Garbage Collection or Serialization? Between a Rock and a Hard Place!

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Abstract

Big data analytics frameworks, such as Spark and Giraph, need to process and cache massive amounts of data that do not always fit on the heap. Therefore, frameworks temporarily move long-lived objects outside the managed heap (off-heap) on a fast storage device. Unfortunately, this practice results in: (1) high serialization/deserialization (S/D) cost, and (2) high memory pressure when off-heap objects are moved back to the managed heap for processing.

In this paper, we propose TeraHeap, a system that eliminates S/D overhead and expensive GC scans for a large portion of the objects in big data frameworks. TeraHeap relies on three concepts. (1) It eliminates S/D cost by extending the managed runtime (JVM) to use a second high-capacity heap (H2) over a fast storage device. (2) It reduces GC cost by fencing the garbage collector from scanning H2 objects. (3) It offers a simple hint-based interface, which allows frameworks to leverage knowledge about objects for populating H2.

We implement TeraHeap in OpenJDK and evaluate it with 15 widely used applications in two real-world big data frameworks, Spark and Giraph. Our evaluation shows that for the same DRAM size, TeraHeap improves performance by up to 73% and 28% compared to native Spark and Giraph, respectively. Also, it provides better performance by consuming up to 8× and 1.2× less DRAM capacity than native Spark and Giraph, respectively. Finally, it outperforms Pantera, a garbage collector for hybrid memories, by up to 69%.

1 Introduction

Managed big data frameworks, such as Spark [54] and Giraph [43], are designed to analyze huge volumes of data. Typically, such processing requires iterative computations over data until a convergence condition is satisfied. Each iteration produces new transformations over data, generating a massive volume of objects spanning long computations.

Hosting these objects on the managed heap increases memory pressure, resulting in frequent garbage collection (GC) cycles with low yield. Each GC cycle reclaims little space because (1) the cumulative volume of allocated objects is several times larger than the size of available heap [49], and (2) objects in big data frameworks exhibit long lifetimes [17,46,50]. Although production garbage collectors efficiently manage short-lived objects, they do not perform well under high memory pressure introduced by long-lived objects [34].

Hence, the common practice of coping with the rapidly growing datasets and high GC cost is to move objects outside the managed heap (off-heap) over a fast storage device (e.g., NVMe SSD). However, frameworks cannot compute directly over off-heap objects, and thus, they (re)allocate these objects on the managed heap to process them. Although some systems support off-heap computation over byte arrays with primitive types [1,10], they do not offer support for computation over arbitrary schema objects, which applications use extensively.

Moving managed objects off-heap has two main limitations. First, it introduces high serialization/deserialization (S/D) overhead for applications that use complex data structures [36,42,48]. Recent efforts [28,29] reduce S/D but demand custom hardware extensions and do not mitigate GC overhead. Second, moving a large volume of off-heap objects to the managed heap for processing raises the GC cost. Although TMO [47] transparently swaps cold application memory to NVMe SSDs and provides direct access to device resident objects (no S/D), it cannot avoid slow GC scans over the device. Our evaluation shows that GC and S/D constitute up to 87% of the execution time in big data applications.

In this work, we propose TeraHeap, a system that eliminates S/D and GC overheads for a large portion of the data in managed big data analytics frameworks. TeraHeap extends the JVM to use a second, high-capacity heap (H2) over a fast storage device that coexists alongside the regular heap (H1). It eliminates S/D by providing direct access to objects in H2 and reduces GC by avoiding costly GC scans over objects in H2. Frameworks use TeraHeap through its hint-based interface without modifications to the applications that run on top of
them. TeraHeap addresses three main challenges, as follows.

**Identifying candidate objects for H2:** Big data frameworks move specific objects outside the managed heap on off-heap storage. For instance, Spark moves off-heap cached intermediate results; Giraph moves the graph’s vertices, edges, and messages. Frameworks organize such data (partitions) as groups of objects with a single-entry root reference [32]. TeraHeap provides a hint-based interface based on key-object opportunism [25], enabling frameworks to mark root key-objects and indicate when to move them to H2. During GC, TeraHeap starts from root key-objects and dynamically computes the remaining group objects for moving to H2.

**Eliminating GC cost for H2:** TeraHeap presents a unified heap (H1+H2), where scans over H2 during GC are eliminated, because they would require significant device I/O. To achieve this, TeraHeap organizes H2 into regions with similar-lifetime objects and deals differently with liveness analysis and space reclamation. For liveness analysis, TeraHeap identifies live H2 regions by tracking forward (H1 to H2) and cross-region (in H2) references during GC. To identify live objects in H1, TeraHeap explicitly tracks backward references (H2 to H1) and fences GC scans in H2. TeraHeap tracks backward references using a card table optimized for storage-backed heaps, minimizing I/O traffic to the underlying device during GC. For reclamation, the collector reclaims H1 objects as usual. For H2 regions, unlike existing region-based allocators [20,37] TeraHeap resolves the space-performance tradeoff for reclaiming space differently. Existing allocators reclaim region space eagerly by moving live objects to another region, which would generate excessive I/O for storage-backed regions. Instead, TeraHeap uses the high capacity of NVMe SSDs to reclaim entire regions lazily, avoiding slow object compaction on the storage device.

**Applying TeraHeap:** Big data frameworks exhibit significant diversity with respect to the objects they move off-heap. We investigate how Spark and Giraph, two widely used frameworks, resolve the trade-off between GC cost due to large heaps and the overhead of off-heap accesses. Spark users explicitly store immutable cached data on the device, while Giraph transparently (without user hints) offloads mutable objects to the device. We modify both frameworks to use TeraHeap for two very different purposes.

We implement TeraHeap and its mechanisms in OpenJDK, extending the Parallel Scavenge garbage collector. We also extend the interpreter and the C1 and C2 Just-in-Time (JIT) compilers to support object updates in H2 during application execution. Our evaluation shows that TeraHeap improves performance by up to 73% and 28% compared to the native Spark and Giraph, respectively. TeraHeap provides similar or better performance by consuming up to $8 \times$ and $1.2 \times$ less DRAM capacity than native Spark and Giraph, respectively. Also, it outperforms Panthera [46], a garbage collector specialized for hybrid memories, by up to 69%.

Overall, our work makes the following contributions:

- We introduce a dual heap approach to reduce S/D and memory pressure in big data frameworks, by adding a second, high-capacity, managed heap over a fast storage device.
- We propose a hint-based interface based on key-object opportunism that enables frameworks to mark candidate objects in a coarse-grain manner and select when to move them to the second heap.
- We show the applicability of TeraHeap as: (1) a large, on-heap, compute cache in Spark to store intermediate results, and (2) a high-capacity heap in Giraph to store messages and edges.

## 2 Background

This section provides background related to JVM garbage collection and serialization/deserialization.

**Garbage Collection:** Modern collectors exploit the generational hypothesis that many objects die young. For this reason, they divide the managed heap into a young generation for new objects and an old generation for objects that survive multiple young (minor) collections [45]. They further divide the young generation into an eden space and two survivor spaces, called from-space and to-space. Application (mutator) threads allocate new objects into the eden space. When the eden space becomes full, garbage collectors perform a minor GC. During minor GC, the garbage collector identifies live objects in the eden space and from-space. Then, it moves live objects to the to-space and the mature objects to the old generation. When the managed heap becomes full, the JVM performs a full (major) GC, which scans and compacts both old and young generations.

Although JVMs used to support only DRAM-resident managed heaps, today, they can allocate either the entire heap or the old generation over a storage device using memory-mapped I/O (e.g., Linux `mmap`). However, existing garbage collectors are tuned for DRAM-backed heaps, increasing the collection overhead drastically for storage-backed heaps [52]. Their design targets DRAM, which provides low latency and high throughput regardless of operation types (read/write) and access patterns (random/sequential). On the other hand, block-addressable storage devices (e.g., NVMe SSDs) exhibit higher latency and lower throughput than DRAM.

**Object Serialization:** Java serialization enables the conversion of a memory-resident object into a form that is convenient
for transportation off-heap (memory, storage, or network) and can even be shared across JVMs. *Serialization* transforms Java objects in the managed heap into a byte stream, and *deserialization* reconstructs the Java objects from byte streams into heap representations (with references). During S/D, the serializer traverses the object graph to identify all objects that need to be serialized, starting from the root object selected for off-heap placement. When serializing an object, the serializer omits fields marked with the *transient* modifier. Transient fields are initialized to a default value during deserialization based on the serializer implementation.

Java serialization is a complex process that introduces significant limitations and overheads during execution. Serialization limits the objects that can be moved off-heap, as it requires self-contained entities without references to and from the managed heap, i.e., only serializable objects [22, 24, 39]. In addition, extracting and recreating the object state requires mechanisms that bypass constructors and ignore class and field accessibility. Performance-wise, traversing the object graph requires effort proportional to the volume of objects in the transitive closure of the root object. Most relevant to our work, S/D generates many temporary objects while transforming objects into byte streams and vice-versa. Temporary objects put more pressure on the heap and lead to more frequent GC cycles. Recent work identifies S/D as a significant performance bottleneck in big data analytics frameworks [35, 36, 42, 44].

3 TeraHeap Design

3.1 Overview

The key idea of TeraHeap is to extend the JVM to use a second, high-capacity managed heap (H2) over a fast storage device that coexists with the regular managed heap (H1). TeraHeap manages the two heaps differently and hides their heterogeneity, providing the abstraction of a large homogeneous managed heap to big data applications. We design TeraHeap based on our observations about objects and their management in big data analytics frameworks.

Which objects to move to H2 and when? We observe that different managed big data frameworks maintain off-heap stores to move specific objects that are long-lived and are reused across computation stages. Also, these objects differ in their update patterns. For example, Spark only moves immutable objects off-heap, Giraph moves objects that are *eventually* immutable. Such objects are those that, once immutable, are reused by later computation stages.

We provide a novel hint-based interface based on key-object opportunism [25] to identify specific objects to move to H2. These objects are ones that frameworks move off-heap. Frameworks use our interface to (1) tag with a label the root key object appropriate for placement in H2 and (2) advise *TeraHeap* when to move objects in H2. Decoupling the selection of the candidate objects from their transfer to H2 enables *TeraHeap* to be framework agnostic. These hints are translated into two native function calls at runtime. Our hint-based interface works at the framework level and is transparent to applications written on top of such frameworks, requiring minimal user effort. We provide more details in §3.2.

How to reclaim dead objects in H2 without GC scans? Scanning the storage-backed H2 for liveness analysis and compacting objects for space reclamation incurs a high GC overhead due to excessive device I/O traffic. TeraHeap reduces the high GC overhead by organizing H2 in virtual memory as a region-based heap. Each region hosts object groups with similar lifetimes to reclaim dead objects in bulk. We observe that analytics frameworks, such as Spark and Giraph, organize groups of objects in data structures, such as array with a single-entry root reference (key objects). Most objects that are reachable by root key-objects exhibit a similar lifetime.

*TeraHeap* leverages the high capacity of NVMe SSDs to resolve the space-performance tradeoff differently than existing work [20, 37]. Current works target DRAM-backed heaps and focuses on freeing address space eagerly by scanning regions and moving live objects with cross-region references to other regions. However, *TeraHeap* reclaims H2 space lazily with low overhead by freeing whole regions and their objects in bulk. To ensure memory safety while reclaiming dead H2 regions, *TeraHeap* must take into account forward (H1 to H2) and cross-region references (details in §3.3).

TeraHeap architecture: At a high level, TeraHeap uses two heaps as shown in Figure 1: regular heap (H1) and second, high-capacity heap (H2). Unlike DRAM-backed H1, H2 is memory-mapped over a storage device, allowing direct access to deserialized objects without S/D. Memory-mapped I/O eliminates the need to use a custom reference lookup mechanism in the JVM to identify objects on the device, as the OS virtual memory mechanism performs this translation. Also, to identify references from H2 to H1, *TeraHeap* uses a card table optimized for storage-backed heaps (details in §3.4).

We have designed TeraHeap to be agnostic to the specific
device that backs H2. However, the intention is to map H2 over fast storage devices, either block-addressable NVMe SSDs or byte-addressable NVM. Such devices are amenable to memory mapped I/O due to their high throughput and low latency for small request sizes (4 KB) regardless of the access pattern [40]. NVMe SSDs are particularly attractive as datasets grow because they provide high density (capacity) and lower cost per bit compared to DRAM and NVM [47].

Next we discuss how TeraHeap solves the three main challenges related to: (1) identifying and moving candidate objects to H2, (2) reclaiming dead objects in H2 without GC scans and I/O traffic, and (3) tracking backward references (H2 to H1) with low GC cost and I/O overhead.

3.2 Identifying and Moving Candidate Objects to H2

TeraHeap provides a hint-based interface, enabling frameworks to tag root key-objects with a label for H2 movement. For the tagging operation of H2 candidate objects, we add a new field (eight bytes for alignment purposes) in the Java object header. Avoiding the extra field requires additional JVM book-keeping and meta-data, increasing GC time. The TeraHeap interface consists of the following function calls.

\[ h_2\_tag\_root(obj, \text{label}) \] The framework uses \( h_2\_tag\_root() \) to tag a root key-object with a label.

\[ h_2\_move(label) \] The framework uses \( h_2\_move() \) to advise TeraHeap to move all objects with specified label to H2. During the next major GC, the garbage collector marks objects in the transitive closure of the root key-object with the label. Typically, frameworks can use \( h_2\_move() \) once their object group becomes immutable, however, immutability is not a strict requirement for movement to H2 and partly depends on storage device characteristics [27]. For instance, in Spark, all objects can be moved when marking the root key-object, whereas, in Giraph, objects are best moved at the end of each computation stage, possibly much later than when marking the root key-object.

Delaying the move to H2 runs the danger of creating out-of-memory errors because H1 may fill before \( h_2\_move() \) is called. To avoid this, TeraHeap monitors the space that live objects occupy at the end of each major GC. If the live objects occupy more space in H1 than a high threshold (e.g., 85% of H1), TeraHeap will move marked objects to H2 during the next major GC without waiting for \( h_2\_move() \).

At this point, if TeraHeap moves all marked objects to H2, it may incur excessive device traffic, e.g., in case some of these objects may be updated frequently prior to the application using \( h_2\_move() \). To mitigate this effect, TeraHeap uses a low threshold mechanism as well, which limits how many marked objects will move to H2 when TeraHeap detects high H1 pressure prior to seeing an \( h_2\_move() \) hint. In our evaluation, we examine the alternative of not using the \( h_2\_move() \) and relying only on the high-low threshold mechanism.

TeraHeap moves all objects with the same label in the same H2 region until it exhausts the region space to reclaim them en masse. However, the transitive closure might include JVM metadata objects and specialized objects which have a longer lifetime than the rest of the objects in the closure. These objects can extend the region’s lifetime, preventing free operations in H2. Thus, TeraHeap excludes from moving to H2: (1) JVM metadata from the transitive closure, such as class objects [4] and the class loader, and (2) specialized objects that inherit \texttt{java.lang.ref.Reference} class [9].

TeraHeap moves marked objects from H1 to H2 during major GC. The main overhead of TeraHeap for major GC is the transfer of objects from H1 to H2. To reduce this cost, TeraHeap uses explicit asynchronous I/O. We avoid multiple system calls for small-sized objects (<1 MB), using a promotion 2 MB buffer per region in H2 that writes objects to the device in batches.

3.3 Reclaiming Dead Regions

Figure 2 shows the region-based organization of H2 in virtual memory and each region metadata in DRAM. We do not impose any restrictions on regions, allowing objects in any region to refer to each other. TeraHeap ensures that while reclaiming a region, none of the objects in the region are referenced from live H1 objects or live H2 objects in other regions. To find such regions, TeraHeap tracks cross-region and forward references without scanning H2 objects, which would generate excessive I/O.

\[ \text{Cross-region references in H2:} \] To allow internal H2 references across regions, TeraHeap tracks the direction of cross-region references. As shown in Figure 2, TeraHeap keeps a dependency list in per-region metadata in DRAM. Each node of the dependency list points to a (different) region referenced by objects of the current region. When we move objects to H2 we check if they have references in existing H2 regions. Then, the H2 allocator adds a new node (if it does not exist) to the dependency list of the region where objects will be moved. The size of dependency lists is small, on average 10 nodes...
Forward references (H1 to H2): TeraHeap avoids scanning H2 objects by fencing the garbage collector from crossing into H2 from H1. This requires identifying all references from H1 to H2 and marking the referenced H2 objects as alive. TeraHeap uses a LIVE bit in the per-region metadata (Figure 2) that signifies the objects in the region are reachable from H1. The garbage collector clears LIVE bits at the beginning of the major GC. Upon encountering a reference from an object in H1 to an object in H2, the collector sets the corresponding region bit. If the dependency list of the current region is not empty, then we traverse the dependency lists of each dependent region recursively, setting their LIVE bits, as well.

Freeing dead regions: At the end of major GC, any H2 region not marked as LIVE is not reachable from any H1 object nor any H2 regions. To free these dead regions, we set their allocation pointer to zero, and delete their dependency list (Figure 2). We note that upon JVM shutdown, we free all H2 metadata in DRAM.

3.4 Tracking Backward References (H2 to H1)

Fencing GC scans in H2 further requires tracking backward references from H2 to H1, as the garbage collector must not reclaim H1 objects referenced by live H2 objects. The key difficulty is that H2 objects can reference objects in both H1 generations and need to be tracked differently. Young objects in H1 change location during minor GC while old objects move only during major GC.

Scanning H2 to identify backward references may incur significant overhead, depending on the size of H2 and its backing device. Instead, we use an extended card table for H2, optimized for use with storage devices. The H2 card table is a byte array (in DRAM) with one byte per fixed-size H2 segment (similar to vanilla JVM). Although using a remembered set provides more precise information about backward references, it increases memory consumption for regions with many references, especially as H2 size grow with storage device capacity. It also requires a more elaborate and expensive post-write barrier [19].

Setting H2 card states: We expect H2 to be much larger than H1. Thus, we increase the size of H2 card segments to reduce the number of cards and the card scanning overhead during collections. However, larger card segments require scanning more objects, in case they are dirty, introducing device I/O. To reduce the number of objects scanned during minor GC, we avoid scanning H2 objects that only reference objects in the old generation of H1. In minor GC, the collector does not move or reclaim objects in the old generation. Thus, we design an H2 card table where each card entry is in one of four states: (1) clean, when there are no backward references, (2) dirty, indicating object update by mutator threads, (3) youngGen, indicating references only to the young generation, or (4) oldGen, indicating references only to the old generation.

When an application thread updates an H2 object, TeraHeap marks the corresponding H2 card as dirty in the post-write barrier. During GC, we change the card value from dirty to OldGen if objects in the dirty card segment only reference objects in the old generation. Otherwise, we change the card value to YoungGen. We set the card value as clean only if there are no backward references in the card segment. In minor GC, we only scan the objects in the card segments whose cards are marked as dirty or youngGen. In major GC we also scan oldGen objects. We adjust all backward references in both minor and major GC to refer to the new H1 object locations.

Scanning H2 card table: GC is multithreaded, and therefore, the H2 card table must support concurrent access from multiple threads without synchronization. We divide H2 into slices to avoid contention between GC threads. Each slice contains a number of fixed-size stripes equal to the number of GC threads. Each GC thread processes the stripe with the same Id within each slice. Therefore, each GC thread operates on the same stripe Id in all H2 slices.

We have to solve the access to the boundary (first and last) cards in each stripe. Objects may span card segments and stripe boundaries. Given that a separate GC thread processes each stripe, two threads may need to access each boundary card. To avoid thread synchronization, the garbage collector can avoid cleaning the boundary cards. If boundary cards become dirty, they can remain dirty throughout execution. However, in every GC, the garbage collector should scan the corresponding card segments for objects with backward references. This drawback is a significant issue for H2 because (1) we use large card segments to reduce H2 card table size,
and (2) the card segments are mapped to a storage device, which results in high I/O traffic when scanning objects.

*TeraHeap* resolves the problem of the dirty boundary cards by aligning objects to stripes and guaranteeing that no two threads will need to access the same card. *TeraHeap* uses a larger stripe size equal to the H2 region size because the *TeraHeap* guarantees that objects do not span H2 regions.

## 4 *TeraHeap* for Parallel Scavenge GC

We implement *TeraHeap* in OpenJDK8 (jdk8u345) which is a long-term-support (LTS) version, extending the Parallel Scavenge (PS) garbage collector and export *TeraHeap*’s interface through the `sun.misc.Unsafe` class to frameworks. PS is a generational garbage collector which divides its heap into young and old generations. Next, we discuss our extensions in (1) the post-write barriers in interpreter and just-in-time (JIT) compilers, (2) minor GC, and (3) major GC.

**Post-write barriers:** PS uses a post-write barrier and a card table to track updates in old generation objects that generate references to young objects. Such updates may originate from interpreted or JIT compiled methods with the C1 and C2 JVM compilers. When a mutator thread updates an object in the old generation, this operation is followed by the post-write barrier that updates the corresponding entry in the H1 card table.

To examine if the mutator thread updates an object that belongs to H1 or H2, we use an additional range check in the post-write barrier code. We extend post-write barriers by augmenting the template-based interpreter and the JIT compilers to generate assembly code for the necessary checks, guarded by the `EnableTeraHeap` flag. We evaluate the overhead of our modifications to post-write barriers using the DaCapo benchmark suite [14]. The overhead is small and within 3% over total execution time on average across all benchmarks. The extra overhead is zero for applications that do not set `EnableTeraHeap`.

**Minor GC:** In minor GC, we perform two key tasks during liveness analysis: (1) fence PS from scanning objects in H2 and (2) prevent reclamation of H1 objects referred from H2 objects (backward references). For the first task, we introduce an additional reference check in the liveness analysis to fence PS from scanning references that cross from H1 to H2. We scan the H2 card table for the second task to identify and update backward references and the H2 card state.

**Major GC:** The major GC in PS is divided into four main phases. In the first phase (*marking*), PS recursively scans both generations starting from roots (e.g., thread stacks, global variables, registers) and marks live objects. We extend the *marking* phase to perform five extra tasks. At the beginning of the marking phase, we reset all LIVE bits of the H2 regions metadata. We mark all objects in H1 that are referenced by H2 as live. We add a reference range check (similar to minor GC) that detects forward references (H1 to H2) to fence the PS from scanning objects in H2 and sets the LIVE bit of the corresponding region. We identify the root objects tagged with a label through *TeraHeap* interface and calculate their transitive closure. At the end, we free all dead regions in H2.

PS assigns a new memory location to each live object in the second phase of major GC (*pre-compaction*). We extend this phase to identify which objects discovered in the *marking* phase should be moved in H2. We assign these objects an address from H2 using their label.

During the third phase (*pointer-adjustment*), PS adjusts the references of each object to point to new object locations. We extend this phase to perform two tasks, update cross-region references and backward references. We detect cross-region references when we adjust the references of newly marked H1 objects that are candidates for H2 transfer by checking if they reference existing H2 regions. This task is performed solely when the objects are still in DRAM. *TeraHeap* scans objects for backward references also when they reside in DRAM and before they are moved to H2. If we detect an object with backward reference, we mark only the corresponding H2 card as dirty. Finally, in the fourth phase (*compaction*), PS moves objects to their new locations in H2.

## 5 Applications of *TeraHeap*

In this section, we describe how we use *TeraHeap* in two widely used frameworks, Spark [54] and Giraph [43]. Note that Spark and Giraph differ significantly in how they use off-heap memory. Spark uses off-heap memory to cache intermediate results, avoiding expensive recomputation. Cached objects are immutable at allocation time. On the other hand, Giraph offloads mutable objects, i.e., vertices, edges, and messages, to off-heap memory to ensure adequate DRAM is available for each superstep. Giraph updates vertex values throughout the computation, whereas edges and messages become immutable after graph loading (edges) or at the end of a superstep (messages).

Spark users explicitly annotate objects that need to be moved off-heap with the `persist()` call. Giraph transparently selects and moves objects to the storage device without application interaction. It maintains an *out-of-core* scheduler that monitors memory pressure in the managed heap and decides which vertices, edges, and messages to move off-heap. The *out-of-core* scheduler selects based on a Least Recently Used (LRU) policy which objects to move off-heap.

Spark maintains deserialized objects in memory; that incurs significant S/D overhead during the off-heap movement. Giraph tries to reduce memory consumption on the managed
heap and serializes vertices, edges, and messages into byte arrays, at allocation time. Therefore, Giraph does not require S/D when moving these byte arrays off-heap on the storage device. Next, we discuss how we extend Spark and Giraph to use TeraHeap.

**Spark:** Each spark executor logically divides its memory into two main spaces, execution memory for computation and storage memory for on-heap caching of intermediate results. Spark abstracts intermediate results as immutable collections using three sets of APIs [23]: resilient distributed datasets (RDDs) [53], dataframes, and datasets.

Spark requires only slight modifications to use TeraHeap. In Spark we mark all cached partitions of RDDs, Dataframes, or Datasets, as root objects for moving to H2. Figure 3 shows the flow of Spark caching operations using TeraHeap.  

1. The application code invokes persist() without any modifications.  
2. The Spark block manager places the selected data in the compute cache, a hashmap that contains all cached partitions. The Spark block manager caches each partition independently, maintaining per-partition entries in the hashmap. When the Spark block manager stores a new partition in the hashmap, we mark the partition descriptor as a root key-object with the h2_tag_root(), providing as label the RDD, dataset, or dataframe Id. At the same time, we advise JVM to move marked partitions to H2, using h2_move().  
3. TeraHeap transparently marks additional objects and moves them to H2 during the major GC.

**Giraph:** Giraph computes in supersteps, with a synchronization barrier between supersteps. It loads and partitions the graph during the input superstep. A graph partition organizes its vertices in a hashmap, with each vertex belonging to a single partition. Each vertex maintains a map containing its outgoing edges. In each superstep, each vertex consumes all of its incoming messages from the previous superstep and updates its value. Then, it sends its updated value to its outgoing edges in a new message (per vertex). Messages produced in the current superstep are only consumed in the next superstep. Messages become immutable at the end of each superstep after the coordination phase guarantees they have been received and saved completely. Thus, in each superstep, Giraph has two message stores: the incoming message store with messages from the previous superstep (immutable) and the current message store with messages of the current superstep (mutable).

To use TeraHeap, Giraph requires small modifications, as well. We extend Giraph by marking edges and incoming messages as root objects. We do not mark vertices because they have frequent updates, and they will increase device (write) traffic. Note that edges and messages constitute a large portion of the heap [43]. Figure 4 shows the flow of Giraph execution using TeraHeap:  

1. When Giraph loads a new vertex at the input superstep, it marks the vertex’s map that contains the outgoing edges with h2_tag_root(), providing as label the superstep id.  
2. At the end of the input superstep, Giraph advises TeraHeap to move marked edges to H2, using h2_move() in the next major GC.  
3. In each superstep, Giraph marks the generated messages of the current message store with h2_tag_root(), providing as label the superstep id.  
4. At the beginning of each (next) superstep, Giraph advises TeraHeap to move in H2 all marked messages from the previous superstep in the next major GC, using h2_move().

### 6 Experimental Methodology

We answer the following questions in our evaluation:

1. How does TeraHeap perform compared to native JVM?
Table 2: Summary of baselines.

and state-of-the-art Panthera with NVMe SSD and NVM?

2. What are the space requirements of H2?

3. What is the overhead of tracking references and moving objects in H2 during GC?

4. How does TeraHeap scale with increasing numbers of mutator threads and dataset sizes?

Server infrastructure: We evaluate TeraHeap both with block-addressable NVMe SSDs and byte-addressable NVM as the backing device for H2. Table 1 shows the properties of each server. Our NVM server operates in two modes: (1) App Direct Mode uses 192 GB DRAM as main memory and 2 TB NVM as persistent storage device. (2) Mixed Mode partitions NVM to use 1 TB in memory mode and 2 TB in App Direct mode. DRAM (192 GB) acts as a cache for 1 TB NVM controlled by the CPU’s memory controller. In AppDirect mode, the system mounts NVM on an ext4-DAX file system to establish direct mappings to the device.

Baseline and TeraHeap configurations: We run Spark with OpenJDK8, OpenJDK11, and OpenJDK17. We run Giraph v1.2 with Hadoop v2.4 and OpenJDK8, as it does not support more recent versions of OpenJDK. We use two garbage collectors in different configurations: PS in OpenJDK8 and OpenJDK11, and Garbage First (G1) in OpenJDK17. We use an executor with eight mutator threads for both Spark and Giraph. For PS, we use 16 GC threads for minor GC and the default single-threaded old generation GC. G1 uses two parameters: (1) the number of parallel GC threads, which we set to eight (max value), and (2) the number of concurrent (to mutator) threads, which we set to two as the recommended configuration [5] is one-fourth of the parallel GC threads.

Table 2 summarizes the Spark and Giraph configurations we use as baselines. The two Spark-SD configurations place executor memory (heap) in DRAM and cache RDDs in the on-heap cache, up to 50% of the total heap size. Any remaining RDDs are serialized in the off-heap cache, over either NVMe SSD (first line of Table 2) or NVM in App Direct Mode (second line of Table 2). Spark-MO places executor memory (heap) over NVM in Memory Mode, caching all RDDs on-heap. Giraph-OOC places the heap in DRAM and offloads vertices, edges, and messages off-heap to the NVMe SSD.

Table 3: Configuration for each workload on NVMe and NVM servers for Spark-SD, Spark-MO, and TeraHeap.

Table 4: Giraph-OOC and TeraHeap configurations for each workload in NVMe server.

We configure TeraHeap to allocate H1 on DRAM and H2 over a file in NVMe SSD or NVM via memory-mapped I/O (mmio). The file in both NVMe and NVM servers is mapped to the JVM virtual address space where the application can access the data with regular load/store instructions [40]. Our experiments show that machine learning (ML) workloads in Spark access the individual elements of cached RDD partitions sequentially. For this reason, we configure TeraHeap for Spark ML workloads to use huge pages (2 MB) in H2 to reduce the frequency of page faults. Instead of the native mmap, we use HugeMap [33] a custom, open source, mmio path that enables huge pages for file-backed mappings.

In Spark-SD, to capture the effect of large datasets and limited DRAM capacity [18], we use a small heap size that caches a limited number of RDDs on-heap and the rest off-heap (fourth column in Table 3). In Spark-MO we find and use the minimum heap size that fits all the cached data on-heap (fifth column in Table 3). In Giraph-OOC, we experimentally find the minimum heap size for each workload (fourth column in Table 4). TeraHeap uses the same amount of DRAM as Spark-SD and Giraph-OOC but divides the capacity into H1 and DR2 (used for Spark and Giraph drivers and I/O page cache). For the division of DRAM, we explore H1 sizes between 50% and 90% of DRAM capacity, and we report results with a configuration hand-tuned for each workload. We omit exploration results due to space constraints. The sixth column
in Table 3 and Table 4 show the H1 size of TeraHeap in each workload, in Spark and Giraph, respectively. DR2 is always 16 GB for Spark, whereas the fifth and seventh column in Table 4 show the DR2 size for Giraph. We limit the available DRAM capacity in our experiments using cgroups. The second column in Table 3 and Table 4 shows total DRAM capacity in the NVMe server for each workload.

Workloads and datasets: We use ten memory-intensive workloads from the Spark-Bench suite [30] and five workloads from the LDBC Graphalytics suite [26] for Giraph. We synthesize datasets for Spark workloads with the SparkBench data generators. For Giraph workloads, we use the datagen-9_0-fb dataset [7]. The first and the third columns in Table 3 and Table 4 depict the workloads and the dataset size.

Execution time breakdowns and S/D overhead: We repeat each experiment five times and report the average end-to-end execution time. We break execution time into four components: other time, S/D + I/O time, minor GC time, and major GC time. Other time includes mutator threads time. In TeraHeap, the other time potentially includes I/O wait due to page faults when accessing the H2 backing device. In Spark-SD (see Table 2), S/D time includes S/D time both for shuffle and caching. In TeraHeap and Spark-MO (see Table 2), all S/D time is due to shuffling. The JVM reports the time spent in minor and major GC.

To estimate the S/D overhead, which occurs in mutator threads, we use a sampling profiler [3] to collect execution samples from the mutator threads. The samples include the stack trace, similar to the flame graph [21] approach. Then we group the samples for all the paths that originate from the top-level writeObject() and readObject() methods of the KryoSerializationStream and KryoDeserializationStream classes. These samples include both S/D for the compute cache and the shuffle network path of Spark. We then use the ratio of S/D samples to the total application thread samples as an estimate of the time spent in S/D, and we plot this separately in our execution time breakdowns. We run the profiler with a 10 ms sampling interval, verifying that this does not create significant overhead (less than 2% of total execution time).

7 Evaluation

7.1 Performance Under Fixed DRAM Size

First, we investigate the performance benefits of TeraHeap under a fixed DRAM size. Figure 5 shows the performance of TeraHeap compared to Spark-SD and Giraph-OOC for the NVMe SSD setup. We normalize the execution time to the first bar in each figure. Missing bars indicate out-of-memory (OOM) errors.

Using the same DRAM size, TeraHeap reduces execution time in Spark between 18% (SSSP) and 73% (BC) compared to Spark-SD. In Giraph, TeraHeap reduces execution time between 21% (CDLP) and 28% (PR). In both cases, the performance improvement results from reducing the GC overhead, by up to 96% and 54% in Spark and Giraph, respectively. This overhead occurs mainly because cached objects in Spark and messages and edges in Giraph occupy almost half of the heap, triggering GC more frequently. TeraHeap transfers objects to H2, stressing H1 less.

In addition, Tera Heap reduces S/D cost in Spark-SD, between 2% (BC) and 93% (LR), as it provides direct access to deserialized objects in H2. Note that S/D cost in TR and BC for TeraHeap is similar to Spark-SD because the cached data fits in the on-heap cache. In Giraph, the impact of TeraHeap on S/D overhead (part of other) is minimal because Giraph serializes objects in the managed heap as well, and not only as part of moving objects off-heap. Also, in LR, LgR, and SVM other time with TeraHeap increases by up to 43% compared to Spark-SD. These workloads perform streaming access on cached RDDs elements in each iteration of the ML training phase, which is the largest part of the execution (100 iterations). Thus, they do not exhibit locality in the I/O page cache, fetching data from the storage device during the computation. The average read throughput in these workloads is 2.9 GB/s, which is the peak device read throughput. Using more NVMe SSDs can reduce other time for LR, LgR, and SVM.

To examine pressure on the managed heap, Figure 6 shows GC behavior for PR with Spark-SD and TeraHeap with a 64 GB heap. We examine the execution time for each minor and major GC cycle and monitor the percentage of the old generation consumed by cached objects. We note that Spark-SD suffers from frequent major GC cycles. There are 171 major GC cycles, each requiring, on average, 3.7 s. Each cycle in Spark-SD reclaims 10% of the old generation objects (0-3000 s in Figure 6), as the remaining objects are live cached objects. However, TeraHeap performs only 13 major GC cycles. Each cycle in TeraHeap takes, on average, 16 s. More than 70% is due to I/O during the compaction phase of major GC. Finally, moving objects directly from the young generation to H2 reduces total minor GC time by 38% compared to Spark-SD. This reduction is because TeraHeap scans fewer cards that track old-to-young references than Spark-SD. We omit similar results for other workloads due to space constraints.

Reducing DRAM capacity demands: We examine the potential benefit of TeraHeap in reducing DRAM capacity demands in Figure 5. Using between 2× and 8× less DRAM, TeraHeap outperforms by up to 65% (SVD) compared to Spark-SD. In Giraph, TeraHeap with 1.2× less DRAM improves performance between 7% (CDLP) and 18% (PR). For example, using TeraHeap in Giraph-PR, the heap usage in the first phase of the application (0-330 s) is between 70%
Figure 5: Overall performance of TeraHeap (TH) compared to Spark-SD and Giraph-OOC in the NVMe server.

Figure 6: GC time and old generation occupancy in PR for (a) Spark-SD and (b) TeraHeap. Heap size = 64 GB.

and 100%. Then, at the end of the fifth major GC, TeraHeap reduces heap usage to 13% because it moves 17 GB of objects to H2. By reducing memory pressure in H1, TeraHeap with less DRAM can provide similar or higher performance than Spark-SD and Giraph-OOC.

Comparison with newer garbage collectors: We next present the performance of TeraHeap compared to an optimized version of PS on OpenJDK11 and G1 on OpenJDK17.

G1 is a generational, region-based garbage collector which uses concurrent and parallel phases to reduce pause time and to maintain high GC throughput. When G1 determines that a GC is necessary, it collects the regions with the least live data first (garbage first). Figure 7 shows the performance of Spark with PS, G1, and TeraHeap, for the same amount of DRAM. G1 outperforms PS between 7% (LR) and 72% (TC) be-
cause it reduces GC time by up to 95%. However, G1 cannot eliminate the high S/D (up to 44%) caused by the limited DRAM size and the amount of cached data. Unlike G1, TeraHeap eliminates S/D overhead, providing direct access to the storage resident objects. Thus, TeraHeap improves performance between 21% (CC) and 48% (LgR) compared to G1.

Note that G1 cannot run SVM, BC, and RL due to fragmentation problems caused by humongous objects. Humongous objects in G1 are those that are bigger than half of the G1 region size. Such objects are allocated separately in contiguous regions (humongous regions). A humongous region can accommodate only one humongous object. The space between the end of the humongous object and the end of the humongous region, which in the worst case can be close to half the region size, is unused. Therefore, when many long-lived humongous objects exist, G1 exhibits significant fragmentation, resulting in OOM errors. PS resolves fragmentation, performing object compaction when the heap becomes full.

We note that TeraHeap can also be used with G1 to eliminate S/D cost and reduce the amount of data subject to GC, by moving long-lived, humongous objects to H2.

### 7.2 Effects of Transfer Hint and Low Threshold

This section examines the performance effect of using the transfer hint `h2_move()`. Figure 8(a) shows the performance of TeraHeap with and without using `h2_move()`. Frameworks use `h2_move()` to advise TeraHeap when to move objects with a specified label to H2. Note that in case of high memory pressure, TeraHeap moves to H2 all marked objects without waiting for `h2_move()` hints. Given that TeraHeap can use only the high threshold mechanism to decide when to move objects to H2, we explore eliminating `h2_move()`.

| Region Size (MB) | 1  | 2  | 4  | 8  | 16 | 32 | 64 | 128 | 256 |
|------------------|----|----|----|----|----|----|----|-----|-----|
| Metadata Size (MB) | 417 | 209 | 104 | 52 | 26 | 13 | 7  | 3   | 2   |

Table 5: Metadata size per TB of H2 regarding region size.

TeraHeap performance between 29% (SSSP) and 55% (WCC) compared to not using the hint. In WCC, using `h2_move()`, we move objects to H2 on average every 215 s, reducing GC cost by 39% compared to not using the transfer hint, which transfers objects on average every 485 s. Moving objects with frequent updates to H2 increases other time by up to 59% (WCC) due to the large cost of read-modify-write operations on an I/O device. This increases device traffic by up to 98% (writes) due to page-based accesses to the device. Thus, using the transfer hint is necessary to delay moving objects with frequent updates to H2 until they become immutable.

Next, we study how effective is the TeraHeap low threshold mechanism. Figure 8(b) shows TeraHeap performance using `h2_move()` with and without a low threshold. We use a low threshold of 50% (and we leave the high threshold to 85%).

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These two workloads trigger the high threshold mechanism. We use 170 GB DRAM and 200 GB DRAM in PR and SSSP, respectively. The percentage of DR1 over total DRAM is similar to the corresponding workload in Figure 8(a).

Using a low transfer threshold improves TeraHeap performance by up to 44% (SSSP), compared to using only the transfer hint with the high threshold. For example, in SSSP, during graph loading, we detect high memory pressure in the fourth major GC. After the fourth major GC, most objects in H1 are related to marked edges. Then, in the fifth major GC, we move 44 GB of marked objects to H2, reducing H1 usage to 50%. Therefore, the low transfer threshold reduces read-modify-write operations on the device by up to 95%, decreasing the other time by up to 65%. Although there may be benefits in setting the low and high thresholds dynamically, we leave this for future work.

### 7.3 Storage Capacity Consumption

This section investigates the storage requirements of H2. TeraHeap organizes object groups with a similar lifetime in fixed-size regions in H2 and reclaims them in bulk. This approach may result in a waste of space for two reasons. First, when the number of objects in a region is small, unused space in the corresponding region can be large. Second, one live object can keep the entire region alive, preventing TeraHeap from reclaiming it. Generally, a smaller region size reduces both of these factors at the cost of increasing metadata in DRAM.

We first show how the region size affects the metadata size for H2. Table 5 shows the metadata size in DRAM per TB of H2, for region sizes between 1 MB and 256 MB. As we increase the region size from 1 MB to 256 MB, the total
metadata in DRAM decreases from 417 MB to 2 MB.

Figures 9(a) and 9(b) show the CDF of the percentage of live objects per region for all allocated regions with 16 MB and 256 MB size, respectively. Figures 9(c) and 9(d) show the CDF of the percentage of space occupied by live objects for 16 MB and 256 MB regions. The number of allocated regions is equal to the sum of reclaimed regions during execution and the active regions before JVM shutdown. Although not shown in these figures, we observe in our measurements that unused space is between 1% and 3% for all workloads in both region sizes. Essentially, TeraHeap is able to use the space in each region it allocates with its append-only placement.

In Figures 9 (a) and 9(b) all regions with 0% live objects are reclaimed during execution. We see that in PR, CDLP, and WCC, TeraHeap reclaims most allocated regions and around 90% in CDLP and PR for both region sizes. In BFS and SSSP, TeraHeap reclaims 28% and 6% of the total allocated regions, respectively. In BFS and SSSP, although most of the objects in a region are live, most of the space is occupied by large dead arrays. For example, in SSSP with 256 MB regions, in 90% of the regions at least 20% of the objects are live. However, in 45% of the regions, the live objects occupy less than 10% of the allocated region space (Figure 9(d)). In these cases, using 16 MB regions is more appropriate because they reduce by 10% (BFS) the space waste compared to 256 MB regions. We believe that future work can investigate object placement policies for H2 that takes into account object size to further improve space efficiency on storage devices.

Figure 9: CDF of the percentage of live objects (Figures (a,b)) and space occupied by live objects (Figures (c, d)) during execution.

7.4 GC Overhead

The garbage collector in TeraHeap performs additional work during minor GC that involves scanning H2 cards and updating backward references. We evaluate this overhead for different card segment sizes in Giraph. Figure 10(a) shows minor GC time in H2 for 1 KB, 4 KB, 8 KB, and 16 KB card segments, normalized to 512 B card segments. We see that increasing the size of card segments from 512 B to 16 KB reduces minor GC time on average by 64%. Larger card segments result in a smaller card table, and less time is required to scan the respective cards. However, increasing card segment size increases the cost of scanning each card segment if the respective card is marked as dirty. For example, increasing the card segment size in PR from 512 KB to 16 KB leads to an increase in minor GC time for scanning and update H2 objects with backward references (H2 to H1) by 5×. In Spark, updates to H2 objects are infrequent compared to Giraph, as RDDs are immutable.

Next, we examine the overheads introduced by TeraHeap during major GC for H1 by moving objects to H2, which involves device I/O when using SSDs as the backing device. Figure 10(b) shows the four phases of major GC time using Giraph-OOC (OC) and TeraHeap (TH). Overall, TeraHeap improves all phases of major GC by up to 75% (BFS) compared to Giraph-OOC because we avoid scanning H2 objects. For example, in PR, the collector avoids following in each GC, on average, note that the compaction phase takes between 37% and 44% of the major GC time in Giraph-OOC (OC) and TeraHeap (TH). We present only Spark-SD, Spark-MO, and TeraHeap in our NVM-based setup. We present only Spark workloads due to space constraints. Our goal is to examine the benefits of TeraHeap when using NVM to increase the heap size, which can eliminate S/D at increased GC cost for native. Figure 11(a) shows that TeraHeap improves per-
formance by up to 79% and on average by 56%, compared to Spark-SD. Unlike the off-heap cache in Spark-SD, TeraHeap allows Spark to directly access cached objects in H2 via load/store operations to NVM, without the need to perform S/D. TeraHeap significantly reduces S/D and GC time compared to Spark-SD by up to 97% and 93%, respectively.

Figure 11(b) shows that TeraHeap improves performance by up to 86% and on average by 48%, compared to Spark-MO. The main improvement of TeraHeap results from the reduction of minor GC and major GC time by up to 88% (on average by 52%) and 96% (on average by 46%) compared to Spark-MO, respectively. In Spark-MO, running the garbage collector on top of NVM (using DRAM as a cache) incurs high overhead due to the latency of NVM [51] and the agnostic placement of objects. For instance, minor GC time in Spark-MO increases on average by 36% compared to Spark-SD (Figure 11b) because objects of the young generation are placed in NVM, resulting in higher access latency for the garbage collector. Unlike TeraHeap that controls object placement in NVM (H2), Spark-MO relies on the memory controller to move objects between DRAM and NVM. We measure that Spark-MO incurs on average 5.3× and 11.8× more read and write operations to NVM compared to TeraHeap, resulting in higher overhead. Thus, the ability to maintain separate heaps allows TeraHeap to both limit GC cost and reduce the adverse impact of the increased NVM access latency on GC time.

We also compare TeraHeap with Panthera [46]¹, a system designed to use NVM as a heap in Spark. Panthera extends the managed heap over DRAM and NVM, placing the young generation in DRAM and splitting the old generation into DRAM and NVM components. We configure Panthera as Wang et. al [46] report: We use a 64 GB heap, 25% on DRAM (16 G), and 75% on NVM. We set the size of the young generation to $\frac{1}{2}$ (10 GB) of the total heap size and place it entirely on DRAM. We set the size of the old generation to the rest of the heap size (54 GB) and place 6 GB on DRAM and the rest (48 GB) on NVM. We configure TeraHeap to use an H1 of 16 GB and map H2 to NVM. Thus, both systems use the same DRAM and NVM capacity.

Figure 11(c) shows that TeraHeap improves performance between 7% and 69% compared to Panthera across all workloads. Panthera bypasses the allocation of some objects in the young generation, allocating them directly to the old generation. However, each major GC still scans all objects in the old generation, which increases overhead as the heap address space grows. Instead, TeraHeap reduces the address space that needs to be scanned by the garbage collector. Note that Panthera increases the accesses to NVM because it allocates mature long-lived objects that are highly read and updated by the mutator threads. Specifically, it increases other by up to 53% because it performs more NVM read (up to 54×) and NVM write (up to 51×) operations, than TeraHeap.

7.6 Performance Scaling

A benefit of TeraHeap is that it allows increasing the number of mutator threads in Spark and Giraph executors. In both Spark and Giraph, each mutator thread processes a separate partition. Thus, as the number of threads in the executor increases, the object allocation rate increases, leading to higher GC cost. Figure 12(a) shows the performance of CC, LR,

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¹ As Panthera is not publicly available, we are thankful to the authors for providing us their code.
and CDLP (other workloads show similar behavior) using Spark-SD, Giraph-OOC, and TeraHeap (TH) with 4, 8, and 16 threads, normalized to 8 threads per configuration. We note that Giraph-OOC with four threads results in an OOM error. TeraHeap allows applications to scale performance further to 23% with 2× more threads. However, Spark-SD does not scale beyond 8 threads in LR because GC cost increases (by 44%), eliminating any benefits from using more threads. We note that increasing the number of threads in Spark-SD reduces S/D cost by up to 55% (CC) because Spark parallelizes the S/D process. Although Giraph-OOC (native) improves performance by 10% using 16 executor threads, it still performs 1.4× more major GCs than eight executor threads. Finally, TeraHeap significantly alleviates memory pressure by moving a large portion of H1 objects to H2, leaving more room for mutator threads to work without the need for frequent GC.

We also investigate the performance benefits of TeraHeap for a larger dataset in Figure 12(b). We observe similar (CDLP) or higher improvements (CC, LR) compared to the smaller datasets. TeraHeap is robust to different dataset sizes and improves performance by up to 70% compared to Spark-SD and Giraph-OOC, while our expectation is that benefit will increase further as dataset size increase.

8 Related Work

TeraHeap combines techniques from several areas, including memory management and storage. Thus, we group the related work in the following categories: (1) region-based memory management, (2) scaling managed heaps beyond DRAM, and (3) mitigating S/D overhead.

Region-based memory management: Managed big data frameworks have started to use region-based memory management for large heaps. Facade [38] provides a compilation framework that transforms programmer-specified classes for off-heap allocation. However, it increases the programmer’s effort because they need to specify when to free objects from native memory. Broom [20] uses region annotations but requires refactoring of applications’ source code. Yak [37] requires programmers to annotate epochs in applications. Yak allocates all objects in an epoch on a second region-based heap to reduce GC time. The epoch abstraction is appropriate for the map-reduce programming pattern. However, it cannot handle objects computed lazily or accessed from arbitrary program locations. Deca [31] proposes lifetime-based memory management for Spark. However, their work only applies to Spark and cannot be used for other frameworks. Unlike prior work, TeraHeap requires adding hints only in the framework layer. Then, TeraHeap dynamically selects all appropriate objects in the transitive closure of root objects. NG2C [17] uses runtime profiling to identify long-lived objects. They incur online profiling overhead. Others use offline allocation site profiling to manage objects [15, 16]. Lifetime profiling complements TeraHeap, further improving efficiency.

Scaling managed heaps beyond DRAM: Recent efforts target NVM for storing managed heaps beyond DRAM. Akram et al. [11, 12] focus on improving NVM write endurance. Yang et al. [52] report high GC overhead with NVM-backed volatile heaps and optimize the G1 GC for Intel Optane persistent memory. Panthera [46] extends the managed heap over hybrid DRAM and non-volatile memory (NVM) to scale on-hep caching in Spark. Panthera increases GC overhead as scanning and compactions on the managed NVM heap costs more than collecting the DRAM heap. Also, TMO [47] monitors application DRAM usage and transparently offloads cold data to NVMe SSD. Unlike these works, TeraHeap control which objects to move to the second heap and eliminates slow GC traversals over objects on NVM or NVMe SSD.

Mitigating S/D overhead: Several libraries [2, 6, 8] improve the efficiency of S/D, but they cannot reduce high GC cost in big data frameworks. Skyway [36] reduces the S/D cost by directly transferring objects through the network in distributed managed heaps, but it does not cope with DRAM limitations and GC overheads. SSDStreamer [13] is a userspace SSD-based caching system that uses DRAM as a stream buffer for SSD devices. Although SSDStreamer reduces S/D cost by providing a lightweight serializer, it cannot reduce GC cost and the memory pressure in the managed heap. Recent work [28,41] reduces S/D overheads in analytics frameworks using custom hardware and modifications to the programming model. Other works [42,44,48] focus on reducing S/D cost by reducing the number of object copies across buffers. This body of work does not mitigate directly GC overhead. TeraHeap is the first work that eliminates both GC and S/D in big data analytics frameworks. TeraHeap works on commodity hardware and uses load/store instructions to access objects in the second heap without data serialization.

9 Conclusions

Managed big data analytics frameworks demand large managed heaps as datasets grow. This work proposes and evaluates TeraHeap, which extends the JVM to use a transparent, high-capacity heap over a fast storage device alongside the regular heap, reducing memory pressure. TeraHeap reduces GC overhead and eliminates S/D cost by fencing the collector from scanning the second heap and providing direct access to objects on the second heap. We find that TeraHeap improves the Spark and Giraph performance by up to 73% and 28%, respectively. Overall, our proposed approach of managing large memory in the JVM as customized, separate heaps is a promising direction for incorporating huge address spaces in
managed environments and reducing memory pressure without incurring high GC overhead.

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