/O) towards lowering memory bandwidth or reducing fast memory capacity. The x-axis in Figure 3 shows the increasing ratio of slow memory bandwidth to fast memory bandwidth, whereas Figure 4 shows the increasing fast memory capacity ratio. The results show that reducing fast memory capacity or lowering slow memory impacts both application and the impact of placing kernel objects to slower memory affecting RocksDB significantly.
What is the lifetime of a typical kernel object? Figure 5 shows the lifetime of OS cache and kernel-buffer pages. Conceptually, kernel buffer pages expire after they are freed. Cache pages remain until they are evicted from memory pressure (we mark them as expired when they are added to the LRU list).

Figure 5 shows that RocksDB and Redis have cache pages with average lifetimes of less than 160 milliseconds, and smaller kernel pages are even shorter-lived, at 60 milliseconds. To understand why kernel objects are short-lived, consider, for example, a file write. A page cache page is allocated, the user data is copied to the cache page, a radix tree node is inserted. The page cache page remains inactive until subsequent reads/writes or commits (i.e., fsync()) to the disk. In contrast, kernel buffers such as radix tree nodes are frequently queried, allocated, and deleted due to tree rebalancing or cache page deletion. Other in-memory structures such as dentry caches and in-memory journals are also frequently allocated and deleted when data and metadata are updated.

These observations showcase the limitations of prior work like Thermostat [8], which uses a 30-second interval between two hotness tracking iterations. This relatively large time period was used to because scans of page tables to ascertain hotness and invalidate TLB entries are long latency events. Our results show, however, that kernel objects are far too short-lived to be amenable to such high intervals.
4  Our Approach: KLOC-Based Tiering

Having quantified the performance challenges posed and opportunities offered by tiering of kernel objects in generic software-controlled heterogeneous memory systems, we consider how to go beyond prior work (which neglects kernel object tiering) and devise kernel tiering. Our goals are high performance and ready implementation in commercial OSes.

At first blush, one might consider extending OS support for NUMA affinity to also include kernel objects. This approach would permit placement of kernel objects – just like application pages – in memory devices in a manner that attempts to minimize distance between CPUs and the data they frequently access. Unfortunately, such NUMA affinity approaches are not viable for kernel objects, which can be shared/reused across applications (making it challenging to assign a single affinity to kernel objects) and have lifetimes much shorter than application pages (making existing ways of measuring hotness and migrating pages inapplicable). Current OSes, which includes Linux, FreeBSD, Solaris, lack capability to associate kernel objects with application entities or provide fine-grained of placement kernel objects. Instead, we use the concept of KLOCs to encapsulate groups of kernel objects into logical entities – associated with files and network sockets – that can be managed together in a lightweight manner. Using these entities as a unit of movement enables finer-grained decision-making about allocations, placements, and migration of kernel objects associated with an entity (i.e., a KLOC), than using NUMA affinity. These benefits are crucial for good performance but does require extending existing file systems, network stacks, the OS slab allocator, journals, and device drivers with support for KLOCs. A key feature of our approach is to use tap into application-level system calls to accurately track KLOCs, and kernel level maps that lets us identify hot kernel objects much faster than traditional approaches that scan the page table. This in turn permits us to migrate kernel objects fast enough so that its benefits are not outweighed by relatively short kernel object lifetimes. Finally, we leverage existing and highly-optimized I/O stack optimizations such as adaptive I/O prefetching (also known as readahead) and techniques to speculatively place I/O cache and filesystem objects to fast memory for further boost performance.

5  KLOC Design

We next discuss the key design and implementation details of KLOC. We base our design discussions on support for the file system and network stacks, followed by ways to support effective kernel object placement and migration and also exploit traditional OS optimizations such as I/O prefetching.

5.1 KLOC Placement Policy

We start with a set of page placement constraints. First, kernel objects are short-lived, and immediate placement of currently active objects to faster memory is critical. Second, because faster memory is usually lower-capacity, migrating inactive objects to slower memory and making way for active objects is critical. Third, reducing the frequency of long-latency hotness scans and reducing migration overheads is critical. Finally, application pages are always prioritized to use faster memory unless their pages become inactive. Importantly, KLOC object grouping, placement, and migration are not tightly bound to a specific placement policy.

5.2 KLOCs for File Systems

The workloads that we use spend a significant fraction of execution time in the file system dealing with page caches, in-memory structures like inodes, dentry caches, radix trees, block-device buffers, and journals, and in the network subsystem where they interact with ingress/egress socket buffers and network I/O queues.

/* KLOC-based dentry object allocation */
void *dentry_alloc(struct inode *inode) {
    struct dentry *dentry;
    /* Get KLOC */
    struct kloc *kloc = inode_to_kloc(inode);
    struct *alloc_policy;

    /* Check if KLOC is active */
    if (kloc_active(kloc)) {
        /* Get KLOC allocation policy */
        alloc_policy = kloc->alloc_policy;
        dentry = allocate_hetero(sizeof(struct dentry), alloc_policy);
        /* Add to KLOC's map */
        add_to_kloc_map(kloc->map, dentry)
    } else {
        /* Use default allocation */
        dentry = allocate(sizeof(struct dentry));
    }
}

/* KLOC support for storage Stack. */

Figure 6: KLOC support for storage Stack. Creation of a kloc map and addition of VFS, file system, and device driver kernel objects. in-memory structures like inodes, dentry caches, radix trees, block-device buffers, and journals, and in the network subsystem where they interact with ingress/egress socket buffers and network I/O queues.

/* Pseudo-code for KLOC-based dentry object allocation and mapping. */

Figure 7: Pseudo-code for KLOC-based dentry object allocation and mapping. Dentry is used to keep track of the hierarchy of files in directories. The pseudo-code checks if a file-based KLOC (represented as inode) is active, allocates the dentry based on KLOC’s allocation policy, and finally adds the dentry object to KLOC map.
allow sharing of kernel objects across applications when required. Consider, for example, the notion of a file, which is visible to both the application and the OS code paths responsible for kernel object allocation and I/O servicing. During a file create operation, a set of in-memory kernel objects such as inode, dentry cache, and journal blocks are allocated. During a file write operation, the virtual file system (VFS) allocates cache pages, radix tree nodes for managing the cache pages, journal records (for crash-consistency), and extents [39]. When the block driver commits in-memory pages of a file to disk, the block driver allocates a file’s block I/O structures. All these allocations, whether initiated by the application or OS, are associated with the notion of a file, making it the appropriate entity around which to group the kernel objects allocated to it. We therefore use a file’s inode used across all layers of file system to create a KLOC to track all associated kernel objects, (i.e., the VFS, the file system, and the device driver).

5.2.2 Managing File System KLOCs
We create a map structure in the inode KLOC for tracking all kernel objects associated with each file. The map structure is implemented as a red-black tree and maintains kernel objects in the virtual file system layer (VFS), the dentry cache (used for name lookup), the page cache, the actual file system (without loss of generality, we use Ext4 file system in our implementation), the log manager (for crash-consistency), and the block device driver. We show an example of this map in Figure 6.

One of the key challenges in maintaining inode KLOCs is to understand when to create and update kernel objects. In order to do this, we use OS system calls such as create(), write(), read(), close() as semantic hints. Figure 6 shows that during file creation, a new inode and its map is created (with the inode as root), and the dentry object is added. On a file write operation, cache pages, their radix tree nodes, and the journal records (JBD2) are added to the map too. After a file is closed, the cache entries are removed. Consequently, the KLOC is deleted only when the file and inode are deleted [33].

5.2.3 Per-CPU Kernel Object Grouping
Modern applications run on tens of CPUs and future applications may run on hundreds of CPUs sharing and access per-thread files. Examples of such applications include those that perform graph computations and maintain key-value stores. In such cases, it is beneficial to be able to manage KLOCs across applications and CPUs.

Therefore, our approach assumes that a file (i.e., inode) becomes active when thread(s) perform I/O on it. To integrate a notion of CPU numbers with KLOCs, we exploit Linux’s per-CPU data structures. Each thread (or CPU) is represented by a task structure (task_struct) that represents the active process currently scheduled on the CPU. We extend the task_struct with an active context state that represents the files actively being accessed by the CPU. We leverage file system I/O system calls, such as open, read, write, close, and others to identify the kernel objects being accessed by each CPU.

These kernel objects are added to the per-CPU context map, as shown in the the pseudocode in Figure 7. This approach enables KLOC to group kernel objects concurrently accessed by multiple CPUs.

5.3 KLOCs for the Networking Subsystem.
To group kernel objects allocated by network subsystem, we use socket descriptors. Within Linux (and other OSes), these are also implemented as inodes, making our file system KLOC design easily extensible to networking. Sockets present an appropriate entity for KLOC creation as they are accessible by both the application and the OS. Page placement and migration policies are applied to pages grouped with respect to sockets.

5.3.1 Associating KLOCs with Kernel Objects
The network stack uses packet buffers (skbuff) to send and receive application data. The packet buffers allocated in the ingress and egress path dominate kernel object allocations. The ingress and egress path in the network stack comprises of multiple layers, including TCP, UDP, IP, and network device driver (e.g., NAPI). To reduce overheads of copying network packets across these layers, user-level buffers are copied to socket buffers and reused across other lower layers (TCP, UDP, IP, and NAPI) before being copied over to the NIC. For the receive path, the device driver is responsible for allocations, which are subsequently reused by upper layers of the networking stack. In addition to the socket buffers, kernel objects such as network queues are also allocated, but constitute a small fraction allocated memory. Our networking KLOCs group these per-socket network kernel objects, enabling better memory placement and migration.

As with inode KLOCs, socket KLOCs also use a map structure to track kernel objects associated with a socket. Therefore, KLOC uses the system calls responsible for socket creation (socket(), open()) to initiate per-socket map structures. When a CPU invokes an egress (send()), ingress (recv()), and polls, KLOC marks the socket active and adds network kernel objects to the per-socket map structure. Whether newly-allocated kernel objects are allocated to fast or slow memory depends on how the socket is managed. In general, all kernel objects of an active socket KLOC are directed to fast memory.

5.3.2 Ingress and Egress Paths
The egress path of a network stack is generally synchronous, and the network stack objects, including the socket buffers, are allocated during send() operations. As a result, grouping socket buffers and network stack kernel objects in the egress path involves simply adding them to the socket’s context map structure. Unlike the egress path, the ingress (network receive) path is dependent upon the asynchronous arrival of packets. As network packets arrive, the device driver process inside the OS allocates a generic packet buffer but does not know the socket information to which this packet belongs. This information is extracted in a higher layer of the TCP stack. This creates a research challenge – how to group egress packet buffers to a socket KLOC as early as possible,
we find that the latency for these steps is sufficiently high which is both CPU-intensive and time-consuming. In practice, we rely on quickly identifying cold/inactive memory, without incurring the cost of tracking each and every kernel object. We use the idea of grouping kernel objects with a socket context deep down to the device driver to improve the flexibility to group kernel objects that are allocated asynchronously and apply uniform allocation and data placement policies.

5.4 Enabling Support for Kernel Object Migration

Grouping kernel objects via inode and socket KLOCs and supporting per-CPU active contexts enables better memory kernel object tiering. Unlike modern OSes, which do not support kernel object tiering, we can allocate kernel objects to fast memory, identify cold/inactive kernel objects, and migrate the latter to slow memory. To build efficient techniques to identify cold/inactive kernel objects, and build support for their migration, we go beyond prior application-level page placement systems. KLOC cannot rely on long-latency hotness scanning and page migrations (that incur TLB invalidations [38, 54]) because the kernel objects are much too short-lived to tolerate long migration latencies.

5.4.1 Reducing Migration-related Costs

Consider page hotness scanning. With KLOC, when a file or socket context is actually used, all kernel objects grouped in the context map are placed in faster memory. If the faster memory capacity is full, the objects of the inactive file or socket KLOCs (currently not accessed by any CPU) are moved from faster to slower memory. Migrating inactive KLOCs is conceptually similar to the idea of garbage collecting in fast memory, without incurring the cost of tracking each and every kernel object. We rely on quickly identifying cold/inactive kernel objects and migrating them to slow memory. To do this, we use and extend the Linux LRU mechanism developed initially for swapping and adopted by prior work [35, 54]. We introduce several extensions critical for kernel object placement in addition to concurrent page migrations introduced by Yan et al. [54].

First, OSes such as Linux (and FreeBSD) maintain an active page list, an active LRU list, and an inactive LRU list of pages. Due to limited faster memory capacity, we not only migrate pages from the inactive list but also from the active LRU list when the demand for fast memory is high. Second, we do not wait for Linux to identify LRU and inactive pages; instead, once a network or file context becomes inactive, we immediately mark and migrate the pages. Third, slab pages could be shared across one or more active and inactive file/socket entities. To avoid undue effects, we do not migrate shared pages with active objects. Finally, repeated migration of kernel pages between fast and slow memory can be detrimental to performance. To avoid repeated migration, we use an 8-bit per-page counter to track migrations and retain such pages in fast memory. We observe a small fraction (less than 1%) of pages that meet these conditions due to the shorter lifetime of kernel objects.

5.4.2 Support for Migration of Slab Pages

Now consider the actual mechanism to migrate kernel objects. Traditionally, kernel buffer pages allocated using the OS slab allocator (which excludes cache pages or kmalloc()) are managed independently of the application pages and are reused across one or more applications. The slab allocator attempts to group objects of the same type or sizes together [23]. Each slab page can contain one or more kernel objects from different subsystems or shared by different tenants. Importantly, slab kernel pages are not directly mapped to an address space or process, and can also be accessed using a physical address. Current OSes do not support migration of slab pages.

To enable migration of slab allocated kernel objects, one might consider entirely redesigning the slab allocator. Although ideal, given the magnitude of changes to the OS design, in KLOC, we propose an alternative solution to support the migration of kernel objects. First, for kernel objects related to files and sockets, we use vmalloc() (virtual malloc) support inside the OS. Using vmalloc() provides the ability to allocate a large region of virtually contiguous memory that also contains an anonymous address space (anon_vma) [17] not backable by a file. Using vmalloc() allows us to allocate and coalesce kernel objects of a context to a virtually contiguous region, and use the anonymous address space to extend Linux’s page migration code to support kernel object migration1.

5.5 Exploiting I/O Stack Prefetching Hints

Using KLOCs also allows us to leverage existing OS-level optimizations such like in-memory buffering, prefetching and

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1Our current approach is limited to support the migration of kernel objects that are not physically dereferenced.
6 Evaluation

Our evaluations answer the following questions:

- What are the benefits and implications of KLOC’s fine-grained placement of file system’s kernel objects in heterogeneous memory systems? What is the impact on fast memory utilization?

- How effective is KLOC’s support for the network subsystem?

- Is the KLOC’s capability to accelerate I/O stack’s prefetching optimization with fast memory pages beneficial?

6.1 Methodology and Baselines

We use a 40-core Intel Xeon 2.67 GHz dual-socket system, with 80GB memory per socket and a 512 GB Intel Optane NVMe with a peak sequential and random bandwidth of 1.2 GB/s and 425 MB/s respectively. We use the memory heterogeneity emulator from section 3 and consider a generic fast (DRAM) and slow (throttled) memory. As discussed in section 3 (see Figure 3), the fast memory capacity and slow memory bandwidth have a direct correlation with performance. We quantify performance sensitivity to slow memory bandwidth. We fix the fast memory capacity to 5 GB (this is representative of recent industrial and academic projections [4,12,18,24,35]). We use the same set of applications studied in 3. To understand the performance of KLOC on real NVM device (for which the bandwidth can be modified) for RocksDB, we use a 64-core, 2 TB Intel’s DC platform.

| Mechanisms         | Description                                                                 |
|--------------------|-----------------------------------------------------------------------------|
| All-SlowMem        | A worst-case slow memory-only system; OS and application pages are always placed to slow memory |
| All-FastMem        | An ideal all fast memory system (best case)                                  |
| Naive              | A greedy approach that naively uses NUMA and attempts to place application and OS pages to low capacity fast memory although they cannot fit |
| Nimble             | State-of-the-art application page placement system with concurrent migration support [54] |
| Migration-only     | Migration based approach that only migrates cold pages from fast to slow memory, freeing fast memory for direct allocation similar to [8,35,54] |
| KLOC-nomigrate     | KLOC’s kernel page placement but without migration for the storage stack |
| KLOC-migrate-fs-noprefetch | KLOC with kernel page migration but without network stack or I/O prefetcher support (section 5.2) |
| KLOC-migrate-fs-nw-noprefetch | KLOC-migrate-fs-noprefetch with support for network stack (section 5.3) |
| KLOC-migrate-fs-nw-prefetch | Uses hints from the OS I/O prefetcher (section 5.5) |

Table 3: Evaluation Mechanisms.

System Configurations. We compare our approach to several other page placement and migration approaches. These are summarized in Table 3: (1) All-SlowMem represents a worst-case baseline on a system with only slow memory. (2) All-FastMem represents an ideal system that can fit the entire application workload in fast memory. (3) Naive represents an approach where the OS greedily places both application and kernel pages in fast memory. When fast memory is full, subsequent allocations for application and OS pages are served from slower memory until fast memory pages become free. (4) Nimble represents the state-of-the-art system for placement of application-level pages. Nimble also employs concurrent page migrations [54]. (5) Migration-only attempts to allocate OS and application pages to fast memory, but also identifies cold pages migrates them to slower memory similar to [8]. (6) KLOC-nomigrate represents a version of our approach using KLOCs that group kernel objects and allocate them to fast memory. What we omit from this is the idea of migrating pages of inactive KLOCs from fast to slow memory. (7) KLOC-migrate-fs-noprefetch, which goes beyond KLOC-nomigrate and also migrates cold/inactive file system kernel objects. Finally, (8) KLOC-migrate-fs-nw-noprefetch and KLOC-migrate-fs-nw-prefetch represent our final, full-blown KLOC approach by also adding support for the network stack and including I/O prefetching optimizations to fast memory.

6.2 Impact of KLOC

We compare the following approaches summarized in Table 3: (1) All-SlowMem - the worst-case baseline, (2) All-FastMem (ideal case), (3) Naive, (4) Migration-only, (5) KLOC-nomigrate – the proposed KLOC based placement of kernel objects related to file and socket without migration, and finally, (6) KLOC-migrate-fs-noprefetch – KLOC. To understand the reduction in the use of slow memory pages for kernel objects (and hence better performance) with KLOC, in Figure 9, we show statistics for RocksDB. The x-axis shows the total page cache, kernel buffer pages (slab pages for kernel in-memory structures, logs, socket buffers, etc.), and inactive
6.3 Sensitivity to Memory Bandwidth

Figure 8b varies the slow memory bandwidth along the x-axis and studies the impact on all RocksDB and Spark for brevity. The x-axis varies slow memory’s bandwidth ratio relative to fast memory, and the y-axis shows throughput. The fast memory capacity is set of 8GB (1/10th) of slow memory. Because RocksDB is highly memory intensive, with a significant fraction of memory pages allocated in kernel and high kernel-level memory references, the results show high performance benefit across all bandwidth configurations. For
As noted in section 3 and section 5, for the network subsystem, (SET) and 75%, fetch (GET) operations, and 1 KB value size for 4-million keys with 75% read (GET) requests. The shorter lifetime of network socket buffers, which lead to incorrect placement and performance slowdown. The network stack, and file system for checking the placement of objects currently accessed by an application and avoiding placement cost of non-critical objects.

### 6.4 Impact of KLOC for Network Stack

We next discuss the benefits of introducing KLOC support for the network stack and controlling the allocation and placement of related kernel objects in heterogeneous memory. Figure 10 shows the performance of Redis, a network-intensive key-value store serving hundreds of clients. In contrast to the KLOC approach studied in Figure 8a without the network stack support, KLOC-migrate-fs-nw-noprefetch in Figure 10 shows the performance of network stack with KLOC support.

For performance analysis, we use the well-known Redis benchmark performing 4 million key operations, 25% insert (SET) and 75%, fetch (GET) operations, and 1 KB value size for each key as used by prior work [25]. Because Redis is a single-threaded application, we run 8 instances of Redis with each instance using a set of dedicated ports. The y-axis shows the throughput of SET and GET operations. Note that, for KLOC-migrate-fs-nw-noprefetch, each socket entity has an independent KLOC map to encapsulate, allocate, and migrate kernel objects and in addition to KLOC's for a file. As noted in section 3 and section 5, for the network subsystem, the socket buffers (a.k.a. skbuff) dominate the kernel object allocation. The socket buffers are allocated and reused across different layers (system calls, TCP, IP, and NAPI) and can be reused across operations.

Redis is a memory-intensive application; the application’s key-value store, the network stack, and file system for checkpointing, all demand memory pages and are sensitive to fast memory capacity and slow memory bandwidth. Compared to the optimal case (fast memory-only system), other approaches with limited faster memory capacity suffer slowdown for both SET and GET operations. For the Naïve approach, contention for fast memory across application and I/O subsystems lead to incorrect placement and performance slowdown. The shorter lifetime of network socket buffers, which are frequently allocated, released, or reused across network operations, makes the Migration-only approach ineffective; this approach suffers from high page migration and related overheads [24, 35, 42] reaping marginal benefits from memory heterogeneity. The KLOC-migrate-fs-noprefetch approach can only handle an efficient kernel page placement of the file system’s kernel object. In contrast, KLOC-migrate-fs-nw-noprefetch can map and efficiently handle the placement of both network and file system kernel objects. The network supported approach first attempts to allocate objects mapped to a socket’s KLOC to faster memory; when a direct allocation is not feasible, it uses the modified Linux LRU-based migration approach to move inactive socket related pages to slow memory and makes room for subsequent allocations to fast memory. As a result, KLOC provides 3.3× higher throughput compared to the migration-based approach.

### Summary

The results highlight the benefits of introducing file context to encapsulate kernel objects and only target placement of objects currently accessed by an application and avoiding placement cost of non-critical objects.

### 6.5 Exploiting I/O Stack Hints in KLOC

Enabling KLOC to group set of kernel-level objects associated with entities like files provides a capability to exploit OS-level hints and optimizations for page placement. To showcase such flexibility, we evaluate the benefits of combining KLOC and the filesystems’ I/O prefetcher as shown in Figure 11. The I/O prefetcher adapts to the application’s I/O access pattern and varies the page cache allocation behavior. In OSes such as Linux, the I/O prefetcher expands the I/O prefetch window size (up to 128 MB) adaptively for both spatial or temporal locality [27]. The page prefetch window shrinks for random access patterns. Capturing such semantic hints can be beneficial for KLOC’s page placement and reducing migration.

Figure 11 shows the throughput of for all applications and Figure 12 shows RocksDB’s throughput for sequential and random access I/O patterns (in the X-axis). To demonstrate the incremental benefits, for brevity, we only compare KLOC without prefetcher support (KLOC-migrate-fs-nw-noprefetch) with prefetcher supported KLOC (KLOC-migrate-fs-nw-prefetch).

Next, combining the prefetch I/O optimization in file system with KLOC improves the performance of several I/O-intensive applications with temporal or spatial locality. For example, applications such as RocksDB, Redis, and Cassandra benefit from proactively placing prefetched I/O pages to faster memory. For example, RocksDB’s overall throughput improves by 1.27×. As shown in Figure 12, RocksDB’s sequential access significantly benefits with prefetching. For Filebench, we use random read and write workload that neither gains nor loses performance; this is because, the prefetch approach uses the ”I/O prefetch window size” as a hint to

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**Figure 10: Redis performance with KLOC for network stack.** Results show cumulative throughput 8 Redis server instances that use 1 KB value size for 4-million keys with 75% read (GET) requests.

| Operation Type | SET | GET |
|----------------|-----|-----|
| All-SlowMem    | 32  | 332 |
| All-FastMem    | 39  | 37  |
| Naive          | 48  | 52  |
| Nimble         | 190 | 1961|
| Migration-only | 293 | 445 |
| KLOC-nomigrate | 2389| 39  |
| KLOC-migrate-fs-noprefetch | 1207| 634 |
| KLOC-migrate-fs-nw-noprefetch | 1185| 571 |

**Figure 11: RocksDB’s throughput for sequential and random access I/O patterns.**

As shown in Figure 12, RocksDB’s sequential access significantly benefits with prefetching. For Filebench, we use random read and write workload that neither gains nor loses performance; this is because, the prefetch approach uses the ”I/O prefetch window size” as a hint to
predict random access and avoids aggressively placing and polluting fast memory that are not likely to be used. As a side effect, this reduces the migration of inactive fast memory pages to slow memory also contributing towards performance benefits. For Redis, the performance gains (1.32 × ) are from a periodic checkpoint of the in-memory key-value store to the storage, which is mostly sequential. The overall Redis performance improves by 4 × compared to migration-only approach.

Summary. The results show the benefits of combining KLOC with traditional OS-level optimizations such as I/O prefetcher. We believe the techniques could be inherited for other subsystems [55].

6.6 KLOC performance on DC-Optane Memory
Finally, to understand the impact of KLOC on DC-Optane memory technologies, we use a 256GB DC-Optane on a memory socket with 16GB DRAM hardware managed cache (memory mode) as a slow memory and a 48GB DRAM only socket (fast memory). In addition to various limitations discussed in Section 2, due to space constraints, we only show the results for RocksDB. First, as shown in Figure 13, only running RocksDB on slower memory shows substantial performance degradation compared to the optimal (using only fast memory) approach. Current DC-Optane technology in a memory mode manages DRAM-cache as a direct-mapped cache. For large working set size, we see a substantial increase in latency as well as throughput reduction, possibly contributed due to a combination of poor cache management and high cache miss overheads. Employing KLOC by maximizing placement of kernel as well as OS pages to faster memory accelerates performance considerably compared to fully leaving it to the hardware and using a naive placement.

7 Conclusion
To provide efficient memory placement and management of kernel objects in heterogeneous memory systems, we present the KLOC, a mechanism that encapsulates kernel objects with fine-grained contexts with entities such as files and sockets and provides efficient data placement and migration without requiring expensive hotness scanning. Our results on real-world applications such as RocksDB and Redis show up to 1.4 × and 4 × higher throughput compared migration-based techniques. Our future work will explore supporting KLOC for other subsystems (e.g., GPU).

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