Abstract

Byte-addressable persistent memories (PM) has finally made their way into production. An important and pressing problem that follows is how to deploy them in existing datacenters. One viable approach is to attach PM as self-contained devices to the network as disaggregated persistent memory, or DPM. DPM requires no changes to existing servers in datacenters; without the need to include a processor, DPM devices are cheap to build; and by sharing DPM across compute servers, they offer great elasticity and efficient resource packing.

This paper explores different ways to organize DPM and to build data stores with DPM. Specifically, we propose three architectures of DPM: 1) compute nodes directly access DPM (DPM-Direct); 2) compute nodes send requests to a coordinator server, which then accesses DPM to complete a request (DPM-Central); and 3) compute nodes directly access DPM for data operations and communicate with a global metadata server for the control plane (DPM-Sep). Based on these architectures, we built three atomic, crash-consistent data stores. We evaluated their performance, scalability, and CPU cost with micro-benchmarks and YCSB. Our evaluation results show that DPM-Direct has great small-size read but poor write performance; DPM-Central has the best write performance when the scale of the cluster is small but performs poorly when the scale increases; and DPM-Sep performs well overall.

1 Introduction

After year’s of research, engineering, and commercializing efforts, persistent memory (PM), non-volatile memories that can be attached to the main memory bus, is finally coming to market [27, 29]. As promised, PM can be accessed like memory and it offers persistence, high density, and performance that is orders of magnitude faster than flash. It has the potential to significantly improve the efficiency and reduce the cost of large-scale data-intensive applications. An immediate question that follows is how to utilize PM and deploy it in existing datacenters.

We believe that a promising approach is to directly attach PM to the network to form disaggregated persistent memory, or DPM. A DPM device only needs a network interface, a hardware PM controller, and some PM; it requires no server packaging or any processors. Datacenters owners can use normal servers as compute nodes (CNs) and store data in DPM.

The DPM model offers several key benefits. First, unlike the alternative approach of attaching PM to a server, DPMs can be integrated into current datacenters without any disruption to existing servers. Second, without the need for a processor or a server to host DPM, the monetary and energy cost of DPM is low. Third, multiple CNs can share one DPM device and one CN can store data on multiple DPMs. Doing so enables better resource packing than attaching and confining the usage of PM to a single node [4, 14, 22, 23, 42]. Fourth, the DPM model offers great elasticity, since DPMs can be freely added, removed, and replaced. The amount of CNs and DPMs can scale independently. Finally, although accessing DPMs involves network communication, this cost is becoming lower as datacenter network speed improves quickly [43, 61].

Despite its benefits, the DPM model presents new challenges. Without any processing power, accesses to DPMs have to come all from the network, or one-way. DPMs cannot perform any management tasks of its own memory resources. Finally, each DPM can fail independently from CNs or other DPMs. These unique issues of DPMs have not been addressed in traditional distributed storage or distributed memory systems.

To confront the challenges and to explore the design tradeoffs of the DPM model, we propose three architectures of organizing DPMs (Figure 1(b) to 1(d)). The first architecture, DPM-Direct, lets CNs directly access DPMs with one-way operations. This architecture is cheap to build. With a fully-distributed architecture, DPM-Direct avoids any throughput bottleneck. However, it is hard and costly to synchronize concurrent accesses to DPMs from multiple CNs [32]. It is also difficult for CNs to manage memory resources in DPMs.

The second architecture, DPM-Central, uses a central server (the coordinator) to orchestrate the accesses from CNs to DPMs and to manage DPM resources. CNs can talk to the coordinator with two-way communication (e.g., through RPC); the coordinator orchestrates concurrent CN requests and issues one-way accesses to DPMs. The coordinator also stores all metadata and performs metadata operations locally. Having a central point of the coordinator makes it easy to manage DPMs and to coordinate concurrent requests, but the coordinator can become the performance bottleneck.

To remedy the performance and scalability limitations of DPM-Direct and DPM-Central, we propose a third architecture, DPM-Sep. The main idea of DPM-Sep is to separate the data plane from the control plane. On the data plane, CNs directly access DPMs. On the control plane, we use a metadata server (MS) to handle all metadata operations and manage DPM resources. CNs talk to the MS with two-way communication to
fetch or update metadata. The MS makes it easy and more efficient to perform control plane tasks, while not being the performance bottleneck on the data path.

Based on these three architectures, we designed three atomic, crash-consistent DPM data store systems. All these systems provide the same guarantees that when writing to a data entry, the data entry either has all new data (if the write is successfully committed) or all old data (if the write fails), and that CNs only read committed data (i.e., the read-committed isolation level). These properties hold even when a DPM crashes during the write and recovers afterwards.

On top of the DPM-Direct architecture, we built a data store, DirectDS. To best fit DPM-Direct and provide good performance, we designed DirectDS with two principles: reducing network round trips (RTTs) between CNs and DPMs and avoiding frequent DPM management tasks or metadata modifications. DirectDS uses two spaces for each data entry, one to write uncommitted new data and one to store committed data. Doing so avoid the need for space allocation after a data entry is created. DirectDS protects each data entry with a lock stored in DPM and accessed with one-sided RDMA operations. We employ techniques like error-detecting code to further reduce RTTs.

On top of DPM-Central, we built CentralDS. CentralDS leverages the centralized coordinator to perform space management, to store metadata, and to serve as the serializing point for concurrent accesses. CNs send RPC read/write requests to the coordinator, which uses lock to protect concurrent accesses, reads/writes data to DPM, and updates metadata locally.

On top of DPM-Sep, we built SepDS. On the data path, SepDS performs out-of-place writes that are similar to log-structured writes. We use a novel data structure that enables CNs to efficiently locate the latest data entry without the need to communicate with the MS. For the control path, the MS stores all metadata and CNs caches hot metadata. We move all metadata operations off performance critical path. To minimize the need for CNs to communicate with MS, CNs perform lazy, asynchronous, batched reclamation of old data entries. We also completely eliminate the need for the MS to communicate with DPMs; it manage DPM space without accessing them.

To sustain non-transient DPM failures, it is not enough to store data in just one DPM. For each of the three systems, we added the support of replication on top of our single-copy designs. We also utilize the data redundancy to provide better load balancing for reads — we dynamically choose which DPM to replicate data to based on the loads of each DPM.

We evaluated the three DPM data stores using real servers as CNs, the coordinator, the MS, and DPM devices, all connected with RDMA. We emulate PM using DRAM on real machines; we perform RDMA read to ensure that data is written to the PM in DPMs [60]. We perform a systematic, extensive set of experiments to evaluate the latency, throughput, scalability, network traffic, and CPU utilization of the three DPM data stores using microbenchmarks and YCSB workloads [12, 71]. Our evaluation results not only confirm findings that are easy to deduce from system designs (e.g., that CentralDS scales poorly with CNs and DPMs and that the performance of SepDS is overall the best), but also reveal more subtle findings (e.g., that DirectDS only scales well when there is no contention of concurrent accesses and that SepDS’s good performance rely on CNs being able to cache hot metadata). Based on our findings, we summarize the tradeoffs of the three DPM data stores in Table 1.

This paper makes the following contributions.

- We propose and compare three DPM architectures.
- We built three DPM data stores. As far as we know, these are the first set of publicly-described and publicly-available DPM systems.
- We provide a detailed design to demonstrate how to best separate data plane and control plane under the DPM model.
- We performed extensive evaluation and learned a set of new findings that can guide future DPM research.

The source code of all our DPM systems will be publicly available soon.

## 2 Using PM in Datacenters

Non-volatile memory technologies such as 3DX-point [28], phase change memory (PCM), spin-transfer torque magnetic memories (STTMs), and the memristor provide byte addressability, persistence, and latency that is within an order of magnitude of DRAM [25, 36–38, 46, 56, 62, 70]. NVMs can attach directly to the main memory bus and we call such NVMs Persistent Memory or PM in this paper. PM is a disruptive technology poised to radically alter the landscape of memory and storage technologies. It has attracted extensive amount of research efforts over the past year, most of which were designed for single-node environments [10, 11, 15, 17, 35, 45, 51, 54, 66, 68].

Despite of these successful prior research efforts, there are at least two remaining challenges to be solved before PMs can be readily used in datacenters. First, in datacenter environments, PMs should support distributed applications. When using PMs to store persistent data, they have to provide high availability and
reliability (i.e., sustain node failures). Unfortunately, there are only limited work in the distributed PM research space [41, 59, 73]. So far, distributed PM systems [41, 59] have all taken a model where each node in a cluster includes some amount of PM used to store data that can be accessed both locally and by other nodes (Figure 1(a)).

Second, it is not clear how to deploy PMs in existing datacenters. The distributed PM model requires PM to be integrated into existing servers or purchasing new servers to host PM. Since PMs attach to the main memory bus, only when existing servers have empty DIMM slots will they be able to host PM. On the other hand, purchasing new servers just to host PM can waste other resources in the new servers. Moreover, applications that desire to use PM can only run on these new servers.

With these challenges, we believe that we should seek new ways to use and deploy PM in datacenters that are flexible, cost-effective, reliable, and can perform well.

3 Disaggregated PM

Similar to disaggregated memory [39, 40] and other resource disaggregation systems [3, 24, 58], disaggregated PM is an architecture that attaches PM devices directly to the network and lets servers (CNs) access them across the network. These PM devices do not have any local processing units and only have a hardware controller and a network interface (we simply call a disaggregated PM device a DPM in this paper). The DPM model organizes DPMs as a pool of PM resources that can be used by any CNs. A CN can store data on multiple DPMs and one DPM can host data for multiple CNs.

The DPM model offers a cost-effective way to deploy PM in datacenters. Without any processor or machine packaging, DPMs are cheap to build. They can easily integrate into existing datacenters without disruption to existing servers. The DPM model also shares many benefits with other resource disaggregation proposals [20, 58]: it offers high resource packing efficiency, since data can be allocated at any DPM; datacenters can grow DPMs independent from other servers; it is easy to add, remove, and upgrade DPMs, and DPMs can fail independently without affecting other servers.

However, building an efficient DPM data store system is not easy. A major technical hurdle is the complete lack of computation power at DPMs. Different from traditional distributed storage and memory systems, DPMs can only be accessed and managed from remote. It is especially hard to provide good performance with concurrent data accesses. In addition, DPMs can fail independently and such failures have to be handled properly to ensure data reliability and high availability.

4 DPM Data Stores

This section first describes the interface of all our DPM data stores and their common features. We then present the three data stores, DirectDS, CentralDS, and SepDS. Finally, we discuss failure handling and load balancing in these data stores.

4.1 System Interface and Overview

To confront the challenges of DPM, we propose three architectures of DPM and built three data stores on top of these architectures. Figure 2 illustrates the read and write operation flow of these systems and Table 1 summarizes the tradeoffs of these systems. We will explain Figure 2 and Table 1 in detail in §4.2 to §4.4.

**Interface and guarantees.** The current data model that our three data stores support is a simple key-value store, but these systems can be extended to other data models. Users can create, read (get), write (put), and delete a key-value entry. Different CNs can have shared access to the same data. We manage the consistency of concurrent data accesses in software instead of relying on any hardware-provided coherence like [8, 21, 50].

All our DPM data stores ensure atomicity of an entry across concurrent readers and writers. A successful write indicates that the data is committed (atomically), and reads only see committed value. We choose single-key atomic write and read committed because these consistency and isolation levels are widely used in many data store systems and can be extended to other levels.

Since our DPM systems store persistent data, it is important to provide data reliability and high availability. Our DPM systems guarantee the consistency of data when crashes happen. After restart, each data entry is guaranteed to either only have new data values or old...
Table 1. Comparison of DPM Data Stores. The Cost column represents energy and monetary cost to build respective DPM data stores. The R-RTT and W-RTT(rep) columns show the number of RTTs required to perform a read and a write (with replication). All RTT values are measured when there is no contention. The Scalability column shows if a system is scalable with the number of CNs, the number of DPMs, both, or neither. † only scalable when there is no contention. The data and metadata columns show the space needed to store a data entry and its metadata. * under common scenario where reclamation can keep up with the speed of foreground write.

| System    | Cost | R-RTT | W-RTT(rep) | Scalability | Data | Metadata | Performance                       |
|-----------|------|-------|------------|-------------|------|----------|-----------------------------------|
| DirectDS  | low  | 3     | 6(6)       | w/ DPF†     | large| large    | OK write performance when no contention |
| DirectDS-C| low  | 1     | 6(6)       | w/ DPF†     | large| large    | Best for small-sized read, not good otherwise |
| CentralDS | high | 2     | 3(3)       | Neither     | small| small    | Best for small-scale writes, not good for reads |
| SepDS     | low  | 1     | 3(4)       | w/ both     | small*| medium   | Good overall when CNs can cache hot metadata |

The only distributed coordination across CNs needed in DPM-Direct is during the creation and deletion of a key-value entry. We currently use Memcached [19] as a metadata server to assist entry creation and delete, but other distributed consensus systems can also work.

Figure 2(a) illustrates the read and write protocol of DirectDS. DirectDS uses locks to isolate data entries from concurrent read and write accesses. Each entry has its own lock and we associate a 8-byte value at the beginning of each data entry to implement its lock. A CN performs a one-sided RDMA c&s (compare-and-swap) operation to the value to acquire the lock (e.g., comparing whether the value is 0 and if so setting it to 1). To release the lock, the CN simply performs an RDMA write and sets the value to 0.

Our lock implementation leverages the unique feature of the DPM model that all memory accesses to DPMs come from the network (i.e., the NIC). Without processor’s accesses to memory, DMA guarantees that network atomic operations like c&s are atomic [13, 64]. Note that an RDMA c&s operation to an in-memory value which can also be accessed locally at the same time does not guarantee the atomicity of the value [13, 44, 67], and thus it cannot be used in distributed PM systems in the same way.

**Read.** To read a data entry, a CN uses its stored metadata to find the location of the data entry’s committed space (and the first 8-byte lock). It first acquires a lock, then performs an RDMA read, and finally releases the lock. Locking reads ensures that CNs will not read intermediate value during concurrent writes. The read latency is 3 RTTs when there is no contention, with one RTT used for data read. Under contention, the c&s operation would fail and CNs will keep retry until succeed.

**Write.** To write a data entry, a CN first locates the entry and locks it. Afterwards, the CN writes the new data to the un-committed space. To sustain crashes, the CN issues an RDMA read to the last byte of the un-committed space to validate that it is actually written to PM. This uncommitted data serves as the redo copy that will be used during recovery if a crash happens. The CN then writes the new data to the committed space with an RDMA write and validates it with an RDMA read. At the end, the CN releases the lock. The total write latency

ones. In addition, all our three systems provide replication across DPMs to ensure that data is still available even after losing N – 1 DPMs (when the degree of replication is N).

**Network layer.** We choose RDMA as the network layer that connects all servers and DPMs, but most of our designs are applicable to other network systems that can perform both one-way and two-way communication. We use RDMA’s RC (Reliable Connection) mode which supports one-sided RDMA operations and ensures lossless and ordered packet delivery. Similar to prior solutions [15, 65], we solve RDMA’s scalability issues using memory huge page or physical memory to register memory regions with RDMA NICs.

**Ensuring data persistence.** For data to be persistent in DPM, it is not enough to just perform a remote write. After a remote write (e.g., RDMA write), the data can be in NIC, PCIe hub, or PM. Only when the data is written to PM can it sustain power failure. To ensure this data persistence, we follow the guidance of SNIA [60] and Mellanox [26, 57] by performing a remote read to ensure that data is actually in PM. Since we use RDMA RC which guarantees ordered data delivery and PCIe also follows ordering [53], we only read the last byte of a data entry to verify its persistence [60].

4.2 Direct Connection

The DPM-Direct architecture (Figure 1(b)) connects CNs directly to DPMs. CNs perform un-orchestrated, direct accesses to DPMs using RDMA one-sided operations. Under DPM-Direct, performing metadata and control operations from CNs is hard and costly (e.g., by performing distributed coordination across CNs). Thus, we made two design choices when building DirectDS.

First, we use two spaces for each data entry, one to store committed data where reads go to (we call it the committed space) and one to store in-flight, new data (un-committed space). Doing so avoids dynamic space allocation and de-allocation. Second, to avoid reading and writing metadata from DPMs and the cost of ensuring metadata consistency under concurrent accesses, CNs in DPM-Direct locally store all the metadata of key-value entries, including the key of a value and the location of its committed and uncommitted spaces.
As we will see in §5, as expected, DPM-Direct systems also require large space for both data and metadata. For each data entry, it doubles the space because of the need to store two copies of data. The metadata overhead is also high, since CNs have to store all metadata.

**Avoid read lock with CRC.** DirectDS uses lock to ensure the read-committed isolation level at the cost of two RTTs to acquire and release the lock for each read. Instead of lock, we can use an error-detecting code for each data entry to detect incomplete data. **DirectDS-C** (Figure 2(b)) uses the CRC code for this purpose.

To perform a read, a CN simply issues an RDMA read to fetch the data and then calculates and validates its CRC. Thus, the read latency of DirectDS-C is one RTT plus the CRC calculation time. Writes in DirectDS-C is similar to DirectDS, except that before writing the new data, the CN needs to first calculate and attach a CRC to the new data entry.

**Discussion.** As we will see in §5, as expected, DPM-Direct data stores scale well when there is no contention of concurrent accesses to data entries. More surprising is that they scale very poorly when contention happens, especially with write. In general, the write performance is not good because of the high RTTs. But write performs especially poorly under contention, because multiple CNs will all try to acquire the lock with the c&s operation and most of them will experience a lot of c&s failures. However, DirectDS-C yields the best read performance when read size is small, since it only requires one lock-free RTT and it is fast to calculate small CRC.

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**4.3 Connecting Through Coordinator**

Most limitations of DPM-Direct come from the fact that there is no central coordination of data, metadata, or management operations. Specifically, DPM-Direct systems have to write data twice, once to the un-committed and once to the committed space, because CNs in DPM-Direct only know a fixed location to read committed data. The DPM-Central architecture (Figure 1(c)) takes the opposite design choice and uses one coordinator to orchestrate all data accesses and to perform metadata and management operations. All CNs send RPC requests to the coordinator (we use the HERD [30, 31] RPC system for this purpose). The coordinator handles RPC requests by performing read/write requests to DPMs. To improve application throughput, we use multiple threads at the coordinator to handle RPC requests.

Since all requests go through the coordinator, it can serve as the serialization point for concurrent accesses to a data entry. We simply use a local read/write lock for each data entry at the coordinator as the synchronization of multiple coordinator threads. In addition to orchestrating data accesses, the coordinator performs all space allocation and de-allocation of data entries. The coordinator uses its local PM to persistently store all the metadata for a data entry including its key, its location, and a read/write lock. With the coordinator handling all read requests, it can freely direct a read to the latest location of committed data. Thus, it does not need to maintain the same location for committed data and changes the location of committed data after each write.

**Read.** To perform a read, a CN sends an RPC read request to the coordinator. The coordinator finds the location of the entry’s committed data using its local metadata, acquires its local lock of the entry, reads the data from the DPM using an RDMA read, releases the lock, and finally replies to the CN’s RPC request. The total read latency (from CN’s perspective) is 2 RTTs, both containing data.

**Write.** After receiving a write RPC request from a CN, the coordinator allocates a new space in a DPM for the new data. It then writes the data and validates it with an RDMA read. Note that we do not need to lock (either at coordinator or at DPM) during this write, since it is an out-of-place write to a location that is not exposed to any other coordinator RPC handlers.

After successfully verifying the write, the coordinator updates its local metadata of where the committed version of the data entry is and flushes this new metadata to local PM for crash recovery (by performing CPU cache flushes and memory barrier instructions [9]). Since concurrent coordinator RPC handlers can update the same information of where the latest data entry is, we use a local lock to protect this metadata change. The total write latency without contention is 3 RTTs, with two of them containing data and one for validation.

**Discussion.** CentralDS largely reduces write RTTs over DirectDS and thus has good write performance when the scale of the cluster is small. However, from our experiments, the coordinator soon becomes the performance
bottleneck when either the number of CNs increases or
the number of DPMs increases. CentralDS’s read perfor-
mance is also worse than DirectDS-C with the extra hop
between a CN and the coordinator. In addition, the CPU
utilization of the coordinator is high, since it needs to
have a high amount of RPC handlers to sustain parallel
requests from CNs (§5). However, unlike DPM-Direct,
CNs in the DPM-Direct architecture does not need to
store any metadata.

Figure 3. SepDS System Design.

4.4 Separating Data and Control

The main issue with DPM-Direct is its poor write perfor-
mance. CentralDS improves the write performance but
suffers from the scalability bottleneck of the central co-
ordinator. To solve these problems of the first two DPM
architectures, we propose a third architecture, DPM-Sep
(Figure 1(d)), and a data store designed for it, SepDS.

The MS stores metadata of all data entries in its local
PM. We keep the amount of metadata small, and 1 TB
of PM (a conservative estimation of the size of PM
a server can host) can store metadata for 64 TB data at
the granularity of 1 KB per data entry, CNs cache
metadata of hot data entries; under memory pressure,
CNs will evict metadata according to an eviction policy
(we currently support FIFO and LRU).

SepDS aims to deliver scalable, good performance at
the data plane and to avoid the MS being the bottleneck
at the control plane. Our overall approaches to achieve
these design goals include: 1) moving all metadata oper-
ations off performance critical path, 2) using lock-free
data structures to increase scalability, 3) employing op-
timization mechanisms to reduce network round trips
for data accesses, and 4) leveraging the unique atomic
data access guarantees of DPM. Figure 3 illustrates the
data structures used in SepDS.

4.4.1 Data Plane

To achieve our data plane design goal, we propose a
new mechanism to perform lock-free, fast, and scalable
reads and writes. The basic idea is to allow multiple
committed versions of a data entry in DPMs and to link
them into a chain. Each committed write to a data entry
will move its latest version to a new location. To avoid
the need to update CNs with the new location, we use a
self-identifying data structure to let CNs be able to find
the latest version.

We include a header with each version of a data entry,
which contains a pointer and some metadata bits used
for garbage collection. The pointers chain all versions
of a data entry together in the order that they are written.
A NULL pointer indicates that the version is the latest.

A CN acquires the header of the chain head from the
MS at the first access to a data entry. It then caches
the header locally to avoid the overhead of contacting MS
on every data access. As a CN reads or writes an entry, it
advances its cached header. We call a CN-cached header
a cursor.

Read. SepDS reads are lock-free. To read a data entry,
the CN performs a chain walk. The chain walk begins
with fetching the data entry its current cursor points to.
It then follows the pointer in the following entries until
it reaches the last entry. All steps in the chain walk use
one-sided RDMA reads. After a chain walk, the CN
updates its cursor to the last entry.

A chain walk can be slow with long chains when a
cursor is not up to date [69]. Inspired by skip-list [55],
we propose to solve this issue by using a shortcut
to directly point to a newer entry. The shortcut of a data
entry is stored in DPM and the location of the shortcut
never changes during the lifetime of the data. MS stores
the locations of all shortcuts and CNs cache the hot ones.
Shortcuts are best effort in that they are intended but not
enforced to always point to the last version of an entry.

The CN issues a chain walk read and a shortcut read
in parallel. It returns to user when the faster one returns
and discards the other result. Note that we do not re-
place chain walks completely with shortcut reads, since
shortcuts are updated asynchronously in the background
and may not be updated as fast as the cursor. When the
CN has a pointer that points to the latest version of data,
a read only takes 1 RTT.

Write. SepDS never overwrites existing data entries and
performs a lock-free out-of-place write before linking
the new data to an entry chain. To write a data entry, a
CN first selects a free DPM buffer assigned to it by MS
in advance (see §4.4.2). It performs a one-sided RDMA
write to write the new data to this buffer and then issues
a read of the last byte to ensure that the data is written
in PM. Afterwards, the CN performs an RDMA c&s
operation to link this new entry to the tail of the entry
chain. Specifically, the c&s operation is on the header
that CN’s cursor points to. It compares if the pointer in
the header is NULL and swaps the pointer to point to
the new entry. If the c&s succeeds, we treat this data as
committed and return the write request to the user. If the pointer is not NULL, it means that the cursor does not point to the tail of the chain and we will do a chain walk to reach the tail and then do another CAS.

Afterwards, the CN uses a one-sided RDMA write to update the shortcut of the entry to point to the new data entry. This step is off the performance critical path. The CN also updates its cursor to the newly written data entry. We do not invalidate or update other CNs’ cursors at this time to improve the scalability and performance of SepDS.

SepDS’ chained structure and write mechanism ensure that writers do not block readers and readers do not block writers. They also ensure that readers can only view committed data. Without high write contention to the same data entry, one write takes only 3 RTTs.

Retire. After committing a write, a CN can retire the old data entry, indicating that the entry space can be reclaimed. To improve performance and minimize the need to communicate with the MS, CNs perform lazy, asynchronous, batched retirement of old data entries in the background. We further avoid the need for MS to invalidate CN-cached metadata using a combination of timeout and epoch-based garbage collection.

4.4.2 Control Plane

CNs communicate with the MS using two-sided operations for all metadata operations. The MS performs all types of management of DPMs. It manages physical memory space of DPM, stores the location and shortcut of a data entry. We carefully designed these MS functionalities to achieve good performance and scalability.

Space allocation. With the data plane out-of-place write model, SepDS has high demand for DPM space allocation. We use an efficient space allocation mechanism where MS packages free space of all DPMs into chunks. Each chunk hosts the same size of data entries and different chunks can have different data sizes, similar to FaRM [15] and Hoard [6]. Instead of asking for a new free entry before every write, each CN requests multiple entries at a time from the MS in the background. This approach moves space allocation off the critical path of writes and is important to deliver good write performance.

Garbage collection. SepDS’ append-only chained data structure makes its writes very fast. But like all other append-only or log-structured data stores, SepDS needs to garbage collect (GC) old data. We designed a new efficient GC mechanism that does not involve any data movement or communication to DPM and minimizes the communication between MS and CNs.

The basic flow of GC is simple: the MS keeps busy checking and processing incoming retire requests from CNs. The MS decides when a data entry can be reclaimed and puts a reclaimed entry to a free list (FreeList). It gets free entries from this list when CNs request for more free buffers. A reclaimed entry can be used by any CN for any new entry, as long as the size fits.

Although the above strawman GC implementation is simple, making GC work correctly, efficiently, and scale well is challenging. First, to achieve good GC performance, we avoid the invalidations of CN cached cursors after reclaiming entries so as to minimize the network traffic between the MS and CNs. However, with the strawman GC implementation, CNs’ outdated cursors can cause failed chain walks. We solve this problem using two techniques: 1) the MS does not clear the header (or the content) of a data entry after reclaiming it, and 2) we assign a GC version to each data entry. The MS increases the GC version number after reclamation a data entry. It gives this new GC version together with the location of the entry when assigning the entry as a new free buffer to a CN, A. Before CN A uses the entry for its new write, the entry content at the DPM still has old header and data (with old GC version). Other CNs that have cached cursors to this entry can thus still use the old pointer to perform chain walk. CNs differentiate if an entry is its intended data or has already been reclaimed and reused for other data by comparing the GC version in its cached cursor and the one it reads from the DPM. After CN A writes the new data with the new GC version number, other CNs that have the old cursor will have a mismatched GC version and discard the entry and invalidates their cursors. Doing so not only avoids the need for MS to invalidate cursor caches on CNs, but also eliminates the need for MS to access DPMs during GC.

The next challenge is related to our targeted guarantee of read isolation and atomicity (i.e., readers should always read the data that is consistent to its metadata header). An inconsistent read can happen if the read to a data entry takes long and during the reading time, this entry has been reclaimed and used to write a new data entry. We use a read timeout scheme similar to [15]. CNs abort a read operation after , an agreed value among CNs and the MS. The MS delays the actual reclamation of an entry to only , time after it receives the retire request of the entry. Specifically, the MS leaves the entry in a ToGCLList for and then moves it to the FreeList.

The final challenge is the overflow of GC version numbers. We can only use limited number of bits for GC version in the header of a data entry (currently 8 bits), since the header needs to be smaller than the size of an atomic RDMA operation. When the GC version of an entry increases beyond the maximum value, we will have to restart it from zero. With just the GC version number and our GC mechanism so far, CNs will have
no way to tell if an entry matches its cached cursor version or has advanced by $2^8 = 256$ versions. To solve this rare issue without invalidation traffic to CNs, we use an epoch-based timeout mechanism. When the MS finds the GC version number of a data entry overflows, it puts the reclaimed entry into OverflowList and waits for $T_e$ time before moving it to the FreeList that can be assigned to CNs. All CNs invalidate their own cursors after an inactive period of $T_e$ (if during this time, the CN access the entity, it would have advanced the cursor already). To synchronize epoch time, the MS sends a message to CNs after $T_e$, and the MS can choose the value of $T_e$. Epoch message is the only communication the MS issues to CNs during GC.

### 4.4.3 Discussion.

The SepDS design offers four benefits. First, SepDS reads and writes are fast, with 1 RTT and 3 RTTs respectively when there is no contention. Even under contention, SepDS still outperforms DirectDS and CentralDS. Achieving this low latency and guaranteeing atomic write and read committed is not easy and is achieved by the combination of four approaches: 1) ensuring the data path does not involve the MS, 2) reducing metadata communication to the MS and moving it off performance critical path, 3) ensuring no memory copy in the whole data path, and 4) leveraging the unique advantages of DPM to perform RDMA atomic operations.

Second, SepDS scales well with the number of CNs and DPMs, since its reads and writes are both lock free. Readers do not block writers or other readers and writers do not block readers. Concurrent writers to the same entity only contend for the short period of RDMA CAS operation. SepDS also minimizes the network traffic to MS and the processing load on MS to make MS scale well with number of CNs and data operations.

Third, we avoid all data movement or communication between the MS and DPMs during GC. To scale and support many CNs with few MSs, we avoid CN invalidation messages completely. The MS does not need to proactively send any other messages to CNs either. Essentially, the MS never pushes any messages to CNs. Rather, CNs pull information from the MS.

Finally, the SepDS data structure is flexible and can support load balancing very well. Different entries of a data entity do not need to be on the same DPM device. As we will see in §4.5.2 and §4.6, this flexible placement is the key to SepDS’ load balancing and data replication needs.

However, SepDS also has its own limitation. It requires CNs to cache metadata. As we will see in §5, when CN’s local metadata cache becomes small, SepDS’s performance drops. Thus, SepDS works the best when CNs have enough memory or when data accesses have good temporal locality.

### 4.5 Failure Handling

DPMs can fail independently from CNs. A DPM system needs to handle both the transient failure of a DPM (which can be rebooted) and a permanent failure of one. For the former, our three DPM systems guarantee crash consistency, i.e., after reboot, the DPM can recover all its committed data. For the latter, we add the support for data replication across multiple DPMs to all the three data store systems. In addition, CentralDS and SepDS also need to handle the failure of the coordinator and the MS.

#### 4.5.1 Recovery from Transient Failures

We now present how each system recovers from a single DPM’s failure when it restarts. We assume that the rest of the system (e.g., CNs, the coordinator, the MS) keeps alive. We will discuss the reliability of the coordinator and the MS in §4.5.2.

**DirectDS.** When recovering a DPM in DirectDS, we need to decide whether to use the data in the committed space or the un-committed space (i.e., where the redo copy is). Note that a crash can happen when writing to the committed space, leaving it in an intermediate state, in which case a correct recovery should use the un-committed space (the redo copy). We use a technique that leverages RDMA’s ordered writes in increasing address order [15, 63] to ensure the integrity of a data space. Specifically, DirectDS extends its write data by attaching a unique 8-byte value to the beginning and the end of a data entry, and writes the extended data entry during its write protocol. The unique value can be calculated by maintaining a monotonically increasing number at each CN. During recovery, we compare the first and last 8 bytes of the committed space. A match indicates the committed space has the complete data. Otherwise, we check the un-committed space and use the same way to tell if it has the complete data.

DirectDS-C does not need this extended write mechanism and can simply validate the data in the committed space with its CRC. If the CRC is incorrect, we copy the data from the redo copy to the committed space.

**CentralDS.** Handling the failure of a DPM in CentralDS is simple, as long as the coordinator stays alive. Since CentralDS performs out-of-place writes and the coordinator stores the state of all writes, we can simply use the information in the coordinator to know what writes have written their redo copies but haven’t committed yet and what writes have not written redo copies. For the former case, we advance to the redo copy, and for the latter, we use the original version.
**SepDS.** SepDS’ recovery mechanism is also simple. If a DPM fails before a CN successfully links the new data it writes to the chain (indicating an un-committed write), the CN simply unsets lock bits (within a pointer) of the data entry (releasing the held lock) and discards the new write (by treating the space as unused).

### 4.5.2 Adding Redundancy

We now present how we add redundancy to DPM in all the three systems and how we handle coordinator and MS failures. With the user-specified degree of replication being \(N\), our data store systems guarantee that data is still accessible after \(N-1\) DPMs have failed.

**DirectDS and DirectDS-C.** In order to sustain DPM failure during a write, we need to replicate both the first write to the un-committed space (the redo copy) and the second write to the committed space. After getting the lock, a CN sends the new data to the un-committed space on \(N\) DPMs in parallel. Afterwards, it performs \(N\) read validation, also in parallel. Once read validation of all the copies succeeds, the CN writes the data to the committed space of the \(N\) DPMs in parallel and performs a parallel read validation afterwards.

**CentralDS.** To handle a replicated write RPC request, the coordinator writes multiple copies of the data to \(N\) DPMs in parallel and performs a parallel read validation of them. After the read validation, the coordinator updates its metadata to record the new locations of all these copies.

**SepDS.** We propose a new atomic replication mechanism designed for the SepDS data structure. The basic idea is to link each data entry version \(D_N\) to all the replicas of the next version (e.g., \(D_{N+1}^a, D_{N+1}^b, D_{N+1}^c\) for three replicas) by placing pointers to all these replicas in the header of \(D_N\). Figure 4 shows an example of replicated data entry. With this all-way chaining, SepDS can always construct a valid chain as long as one copy of each version in an entry survives.

Each data entry has a primary copy and one or more secondary copies. To write a data entry \(D_{N+1}\) with \(R\) replicas to an entry whose current tail is \(D_N\), a CN first writes all copies of \(D_{N+1}\) to \(R\) DPMs. In parallel, a CN performs a one-sided \(c+s\) to a bit, \(B_w\), in the header of the primary copy of \(D_N\) to test if the entry is already in the middle of a replicated write. If not, the bit will be set, indicating that the entry is now under replicated write. All the writes and the \(c+s\) operation are sent out together to minimize latency.

After the CN receives the hardware acknowledgment of all the operations, it constructs a header that contains \(R\) pointers to the copies of \(D_{N+1}\) and writes it to all the copies of \(D_N\). Once the new header is written to all copies of \(D_N\), the system can recover \(D_{N+1}\) from crashes (up to \(R-1\) concurrent DPM failure).

**Backup coordinator and MS.** To avoid the coordinator or the MS being the single point of failure in CentralDS and SepDS, we implement a mechanism to enabling one or more backup coordinator (MS), by having the primary coordinator (MS) replicate the metadata that cannot be reconstructed (i.e., keys and locations of values) to the backup coordinator (MS) when changing these metadata.

### 4.6 Load Balancing

With the DPM model, a system will have a pool of DPMs. Thus, it is beneficial to balance the load to each of them.

With a centralized place to initiate all requests, it is easy for CentralDS to perform load balancing. The coordinator simply records the load to each DPM and directs new writes to the DPM with lighter load. When DPM is replicated, the coordinator can also balance read loads by selecting the replica that is on the DPM with lighter load.

We use a novel two-level approach to balance loads in SepDS: globally at MS and locally at each CN. Our global management leverages two features in SepDS: 1) MS assigns all new space to CNs; and 2) data entries of the same entity in SepDS can be on different DPMs. To reduce the load on a DPM, MS directs all new writes to other devices. At a local level, each CN internally balances the load to different DPMs. Each CN keeps one bucket per DPM to store free entries. It chooses buckets from different buckets for new writes according to its own load balancing needs.

However, balancing loads with the DPM-Direct architecture is hard, since there is no coordination across CNs.

### 5 Evaluation Results

This section presents the evaluation results of different DPM systems including DirectDS, DirectDS-C, CentralDS, and SepDS. All our experiments were carried out in a cluster of 14 machines, connected with a 40 Gbps Mellanox InfiniBand Switch. Each machine is equipped with two Intel Xeon E5-2620 2.40GHz CPUs, 128 GB DRAM, and one 40 Gbps Mellanox ConnectX-3 NIC.

#### 5.1 Micro-benchmark Results

We then evaluate DPM data stores’ read and write performance and compare them to LITE [65]. We chose LITE for comparison since it offers low latency and uses a similar physical memory registration method as our data stores.

Figure 5 plots the average write latency with different request size. LITE performs a write without read validation and only models the latency of un-validated writes. Its latency is thus the lowest. Among DPM systems, SepDS and CentralDS achieve the best write latency.
SepDS outperforms CentralDS slightly when request size is big because of its smaller network traffic. DirectDS and DirectDS-C have similar write performance when request size is small. However, when request size increases, the overhead of CRC calculation dominates, making DirectDS-C perform poorly.

We also evaluated all the DPM systems’ write performance without read validation (i.e., treating DPM as volatile memory). We found each read validation to cost a constant of $1.5 \mu s$ overhead.

Figure 5 plots the write latency. Overall, SepDS’s performance is the best among DPM systems and is only slightly worse than LITE. However, when request size is small, DirectDS-C outperforms SepDS because of DirectDS-C’s read only requires one round trip under any circumstance. However, like writes, the read performance of DirectDS-C dramatically drops as request size increases because of the CRC calculation overhead. As expected, DirectDS and CentralDS perform worse than SepDS because of their reads involve 3 RTTs and 2 RTTs.

### 5.2 YCSB Results

We now present our evaluation results using the YCSB benchmark [12, 71]. We use a total of 100K key-value entries where the key size is 8 bytes and the value size is 1 KB. The accesses to keys follow the Zipf distribution. And we use four workloads with different read and write intensity: read only (workload C), 5% write (workload B), 50% write (workload A), and write only.

**Basic performance.** We first evaluate the performance of all our DPM systems under our default setting: 4 CNs and 4 DPMs, each CN runs 8 application threads. Figure 7 shows the overall performance of DPM data stores, replicated DPM data stores (with degree of replication 2), and Hotpot [59]. The Hotpot runs use four servers, each running 8 application threads, and we ran Hotpot with its MRSW (multiple reader single writer) consistency level without replication. Hotpot serves as a comparison of the distributed PM model.

SepDS performs the best among all systems regardless of read/write intensity, even under high contention (with Zipf distribution to keys). DirectDS-C performs well with workloads that are read intensive. DirectDS-C’s read performance is not affected by contention, since it does not need to perform any lock. In contrast, DirectDS’s read performance is the worst under contention because of it needs to lock a data entry for each read. CentralDS’s read performance is worse than DirectDS-C and SepDS because each read in CentralDS requires 2 RTTs and under contention the coordinator becomes the bottleneck.

For write-intensive workloads, CentralDS and SepDS perform better than the DirectDS systems. This is because under high contention, the lock overhead of the DirectDS systems become high, while CentralDS and SepDS both avoid the lock contention. CentralDS avoids it by using a local lock to protect metadata update (not the write itself) and SepDS uses the lock-free out-of-place chained data structure.

The overall performance of Hotpot is orders of magnitude worse than all DPM data stores. The reason is that each read and write in Hotpot involves a complex protocol that requires RPCs across multiple nodes. Hotpot’s performance is especially poor with writes, since the distributed PM consistency protocol involves frequent invalidation of cached copies, especially under high write contention to the same data. To confirm this, we also ran Hotpot with workloads with uniform distribution and found the results to be better, but still much worse than DPM systems.

**Replication overhead.** As expected, adding redundancy lowers the throughput of all data stores with write-heavy workloads. Even though all systems issue the replication requests in parallel, they only use one thread to perform asynchronous RDMA read/write operations and doing so still has an overhead.

**Network traffic.** To further understand the cause of performance differences, we record the total network traffic during each run. Figure 8 plots the average amount of traffic that each data store incurs to complete one operation under different workloads. SepDS, DirectDS, and DirectDS-C send less traffic in read-heavy workloads since these data stores access DPMs directly. In contrast, CentralDS incurs high traffic because data is sent once between the CN and the coordinator and once between the coordinator and the DPM. As expected, DirectDS and DirectDS-C send more data for writes because of their writes involve 2 RTTs with data.
Scalability. Next, we evaluate the scalability of different DPM data stores with respect to the number of CNs and the number of DPMs. Figure 9 shows the scalability of DPM data stores w.r.t. the number of DPMs. Both DirectDS-C and SepDS scale well with DPMs because DirectDS-C and SepDS both let CNs access DPMs directly, improving the network bandwidth utilization to DPMs. DirectDS does not scale with DPMs because of lock contention which increases total CPU utilization. For read-intensive workload, DirectDS-C and SepDS use less CPU than other data stores mainly because SepDS has higher throughput and separates data plane and control plane which reduces CPU usage.

Metadata size. Different DPM data stores cache different amounts of metadata in CNs. DirectDS and DirectDS-C cache all keys and pointers to each entity for direct access to DPMs. CNs in CentralDS only cache keys, and rely on coordinators to keep metadata. CNs in DirectDS and DirectDS-C keep the mapping from keys to DPMs. Similarly, SepDS caches a shortcut pointer for each entity to improve performance. SepDS further supports different sizes of metadata cache.

Metadata caching effect. To evaluate the effect of different sizes of metadata cache at CNs in SepDS, we ran the same YCSB workloads and configuration as Figure 7 and plot the results in Figure 12. Here, we use the
FIFO eviction policy (we also tested LRU and found it to similar or worse than FIFO). With smaller metadata cache, all workloads’ performance drop because a CN has to get the metadata from the MS before accessing the data entry that does not have local metadata cache. With no metadata cache (0%), CNs need to get metadata from the MS before every request. However, under Zipf distribution, with just 10% metadata cache, SepDS can already achieve satisfying performance.

**Data caching effect.** We do not cache data at CNs because doing so would require coherence traffic, resulting in performance that is similar to distributed PM. However, it is possible to cache data at the coordinator with the DPM-Central architecture, because that is the only copy and does not need any coherence traffic. By caching hot data in a coordinator, the coordinator does not need to access DPMs to get data for every read which can reduce network traffic and improve performance. We built a FIFO data cache at the coordinator for CentralDS to analyze the effect of data caching. Figure 13 plots the throughput with different percentages of the data cache in a coordinator. With bigger data cache, the performance increases. However, the overall performance is still limited by network bandwidth. Furthermore, we observe that data cache improves read traffic but not write traffic. Overall, we found the effect of data caching to be small with CentralDS, but the only copy and does not need any coherence traffic. By caching hot data in a coordinator, the coordinator can reduce network traffic and improve performance. We built a FIFO data cache at the coordinator for CentralDS to analyze the effect of data caching. Figure 13 plots the throughput with different percentages of the data cache in a coordinator. With bigger data cache, the performance increases. However, the overall performance is still limited by network bandwidth. Furthermore, we observe that data cache improves read traffic but not write traffic. Overall, we found the effect of data caching to be small with CentralDS, but the only copy and does not need any coherence traffic.

**Load balancing.** To evaluate the effect of SepDS’s load balancing mechanism, we use a synthetic workload with three entities, A, B, and C. We first create A (without replication) and B (with 2 replicas) and read these two entities heavily. Then, we create C (without replication) and keep updating C. One CN runs this synthetic workload on three DPMs. Figure 14 shows the total traffic to the three DPMs with and without load balancing. With a naive allocation policy of round-robin across DPMs, write traffic spreads among all DPMs and read traffic only goes to the first DPM. With load balancing, SepDS spreads read traffic across different replicas depending on the load of DPMs. At the same time, MS allocates free entries for new writes from the least accessed DPM. As a result, the total loads across the three DPMs are balanced.

6 Related Work

Lim et al. [39, 40] first proposed the concept of disaggregating memory from processor. Recent years have seen more industry and academic efforts in network support for disaggregated memory [8, 18, 21, 48, 50] and software systems to manage remote memory [2, 15, 23, 34, 49]. FaRM [15, 16] is an RDMA-based distributed memory platform. FaRM use one-way communication for reads and perform both two-way and one-way communication for replicated writes (depending on whether it is to the primary copy). Pilaf [47] and HERD [30, 31] are two RDMA-based key-value store systems. These systems rely on two-way communication for writes and HERD and FaSST use two-way communication for reads too.

NAM-DB [7, 72] is a RDMA-based database system that uses one-sided communication for both read and write. Infiniswap [23] is an RDMA-based remote memory paging system. Remote regions [1] is a system that exposes remote memory as files that other host servers can access (through a file system interface). Although these three systems do not use two-way communication for data path, they both rely on processing power at remote nodes to run data management tasks. SepDS runs all management tasks (control path) at MS, a separate node from remote memory.

Mojim [73], Hotpot [59], and Octopus [41] are three recent distributed PM systems. Mojim [73] is the first system that targets using PM in distributed, datacenter environments. Mojim provides an efficient, RDMA-based, asynchronous replication mechanism for PM, to make it more reliable and available. Hotpot [59] is the first distributed shared persistent memory system. It integrates the idea of distributed shared memory and distributed storage systems to provide a globally coherent, crash-consistent, and reliable distributed PM system that applications can access with memory instructions. Octopus [41] is a distributed file system built on top of PM. None of these systems build on the DPM model, which presents a whole new set of challenges.

ReFlex[33] is a software-based system builds on IX [5] and exposes a logical block interface for users to access remote Flash with nearly identical performance as accessing local Flash. RAMCloud [52] is a remote key-value storage system that stores a full copy of all data in DRAM and backups in disks or SSDs. Kamino-Tx [45] proposes a new mechanism to perform transactional updates on PM without any copying of data in the critical path. These systems all rely on local computation power at remote memory/storage servers to perform various online and recovery management services which differs from DPM model.

7 Conclusion

This paper presents the disaggregated PM model, where PM is attached directly to the network without any local processors. We proposed three DPM architectures, built three atomic, crash-consistent, and reliable data stores on top of these architectures, and performed extensive evaluation of these data stores. Our findings will be able to guide future DPM system builders.
References

[1] Marcos K. Aguilar, Nadav Amit, Irina Calciu, Xavier Deguil-lard, Jayneel Gandhi, Stanko Novaković, Arun Ramanathan, Pratap Subrahmanyan, Lalith Suresh, Kiran Tati, Rajesh Venkatasubramanian, and Michael Wei. 2018. Remote regions: a simple abstraction for remote memory. In 2018 USENIX Annual Technical Conference (ATC '18), Boston, MA.

[2] Marcos K. Aguilar, Nadav Amit, Irina Calciu, Xavier Deguil-lard, Jayneel Gandhi, Pratap Subrahmanyan, Lalith Suresh, Ki-ran Tati, Rajesh Venkatasubramanian, and Michael Wei. 2017. Remote Memory in the Age of Fast Networks. In Proceedings of the 2017 Symposium on Cloud Computing (SoCC ’17).

[3] Krste Asanović. 2014. FireBox: A Hardware Building Block for 2020 Warehouse-Scale Computers. Keynote talk at the 12th USENIX Conference on File and Storage Technologies (FAST ’14).

[4] Luiz André Barroso and Urs Hölzle. 2007. The Case for Energy-Proportional Computing. Computer (Dec. 2007).

[5] Adam Belay, George Prekas, Ana Klimovic, Samuel Grossman, Philip Lantz, Dheeraj Reddy, Rajesh Sankaran, and Jeff Jackson. Proceedings of the 30th Symposium on Operating Systems and Applications (SOSS ’09), San Francisco, CA, USA.

[6] Emery D. Berger, Kathrin S. McKinley, Robert D. Blumofe, and Paul R. Wilson. 2000. Hoard: A Scalable Memory Allocator for Multithreaded Applications. In Proceedings of the Ninth International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ’00), Cambridge, MA, USA.

[7] Carsten Binnig, Andrew Crotty, Alex Galakatos, Tim Krasa, and Erfan Zamanian. 2016. The End of Slow Networks: It’s Time for a Redesign. Proceedings of the VLDB Endowment 9, 7 (2016), 528–539.

[8] Cache Coherent Interconnect for Accelerators. 2018. https://www.ccixconsortium.com/.

[9] Tao Chen and G. Edward Suh. 2016. Efficient Data Supply for Hardware Accelerators with Prefetching and Access/Execute Decoupling. In The 49th Annual IEEE/ACM International Symposium on Microarchitecture (MICRO’49), Taipei, Taiwan.

[10] Joel Coburn, Adrian M. Caulfield, Ameen Akel, Laura M. Grupp, Rajesh K. Gupta, Ranjith Jhala, and Steven Swanson. 2011. NV-Heaps: Making Persistent Objects Fast and Safe with Next-generation, Non-volatile Memories. In Proceedings of the 16th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ’11), New York, New York.

[11] Jeremy Condit, Edmund B. Nightingale, Christopher Frost, Engin İpek, Benjamin Lee, Doug Burger, and Derrick Coetzee. 2009. Better I/O Through Byte-addressable, Persistent Memory. In Proceedings of the ACM SIGOPS 22Nd Symposium on Operating Systems Principles (SOSP ’09), Big Sky, MT, USA.

[12] Brian F. Cooper, Adam Silverstein, Erwin Tam, Raghu Ramakrishnan, and Russell Sears. 2010. Benchmarking Cloud Serving Systems with YCSB. In Proceedings of the 2nd ACM Symposium on Cloud Computing (SoCC ’10), New York, New York.

[13] Alexandradas Daglis, Dmitrii Ustiuov, Stanko Novaković, Edouard Bugnion, Babak Falsafi, and Boris Grot. 2016. SABRes: Making Persistent Objects Fast and Safe with Next-generation, Non-volatile Memories. In Proceedings of the 16th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ’16). Taipei, Taiwan.

[14] Christina Delimitrou and Christos Kozyrakis. 2014. Quasar: Resource-efficient and QoS-aware Cluster Management. In Proceedings of the 19th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ’14). Taipei, Taiwan.

[15] Aleksandr Dragojević, Dushyant Narayanan, Orion Hodson, and Miguel Castro. 2014. FaRM: Fast Remote Memory. In Proceedings of the 11th USENIX Conference on Networked Systems Design and Implementation (NSDI ’14), Seattle, WA, USA.

[16] Aleksandr Dragojević, Dushyant Narayanan, Edmund B. Nightingale, Matthew Renzelmann, Alex Shamis, Aniruddh Badam, and Miguel Castro. 2015. No Compromises: Distributed Transactions with Consistency, Availability, and Performance. In Proceedings of the 25th Symposium on Operating Systems Principles (SOSP ’15), Monterey, CA, USA.

[17] Subramanya R. Dulloor, Sanjay Kumar, Anil Keshavamurthy, Philip Lantz, Dheeraj Reddy, Rajesh Sankaran, and Jeff Jackson. 2014. System Software for Persistent Memory. In Proceedings of the EuroSys Conference (EuroSys ’14), Amsterdam, The Netherlands.

[18] Paolo Faraboschi, Kimberly Keeton, Tim Marsland, and Dejan Milojicic. 2015. Beyond Processor-centric Operating Systems. In 15th Workshop on Hot Topics in Operating Systems (HotOS ’15). Karlsruhe, Germany.

[19] Brad Fitzpatrick. 2005. Distributed Caching with Memcached. Linux Journal 2004, 124 (2004), 5.

[20] Peter X. Gao, Akshay Narayan, Sagar Karandikar, Joao Car-reira, Sang chin Han, Rachit Agarwal, Sylvia Ratnasamy, and Scott Shenker. 2016. Network Requirements for Resource Disaggregation. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI ’16), Savannah, GA.

[21] Gen-Z Consortium. 2018. https://genzconsortium.org.

[22] Albert Greenberg, James Hamilton, David A. Malz, and Parveen Patel. 2008. The Cost of a Cloud: Research Problems in Data Center Networks. SIGCOMM Sigcomm Computer Communication Review 39, 1 (Dec 2008), 68–73.

[23] Juncheng Gu, Youngmoon Lee, Yiwen Zhang, Mosharaf Chowdhury, and Kang Shin. 2017. Efficient Memory Disaggregation with Infiniswap. In Proceedings of the 14th USENIX Symposium on Networked Systems Design and Implementation (NSDI ’17), Boston, MA, USA.

[24] Hewlett Packard. 2005. The Machine: A New Kind of Computer. http://www.hpl.hp.com/research/systems-research/machine/.

[25] M.Hosomi, H.Yamagishi, T.Yamamoto, K.Besso, Y.Yago, K.Yaman, H.Yamada, M.Shoji, H.Hachino, C.Fukumoto, et al. 2005. A Novel Nonvolatile Memory with Spin Torque Transfer Magnetic Switching: Spin-RAM. In Electron Devices Meeting, 2005. IEDM Technical Digest. IEEE International. 459–462.

[26] InfiniBand Trade Association. 2015. InfiniBand Architecture Specification. https://www.infinibandta.org/document/d4/7859.

[27] Intel. 2019. Intel Optane technology. https://www.intel.com/content/www/us/en/architecture-and-technology/intel-optane-technology.html.

[28] Intel Corporation - Product and Performance Information. 2018. Intel Non-Volatile Memory 3D XPoint. http://www.intel.com/content/www/us/en/architecture-and-technology/non-volatile-memory.html?wapkw=3d+xpoint.

[29] Intel Corporation - Product and Performance Information. 2019. Reimagining the Data Center Memory and Storage Hierarchy. https://newsroom.intel.com/editors/re-architecting-data-center-memory-storage-hierarchy/.

[30] Anuj Kalia, Michael Kaminsky, and David G. Andersen. 2014. Using RDMA Efficiently for Key-Value Services. In Proceedings of the 2014 ACM Conference on Special Interest Group on Data Communication (SIGCOMM ’14), Chicago, IL, USA.

[31] Anuj Kalia, Michael Kaminsky, and David G. Andersen. 2016. Design Guidelines for High Performance RDMA Systems. In Proceedings of the 2016 USENIX Annual Technical Conference (ATC ’16), Denver, CO, USA.

[32] Anuj Kalia, Michael Kaminsky, and David G. Andersen. 2016. FaSST: Fast, Scalable and Simple Distributed Transactions with Two-Sided (RDMA) Datagram RPCs. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI ’16), Savannah, GA, USA.

[33] Ana Klimovic, Heiner Litz, and Christos Kozyrakis. 2017. Re-Flex: Remote Flash ≈ Local Flash. In Proceedings of the Twenty-Second International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ’17), Xi’an, China.

[34] Ana Klimovic, Heiner Litz, and Christos Kozyrakis. 2018. Selecta: Heterogeneous Cloud Storage Configuration for Data Analytics. In 2018 USENIX Annual Technical Conference (ATC ’18), Boston, MA, USA.

[35] Aasheesh Kolli, Steven Pelley, Ali Saidi, Peter M. Chen, and Thomas F. Wenisch. 2016. High-Performance Transactions for Persistent Memories. In Proceedings of the Twenty-First International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ’16), Atlanta, GA.

[36] Benjamin C. Lee, Engin İpek, Onur Mutlu, and Doug Burger. 2010. Phase Change Memory Architecture and the Quest for Scalability. Commun. ACM 53, 7 (2010), 99–106.

[37] Benjamin C. Lee, Ping Zhou, Jun Yang, Youtao Zhang, Bo Zhao, Engin İpek, Onur Mutlu, and Doug Burger. 2010. Phase-change Technology and the Future of Main Memory. IEEE micro 30, 1 (2010), 143.
