Mitigating the Performance-Efficiency Tradeoff in Resilient Memory Disaggregation

Youngmoon Lee, Hassan Al Maruf, Mosharaf Chowdhury, Kang G. Shin
University of Michigan
{ymoonlee,hasanal,mosharaf,kgshin}@umich.edu

ABSTRACT
Memory disaggregation has received attention in recent years as a promising idea to reduce the total cost of ownership (TCO) of memory in modern datacenters. However, relying on remote memory expands an application’s failure domain and makes it susceptible to tail latency variations. In attempts to making disaggregated memory resilient, state-of-the-art solutions face the classic tradeoff between performance and efficiency: some double the memory overhead of disaggregation by replicating to remote memory, while many others limit performance by replicating to the local disk.

We present Hydra, a configurable, erasure-coded resilience mechanism for common memory disaggregation solutions. It can transparently handle uncertainties arising from remote failures, evictions, memory corruptions, and stragglers from network imbalance with a significantly better performance-efficiency tradeoff than the state-of-the-art. We design a fine-tuned data path to achieve single μs read/write latency to remote memory, develop decentralized algorithms for cluster-wide memory management, and analyze how to select parameters to mitigate independent and correlated uncertainties. Our integration of Hydra with two major memory disaggregation systems and evaluation on a 50-machine RDMA cluster demonstrates that it achieves the best of both worlds: it improves the latency and throughput of memory-intensive applications by up to 64.78× and 20.61×, respectively, over the state-of-the-art disk backup-based solution. At the same time, it provides performance similar to that of in-memory replication with 1.6× lower memory overhead.

1 INTRODUCTION
In recent years, DRAM has become a critical bottleneck for scaling datacenters due to the confluence of two trends. First, the slowdown of device-level scaling prevents the reduction in cost per GB of DRAM [36, 41, 55]. Second, DRAM demand has skyrocketed with the increasing popularity of in-memory workloads [9, 12, 31, 32], many of which suffer from disproportionate performance loss when their working sets do not completely fit in memory [33]. Together, they have led to memory over-provisioning, load imbalance, and an increased total cost of ownership (TCO) [33, 40, 56]. The prevalence of memory stranding – i.e., unused memory in one machine remains inaccessible to memory-constrained applications outside the machine boundary – further deteriorates the problem.

Memory disaggregation has been proposed as a promising far memory technique to logically pool together stranded memory throughout the cluster to improve the performance of applications that are running out of memory and to increase cluster memory utilization [14, 44]. By leveraging disaggregated memory, the cluster operator can perform the same jobs with a lower total DRAM capacity in the cluster or run more jobs. Indeed, with the advent of low-latency technologies such as RDMA over InfiniBand and Ethernet [17, 47], recent memory disaggregation solutions [13, 33, 60] are now close to meeting the single μs latency required to support acceptable application-level performance [30, 40].

However, realizing memory disaggregation for heterogeneous workloads running in a large-scale cluster faces considerable challenges [14, 20] stemming from two root causes:

1. Expanded failure domains: Because applications rely on memory across multiple machines in a disaggregated cluster, they become susceptible to many uncertainties. Examples include remote machine failures, evictions from
and corruptions of remote memory, and network partition.

(2) Tail at scale: Applications also suffer from stragglers or late-arriving remote responses. Stragglers can arise from many sources including latency variabilities in a large network due to congestion and background traffic [24]. While one leads to catastrophic failures and the other manifests as service-level objective (SLO) violations, both are unacceptable in production [40, 48].

Clearly, one must consider making memory disaggregation resilient to these uncertainties without violating its single μs latency requirement. To this end, state-of-the-art solutions take two primary approaches: (i) local disk backup [33, 60] and (ii) remote in-memory replication [29, 46]. The former has no additional memory overhead, but the access latency is intolerably high in the presence of any of the aforementioned uncertainties. The latter provides the stark opposite – lower latency at the cost of higher memory overhead. It also doubles the network bandwidth requirement. In essence, they represent two extreme points in the classic performance-vs-efficiency tradeoff space for resilient memory disaggregation (Figure 1). Some relevant works have explored this tradeoff and proposed compression [40] and erasure coding [56, 59, 64, 65] as two alternatives with better tradeoffs. However, compressed data must still be replicated for resilience, leading to more than 10μs latency for 4 KB pages. Erasure codes such as Reed-Solomon (RS) [57] can provide even lower memory overhead, but they have a significantly higher latency. Introducing RDMA can decrease their latency – to about 20μs using an (8, 2) RS code on 4 KB pages – but it is still insufficient.

In this paper, we consider how to further mitigate the tradeoff and present Hydra, a low-latency, low-overhead resilience mechanism for disaggregated memory. While erasure codes are known for reducing storage overhead and for better load balancing, we demonstrate how to achieve erasure-coded disaggregated cluster memory with single μs latency. Specifically, we make the following contributions:

- We analyze how to select erasure coding parameters in Hydra to mitigate independent and correlated uncertainties, as well as Hydra’s impact on cluster-wide memory usage load balancing (§5).
- We implement Hydra on Linux kernel 4.11.0 and integrate it with the two major logical memory disaggregation approaches today: disaggregated virtual memory manager (VMM) (used by Infiniswap [33] and LegoOS [60]) and disaggregated virtual file system (VFS) (used by Remote Regions [13]) (§6). Our evaluation using multiple memory-intensive applications with production workloads shows that Hydra achieves the best of both worlds. On the one hand, it closely matches the performance of replication-based resilience with 1.6× lower memory overhead with or without the presence of uncertainties. On the other hand, it improves latency and throughput of the benchmark applications by up to 64.78× and 20.61×, respectively, over SSD backup-based resilience with only 1.25× higher memory overhead. Hydra also reduces memory usage skew across our 50-machine cluster from 6.92× and 2.77× to 1.74× w.r.t. SSD backup and replication, respectively (§7).

2 BACKGROUND AND MOTIVATION

2.1 Memory Disaggregation

Memory disaggregation exposes memory available in remote machines as a pool of memory shared by many machines. It is often implemented logically by leveraging unused/stranded memory in remote machines via well-known abstractions, such as the file abstraction [13], remote memory paging [30, 42], and virtual memory management for distributed OS [60]. In the past, specialized memory appliances for physical memory disaggregation were proposed as well [44, 45].

In such systems, as an application’s working set spans multiple machines, chances of its failures due to remote events increases as well. Existing memory disaggregation systems propose using disk backup [33, 60] and in-memory replication [29, 46] to provide availability in the event of failures.

2.2 Uncertainties in Disaggregated Memory

In a large memory-disaggregated cluster, (1) servers may crash or the network become partitioned; (2) servers may experience memory corruption; (3) the network may become congested due to background traffic; and (4) workloads may have bursty access patterns. These events can lead to catastrophic failures for applications, high tail latencies, or unpredictable performance because application failure domains...
are expanded and they are more susceptible to cluster-wide events [20, 40].

To illustrate possible performance penalties in the presence of such unpredictable events, we consider a resilience solution from the existing literature [33], where each page is asynchronously backed up to a local SSD. We run a transaction processing benchmark (TPC-C [11]) on an in-memory database system, VoltDB [12]. We set the available memory for the VoltDB container to 50% of its peak memory to force remote paging for up to 50% of its working set.

1. Remote Failures and Evictions. Machine failures are the norm in large-scale clusters [66]. Without resilience, applications relying on remote memory may fail when a remote machine fails or remote memory pages are evicted. Because disk operations are significantly slower than the latency requirement of memory disaggregation, disk-based fault-tolerance is also far from being practical. In the presence of a remote failure, VoltDB experiences almost 90% cascading throughput loss (Figure 2a); throughput recovery takes a long time after the failure happens.

2. Memory Corruption. In a single-machine setup, an application shares its fate with the local machine. It assumes that the memory address space is private and safe, memory bus is physically secured, and the kernel protects pages against abnormal accesses (segmentation faults). However, in a disaggregated system, an application’s memory can be corrupted outside a single machine’s boundary. During a remote corruption event (Figure 2b), disk access causes failure-like performance loss.

3. Background Network Load. Network load throughout a large cluster can experience significant fluctuations [24, 35], which can inflate RDMA latency and application-level stragglers, causing unpredictable performance issues [67]. In the presence of an induced bandwidth-intensive background load, VoltDB throughput drops by about 50% (Figure 2c).

4. Request Bursts. Applications themselves can have bursty memory access patterns. Existing solutions maintain an in-memory buffer to absorb temporary bursts [13, 33, 53]. However, if a workload experiences a prolonged burst, this buffer can become the bottleneck; this is because the buffer ties remote access latency to disk latency when it is full. While a page read from remote memory is still fast, backup page writes to the local disk become the bottleneck after the 100th second in Figure 2d. As a result, throughput drops by about 60%. Increasing the size of the in-memory buffer for caching or staging cannot address this fundamental problem.

2.3 Performance vs. Efficiency Tradeoff for Resilience

In all of the aforementioned scenarios, the obvious alternative—in-memory 2x or 3x replication [29, 46]—is effective in mitigating the uncertainties (Figure 2). When one in-memory copy becomes unavailable, we can switch to an alternative. Unfortunately, replication incurs high memory overhead in proportion to the number of replicas. This defeats the purpose of memory disaggregation. Hedging requests to avoid stragglers [24] in a replicated system doubles its bandwidth requirement as well.

This leads to an impasse: one has to either settle for high latency in the presence of an uncertainty or incur high memory overhead. Figure 1 depicts this performance-vs-efficiency tradeoff measured in terms of remote memory read latency under failures and memory usage overhead to provide resilience.

Beyond the two extremes in the tradeoff space, there are two primary alternatives to achieve high resilience with low overhead. The first is replicating pages to remote memory after compressing them (e.g., using zswap) [40], which improves the tradeoff in both dimensions. However, its latency can be more than 10µs when data is in remote memory. Additionally, this approach suffers from similar issues as replication such as latency inflation due to stragglers. The alternative is erasure coding, which has made its way from disk-based storage to in-memory cluster caching in recent years to reduce storage overhead and improve load balancing [15, 21, 56, 63–65]. Unfortunately, most existing erasure-coded memory solutions deal with large objects (e.g., larger than 1 MB [56]), where hundreds-of-µs latency of the TCP/IP stack can be ignored. Simply replacing TCP with RDMA is not enough either. For example, the (8, 2) Reed-Solomon code shown in Figure 1 provides a lower storage overhead than compression but with a latency around 20µs.
HYDRA Resilience Manager
Remote Machines
M1
Resource Monitor
k split Encode
r parities
Decode
first k arrivals
ATC’18
Paging
(Infiniswap - NSDI’17)
Distributed VMM
(LegoOS – OSDI’18)
Page Access Request
Local Machine
[0x0]Encode
[0x0]Remote Read
[0x0]ATC’18
[0x0]async
[0x0]NSDI’17
[0x0]OSDI’18
[12x70](k+r)
address range
slab address ranges
remote slabs
(k+r) remote slabs
for each
address range
HYDRA Resilience Manager Address Space

Figure 3: HYDRA consists of Resilience Manager and Resource Monitor – both can be present in a machine. HYDRA can provide resilience for different remote memory systems.

In this paper, we present HYDRA to achieve disaggregated cluster memory with single µs latency while maintaining the storage overhead and load balancing benefits of erasure codes.

3 HYDRA ARCHITECTURE

HYDRA is an erasure-coded resilience mechanism for existing memory disaggregation techniques to provide better performance-efficiency tradeoff under remote uncertainties. It has two main components (Figure 3): (i) Resilience Manager coordinates erasure-coded resilience operations during remote read/write; (ii) Resource Monitor handles the memory management in a remote machine. Both can be present in every machine and work together without central coordination.

3.1 Resilience Manager

HYDRA Resilience Manager enables configurable resilience when applications use remote memory through different state-of-the-art memory disaggregation solutions – e.g., via a virtual file system (VFS) [13] or via paging through a virtual memory manager (VMM) [33, 60]. It transparently handles all aspects of RDMA communication and erasure coding.

Erasure codes are usually defined by two configurable parameters k and r (typically, k > r). Every k original splits (called data splits) are encoded into additional r equal-size coded splits (called parity splits), and they are stored across (k + r) different failure domains. Following this construction, the Resilience Manager divides its remote address space into fixed-size address ranges. Each address range resides in

\[ \text{address range} = k+r \]

(k + r) remote slabs: k slabs for page data and r slabs for parity (Figure 4). Each of the (k+r) slabs of an address range are distributed across (k + r) independent failure domains. Page accesses are directed to the designated (k+r) machines according to the address–slab mapping. Although remote memory access happens at the page level, the Resilience Manager coordinates with remote Resource Monitors to manage coarse-grained memory slabs to reduce metadata overhead and connection management complexity.

3.2 Resource Monitor

HYDRA Resource Monitor manages a machine’s local memory and exposes them to the remote Resilience Manager in terms of fixed-size (SlabSize) memory slabs. Different slabs can belong to different machines’ Resilience Manager. During each control period (ControlPeriod), the Resource Monitor tracks the available memory in its local machine and proactively allocates (reclaims) slabs to (from) remote mapping when memory usage is low (high). It is also responsible for slab regeneration during remote machine failures or slab corruptions.

Figure 4: HYDRA’s address space is divided into fixed-size address ranges, each of which spans (k + r) memory slabs in remote machines; i.e., k for data and r for parity (k=2 and r=1 in this figure).

4 DESIGN DETAILS

HYDRA encodes and decodes each 4 KB page independently instead of batch-coding across multiple pages. This decreases latency by avoiding the “batch waiting” time. Moreover, the Resilience Manager does not have to read unnecessary pages within the same batch during remote reads, which reduces bandwidth overhead. Distributing remote I/O across many remote machines increases I/O parallelism too. These benefits, however, come with a latency penalty. In this section, we elaborate on these challenges, followed by HYDRA’s data path design and memory management algorithms to address them.
Figure 5: HYDRA remote write/read: (a) HYDRA first writes data splits, then encodes/writes parities to hide encoding latency; (b) HYDRA reads from \((k + \Delta)\) slabs and completes as soon as the first \(k\) splits arrive, avoiding stragglers.

4.1 Challenges in Erasure-Coded Disaggregated Memory

Individually erasure coding 4 KB pages that are already small lead to even smaller data chunks (\(\frac{4}{r}\) KB), which contributes to the 20\(\mu\)s latency of erasure-coded remote memory over RDMA due to four primary reasons:

1. **Non-negligible coding overhead**: When using erasure codes with on-disk data or over slower networks that have hundreds-of-\(\mu\)s latency, its 0.7\(\mu\)s encoding and 1.5\(\mu\)s decoding overheads can be ignored. However, they become non-negligible when dealing with DRAM and RDMA.

2. **Stragglers and errors**: Because erasure codes require \(k\) splits before the original data can be constructed, any straggler can slow down a remote read. To detect and correct an error, erasure codes require additional splits; an extra read adds another round-trip to double the overall read latency.

3. **Interruption overhead**: Splitting data also increases the total number of RDMA operations for each request. Any context switch in between can further add to the latency.

4. **Data copy overhead**: In a latency-sensitive system, additional data movement can limit the lowest possible latency. During erasure coding, additional data copy into different buffers for data and parity splits can quickly add up.

4.2 HYDRA Remote Memory Data Path

We address the aforementioned challenges by incorporating four latency-minimizing design principles in HYDRA’s data path to remote memory in the Resilience Manager. A breakdown of the latency benefits of each of these techniques in HYDRA’s data path is explained in our evaluation (Figure 11).

4.2.1 Asynchronously Encoded Write. During a remote write, HYDRA Resilience Manager applies erasure coding within each individual page by dividing it into \(k\) splits (the size of each split is \(\frac{4}{r}\) KB for a 4 KB page), encodes these splits using Reed-Solomon (RS) codes [57] to generate \(r\) parity splits. Then, it writes these \((k + r)\) splits to different \((k + r)\) slabs that have already been mapped to unique remote machines. Each Resilience Manager can have a different choice of \(k\) and \(r\).

To hide encoding latency, the Resilience Manager sends the data splits first and responds back; then it encodes and sends the parity splits asynchronously. Any \(k\) successful writes of the \((k + r)\) writes allow the page to be recovered, but all \((k + r)\) must be written to guarantee resilience in the event of \(r\) failures. Decoupling the two hides encoding latency and subsequent write latencies for the parities without affecting the resilience guarantee. A write is considered complete after all \((k + r)\) have been written. Figure 5a depicts the timeline of a page write.

4.2.2 Late-Binding Resilient Read. Because HYDRA uses RS codes, any \(k\) out of the \((k + r)\) splits suffice to reconstruct a page. However, to be resilient in the presence of \(\Delta\) uncertainties, during a remote read, HYDRA Resilience Manager reads from \((k + \Delta)\) randomly chosen splits in parallel. A page can be decoded as soon as any \(k\) splits arrive out of \((k + \Delta)\). The additional \(\Delta\) reads mitigate the impact of stragglers on tail latencies as well. Figure 5b provides an example of a read operation with \(k = 2\) and \(\Delta = 1\), where one of the data slabs (Data Slab 2) is a straggler. \(\Delta = 1\) is often enough in practice.

4.2.3 Shared Latency Optimizations. In addition to asynchronous coding during writes and late binding during reads, HYDRA employs two additional optimizations in both cases.

**Run-to-Completion.** As Resilience Manager divides a 4 KB page into \(k\) smaller pieces, RDMA messages become smaller. In fact, their network latencies decrease to the point that run-to-completion becomes more beneficial than a context switch. Hence, to avoid interruption-related overheads, the remote I/O request thread waits until the RDMA operations are done.

**In-Place Coding.** To reduce the number of data copies, HYDRA Resilience Manager uses in-place coding with an extra buffer of \(r\) splits. During a write, the data splits are always...
kept in-page while the encoded \( r \) parities are put into the buffer (Figure 6a). Likewise, during a read, the data splits arrive at the page address, and the parity splits find their way into the buffer (Figure 6b).

Because a read can complete as soon as any \( k \) valid splits arrive, there is a possibility where, corrupted/straggler data splits arrive and overwrite valid page data. To address this, as soon as HYDRA Resilience Manager detects the arrival of \( k \) valid splits, it deregisters relevant RDMA memory regions. It then performs decoding and directly places the decoded data in the page destination. Because the memory region has already been deregistered, any late data split cannot access the page now. During all remote I/O, requests are forwarded directly to RDMA dispatch queues without additional copying.

### 4.3 Handling Uncertainties

Late binding during remote reads automatically mitigates stragglers due to a slow network. We discuss HYDRA mechanisms for handling failures, evictions, and corruptions below.

**Remote Failure and Eviction.** HYDRA uses reliable connections (RC) for all RDMA communication. Hence, we consider unreachability of remote machines due to machine failures/reboots or network partition as the primary cause of failure. When a remote machine becomes unreachable, the Resilience Manager is notified by the RDMA connection manager. Upon disconnection, it processes all the in-flight requests in order first. For ongoing I/O operations, it resends the I/O request to other available machines. Since RDMA guarantees strict ordering, in the read-after-write case, read requests will arrive at the same RDMA dispatch queue after write requests; hence, read requests will not be served with stale data. Finally, Resilience Manager marks the failed slab, and future requests are only directed to the available ones.

Eviction handling is similar to that of a failure, except that the Resource Monitor sends an explicit message to the corresponding Resilience Manager.

**Corruption.** So far we have only considered unavailability of a correct split due to failures and stragglers. However, in the presence of remote memory corruption, the Resilience Manager needs \( (k + \Delta) \) splits to detect \( \Delta \) errors and \( (k + 2\Delta + 1) \) splits to locate and correct the errors (§5.1). If the Resilience Manager detects an error, it requests additional \( \Delta + 1 \) reads from the rest of the \( (k + r) \) machines. It also marks the machine(s) with corrupted splits as probable erroneous machines.

If the error rate for a remote machine exceeds a user-defined threshold \( \text{ErrorCorrectionLimit} \), subsequent read requests involved with that machine will be initiated with \( (k + 2\Delta + 1) \) split requests as there is a high probability to reach an erroneous machine. This will reduce the wait time for additional \( \Delta + 1 \) reads. Resilience Manager continues this until the error rate for the involved machine gets lower than the \( \text{ErrorCorrectionLimit} \). If this continues for long and/or the error rate for a machine goes beyond another threshold \( \text{SlabRegenerationLimit} \), the Resilience Manager initiates a slab regeneration request for that machine.

### 4.4 Cluster Memory Management

Now we describe HYDRA’s memory management techniques, including, how the Resilience Manager finds remote slabs in a load-balanced manner, and the Resource Monitor adaptively allocates/reclaims local memory slabs and regenerates unavailable slabs in the background.

**Load-Balanced Slab Placement.** HYDRA Resilience Manager uses a decentralized mechanism to place remote memory slabs to avoid the latency, scalability, and fault-tolerance concerns of a centralized solution. Specifically, it distributes \( (k + r) \) slabs of each address region across the least-loaded \( (k + r) \) machines. While looking for \( (k + r) \) machines, instead of checking one-by-one, it exploits the generalized power of many choices \([54, 61]\) – it contacts \( 2 \times (k + r) \) machines and picks the least-loaded \( (k + r) \) of them. We refer to this as batch placement. This additional number of choices significantly improves load balancing as the cluster size increases (§5.3).

**Adaptive Slab Allocation/Eviction.** HYDRA Resource Monitor allocates memory slabs for remote Resilience Managers as well as proactively frees/evicts them to avoid local performance impacts (Figure 7). It periodically monitors local memory usage and maintains a headroom to always provide enough memory for local applications.

When the amount of free memory shrinks below the headroom (Figure 7a), the Resource Monitor first proactively frees/evicts slabs to ensure local applications are unaffected. It uses the decentralized batch eviction algorithm \([33]\),
whereby \((E + E')\) block devices are contacted to determine and evict \(E\) least-frequently-accessed slabs.

When the amount of free memory grows above the headroom (Figure 7b), the Resource Monitor first attempts to make the local Resilience Manager to reclaim its pages from remote memory and unmap corresponding remote slabs. Furthermore, it proactively allocates new, unmapped slabs that can be readily mapped and used by remote Resilience Managers.

**Background Slab Regeneration.** The Resource Monitor also regenerates unavailable slabs – marked by the Resilience Manager – in the background. During regeneration, writes to the slab are disabled to prevent overwriting new pages with stale ones; reads can still be served without interruption.

Hydra Resilience Manager uses the placement algorithm to find a new regeneration slab in a remote Resource Monitor with a lower memory usage. It then hands over the task of slab regeneration to that Resource Monitor. The selected Resource Monitor decodes the unavailable slab by directly reading the \(k\) randomly-selected remaining valid slab for that address region. Once regeneration completes, the Resource Monitor contacts the Resilience Manager to mark the slab as available. Requests thereafter go to the regenerated slab.

### 5 ANALYSIS

In this section, we provide analytical explanations for the benefits offered by Hydra.

**5.1 Requirements for Providing Guarantees**

Hydra can handle \(r\) remote failures and correct \(\left\lfloor \frac{\Delta}{2} \right\rfloor\) corruptions. In the absence of corruption, waiting for any \(k\) writes of \((k + r)\) splits are enough to guarantee resilience to failures. The same holds for the read; a read request can complete just after the arrival of the \(k^{th}\) split.

However, to guarantee correction in the presence of corruption, remote I/O operations must wait for additional splits. Hydra needs additional \(\Delta\) splits to detect \(\Delta\) corruptions and \(2\Delta + 1\) splits to locate and fix the error. Hence, to provide the correctness guarantee over \(\Delta\) corruptions, both asynchronous encoding and late binding need to wait for \((k + 2\Delta + 1)\) splits to be written into or read from remote machines.

Table 1 summarizes the requirements for different scenarios.

**What About Replication?** During in-memory replication, to continue after \(r\) failures, there should be at least \(r + 1\) copies of an entire 4 KB page; as such, the memory overhead is \((r + 1)\times\). However, a remote I/O operation can complete just after the confirmation from one of the \(r + 1\) machines. To detect and fix \(\Delta\) corruptions, replication needs \(\Delta + 1\) and \(2\Delta + 1\) copies of the entire page, respectively. Thus, to provide correctness guarantee over \(\Delta\) corruptions, replication needs to wait until it writes to or reads from at least \(2\Delta + 1\) of the replicas along with a memory overhead of \((2\Delta + 1)\times\).

### 5.2 Availability Under Correlated Events

We analyze the resilience of disk backup, replication, and Hydra under cluster-wide correlated unavailability events. For example, power outages can cause 0.5%-1% machines to fail or go offline concurrently [23]. Disk backup-based solutions can tolerate any number of concurrent remote unavailability as long as its local disk is functional. Hydra and replication rely on redundancies in remote memory that may be lost when multiple machines fail before the data can be regenerated. Data loss can happen if a concurrent failure kills more than \((r + 1)\) machines out of \((k + r)\). Given an \(N\)-machine cluster and \(f\) fraction of cluster-wide failures, the probability of data loss is 

\[
\sum_{i=r+1}^{k+r} \binom{k+r}{i} \frac{N-f}{N} \cdot \frac{f^i}{\binom{N}{i}}
\]

Figure 8 compares the probabilities of loss for different \((k, r)\) parameters for an extreme cluster-wide unavailability rate of 5% on a 1000-machine cluster. For resilience, the number of parity \(r\) needs to be increased (Figure 8a). For memory efficiency, the number of data splits \(k\) needs to be increased, but, then, the probability of data loss also increases (Figure 8b). Assuming a power outage occurs once a year.
Load Imbalance $d = d \geq O$ with batch placement leads to an imbalance of which is comparable to the annual disk failure rate of 2.07% instructions and the ISA library [6] that achieves over 4 GB/s virtive remote machine. For erasure coding, we use x86 AVX Resilience Manager maintains one connection for each ac- chronization. All RDMA operations use reliable connection are independent across threads and processed without syn- memory registration, RDMA posting/polling, erasure coding) tual file system (VFS). All I/O operations (e.g., slab mapping, manager (VMM) and Remote Regions, a disaggregated vir- gation systems: Infiniswap, a disaggregated virtual memory [13, 33, 60]. We integrated block device for different memory disaggregation systems Hydra Resilience Manager is implemented as a loadable kernel module for Linux kernel 4.11 or later. Kernel-level implementation facilitates its deployment as an underlying block device for different memory disaggregation systems [13, 33, 60]. We integrated Hydra with two memory disaggregation systems: Infiniswap, a disaggregated virtual memory manager (VMM) and Remote Regions, a disaggregated virtual file system (VFS). All I/O operations (e.g., slab mapping, memory registration, RDMA posting/polling, erasure coding) are independent across threads and processed without syn- chronization. All RDMA operations use reliable connection and one-sided RDMA verbs (RDMA WRITE/READ). Each Resilience Manager maintains one connection for each ac- tive remote machine. For erasure coding, we use x86 AVX instructions and the ISA library [6] that achieves over 4 GB/s encoding throughput per core for (8+2) configuration in our evaluation platform.

Hydra Resource Monitor is implemented as a user-space program. It uses RDMA SEND/RECV operations for all control messages.

7 EVALUATION

We have integrated Hydra with both Infiniswap [33] and Remote Regions [13] and evaluated on a 50-machine 56 Gbps InfiniBand CloudLab cluster. Our key findings are as follows:

- Hydra makes erasure-coded disaggregated memory feasible by ensuring single µs page access latency alongside low memory overhead (§7.1).
- During normal operations, application-level performance using Hydra remains close to that of replication but with 1.6× lower memory overhead (§7.2).
- In the presence of uncertainties, Hydra again performs similar to replication; both improve over SSD backup by up to 13.6× for latency and 5.75× for throughput (§7.3).
- Hydra reduces cluster-wide memory utilization skew from 6.92× (2.77×) to 1.74× w.r.t. SSD backup (replication). Application performance improves by up to 64.7× for latency and 20.61× for throughput w.r.t. SSD backup (§7.4).

Experimental Setup. Unless otherwise specified, we use $k=8$, $r=2$, and $\Delta=1$, targeting 1.25× memory and bandwidth overhead. We select $r=2$ because late binding is still possible even when one of the remote slab fails. The additional read $\Delta=1$ incurs 1.125× bandwidth overhead during reads. We use SlabSize = 1GB, the additional number of choices for eviction $E^{*} = 2$. Free memory headroom is set to 25%, and the control period is set to 1 second. Each machine has 64 GB of DRAM and 2× Intel Xeon E5-2650v2 with 32 virtual cores.

We compare against the two extremes of the tradeoff space:

- SSD Backup: A copy of each page is backed up in a local SSD for the minimum 1× remote memory overhead. We consider both a disaggregated VMM system (Infiniswap) and a disaggregated VFS system (Remote Regions).
- Replication: We directly write each page over RDMA to two remote machines’ memory for a 2× overhead.

7.1 Microbenchmarks

We start by evaluating Hydra’s baseline performance char- acteristics so that we can better understand its benefits in the presence of cluster-wide uncertainties later in the section.

5.3 Impact on Load Balancing

Finally, we analyze how much more balanced memory usage becomes due to splitting address regions into finer-grained slabs and placing them via batch placement.

Given $n$ slabs and $n$ machines, placing each slab into one of $d$ randomly chosen machine will lead to an imbalance of $O(\frac{\log \log n}{\log d})$ [19]. In Hydra, splitting due to erasure coding allows fine-grained load spreading while still leveraging the power of multiple choices. For $k$ splits, splitting together with batch placement leads to an imbalance of $O(\frac{\log \log n}{k \log(d/k)})$ if $d \geq 2 \times k$ [54]. Using just two splits and four choices ($k = 2$, $d = 4$), Hydra further improves load balancing over an non- splitting load balance with four choices ($d = 4$) (Figure 9).

6 IMPLEMENTATION

Hydra Resilience Manager is implemented as a loadable kernel module for Linux kernel 4.11 or later. Kernel-level implementation facilitates its deployment as an underlying block device for different memory disaggregation systems [13, 33, 60]. We integrated Hydra with two memory disaggregation systems: Infiniswap, a disaggregated virtual memory manager (VMM) and Remote Regions, a disaggregated virtual file system (VFS). All I/O operations (e.g., slab mapping, memory registration, RDMA posting/polling, erasure coding) are independent across threads and processed without syn-chronization. All RDMA operations use reliable connection and one-sided RDMA verbs (RDMA WRITE/READ). Each Resilience Manager maintains one connection for each active remote machine. For erasure coding, we use x86 AVX instructions and the ISA library [6] that achieves over 4 GB/s

![Figure 9: Simulated load imbalance vs the number of machines showing the benefit of splitting and batch placement.](image-url)
Figure 10: HYDRA provides better latency characteristics during both disaggregated VMM and VFS operations.

Disaggregated VMM Latency. We use a simple application with its working set size set to 2GB. It is provided 1GB memory to ensure that 50% of its memory accesses cause paging. While using disaggregated memory for remote page-in, HYDRA improves page-in latency over Infiniswap by 1.79× at median and 1.93× at the 99th percentile. Page-out latency is improved by 1.9× and 2.2× over Infiniswap at median and 99th percentile, respectively. Replication provides at most 1.1× improved latency over HYDRA, while incurring 2× memory and bandwidth overhead (Figure 10a).

Disaggregated VFS Latency. We use fio [3] to generate one million random read/write requests of 4 KB block I/O. During reads, HYDRA provides improved latency over Remote Regions by 2.13× at median and 2.04× at the 99th percentile. During writes, HYDRA also improves the latency over Remote Regions by 2.22× at median and 1.74× at the 99th percentile. Replication does not show significant latency gain over HYDRA, improving latency by at most 1.18× (Figure 10b).

Latency Breakdown. Due to its coding overhead, HYDRA without optimizations performs worse than disk backup-based solution. Figure 11 highlights how each component of HYDRA’s data path design contributes toward reducing its latency.

1. Run-to-completion avoids interruptions during remote I/O, reducing the median latency of read and write by 51%.
2. In-place coding saves additional time for data copying, which substantially adds up in memory disaggregation systems, reducing 28% of the read and write latency.
3. Late binding specifically improves the tail latency during remote read by 61% by avoiding stragglers. The additional read request increases the median latency only by 6%.
4. Asynchronous encoding hides erasure coding overhead during writes, reducing the median write latency by 38%.

Figure 11: Latency breakdown of HYDRA.

7.1.1 Latency Characteristics. We measure HYDRA’s latency characteristics for VMM- and VFS-based memory disaggregation systems in the absence of uncertainties. Then we analyze the impact of each of its design components.

7.1.2 Sensitivity Analysis. Here we focus on HYDRA’s sensitivity to its different parameters as well as its overheads.

Impact of \((k, r, \Delta)\) Choices. Figure 12a shows read latency characteristics for varying \(k\). Increasing from \(k=1\) to \(k=2\) reduces median latency by parallelizing data transfers. Further increasing \(k\) improves space efficiency (measured as \(\frac{1}{k+r}\)) and load balancing, but latency deteriorates as well.

Figure 12b shows read latency for varying values of \(\Delta\). Although just one additional read (from \(\Delta=0\) to \(\Delta=1\)) helps tail latency, more additional reads have diminishing returns; instead, it hurts latency due to proportionally increasing communication overheads.

Figure 12c shows write latency variations for different \(r\) values. Increasing \(r\) does not affect the median write latency. However, the tail latency increases from \(r=3\) due to the increase in overall communication overheads.

CPU Overhead. We measure average CPU utilization of HYDRA components during I/O requests. HYDRA Resilience Manager uses event-driven I/O and consumes only 0.001% CPU cycles in each core. Erasure coding adds an additional 0.09% CPU usage in each core. Because HYDRA uses one-sided RDMA, remote HYDRA Resource Monitor does not have CPU overhead in the data path.
Table 2: HYDRA (HYD) provides similar performance to replication (REP) for VoltDB and Memcached workloads (ETC and SYS). Higher is better for throughput-related, and the lower is better for the latency-related numbers.

Figure 13: HYDRA also provides similar completion time to replication for graph analytic applications.

Background Slab Regeneration. We manually evict one of the remote slabs and measure the time for it to be regenerated. When it is evicted, HYDRA Resilience Manager places a new slab and provides the evicted slab information to the corresponding HYDRA Resource Monitor, which takes 54 ms. Then the Resource Monitor randomly selects \( k \) out of remaining remote slabs and read the page data, which takes 170 ms for a 1 GB slab. Finally, it decodes the page data to the local memory slab within 50 ms. Therefore, the total regeneration time for a 1 GB size slab is 274 ms, as opposed to taking several minutes to restart a server after failure.

7.2 Application Performance During Normal Operations

We now focus on HYDRA’s benefits for memory-intensive applications and compare it with that of SSD backup and replication. We evaluated using the following workloads:

- TPC-C benchmark [11] on VoltDB [12];
- Facebook workloads [18] on Memcached [9];

Figure 14: HYDRA latency in the presence of background network flow and remote failure.

- PageRank with Twitter data [39] on PowerGraph [31] and GraphX [32].

We consider container-based application deployment [62] and run each application in an lxc container with a memory limit to fit 100%, 75%, 50% of the peak memory usage for each application. For 100%, applications run completely in memory. For 75% and 50%, applications hit their memory limits and access pages in remote memory via HYDRA.

We present HYDRA’s application-level performance against replication (Table 2 and Figure 13) to show that it can achieve similar performance with a lower memory overhead, even in the absence of any failures. For brevity, we omit the plots for SSD backup, which performs much worse than both HYDRA and replication – albeit with no memory overhead.

For VoltDB, when half of its data is in remote memory (50%), HYDRA achieves 0.82× throughput and almost transparent latency characteristics compared to the fully in-memory case (100%). For memcached, HYDRA achieves 0.97× throughput with GET-dominant ETC workloads and 0.93× throughput with SET-intensive SYS workloads; additionally, it provides almost zero latency overhead compared to the fully in-memory scenario (100%). For graph analytics, HYDRA could achieve almost transparent application performance for PowerGraph; thanks to its optimized heap management. However, it suffers from increased job completion time for GraphX due to massive thrashing of in-memory and remote memory data. Replication does not have significant gains over HYDRA.

7.3 Resilient Performance Under Uncertainties

Now we analyze HYDRA’s performance in the presence of uncertainties and compare against the alternatives.

7.3.1 Microbenchmark. We start with the latency microbenchmarks from Section 7.1.

Background Flows. In this case, we generate RDMA flows on the remote machine constantly sending 1 GB messages.
Unlike SSD backup and replication, HYDRA maintains consistent latencies due to late binding. HYDRA’s latency improvement over SSD backup is 1.97–2.56×, and it even outperforms replication at the 99th percentile by 1.33× for read and 1.50× for write (Figure 14a).

Remote Failures. Figure 14b shows that both read and write latencies are disk-bound when it is necessary to write to and read from the backup SSD. HYDRA reduces latency over SSD backup by 8.37–13.6× and 4.79–7.30× during remote read and write, respectively. Furthermore, it matches replication’s performance.

7.3.2 Application Performance Under Uncertainties. In terms of impact on applications, we first go back to the scenarios discussed in Section 2.2 regarding to VoltDB running with 50% memory constraint. Except for the corruption scenario where we set \( r = 3 \), we use HYDRA’s default parameters. At a high level, we observe that HYDRA performs similar to replication with 1.6× lower memory overhead (Figure 15).

Next, we start each benchmark application in 50% settings and introduce one remote failure while it is running. HYDRA’s application-level performance is transparent to the presence of remote failure. Figure 16 shows HYDRA provides almost similar completion times to that of replication at a lower memory overhead in the presence of remote failure. In comparison to SSD backup, workloads experience 1.3–5.75× lower completion times using HYDRA.

7.4 Cluster-Wide Load Balancing

For the large-scale evaluation, we run 250 containerized applications across 50 machines. We create an equal number of containers for each application and workload, and randomly distributed them across the cluster. Their total memory footprint is 2.76 TB; our cluster has 3.20 TB of total memory. Half of the containers use 100% configuration; about 30% use the 75% configuration; and the rest use the 50% configuration.

Impact on Memory Imbalance and Stranding. Figure 17 shows that HYDRA reduces memory usage imbalance w.r.t. coarser-grained memory management systems: in comparison to SSD backup-based (replication-based) systems, memory usage variation decreased from 18.5% (12.9%) to 5.9% and the maximum-to-minimum utilization ratio decreased from 6.92× (2.77×) to 1.74×. HYDRA better exploits unused memory in under-utilized machines, increasing the minimum memory utilization of any individual machine by 46%. HYDRA incurs about 5% additional total memory usage compared to disk backup, whereas replication incurs 20% overhead.

Application Performance. We compare application performance in terms of completion time (Figure 18) and latency (Table 3) that demonstrate HYDRA’s performance benefits in the presence of cluster dynamics. HYDRA’s improvements increase with decreasing local memory ratio. Its throughput improvements w.r.t. SSD backup were up to 4.87× for 75% and up to 20.61× for 50%. Its latency improvements were up
We limit our TCO analysis only to memory provisioning. The TCO savings of Hydra is the revenue from leveraged unused (disaggregated) memory after deducting the TCO of RDMA hardware. We consider capital expenditure (CAPEX) of acquiring RDMA hardware and operational expenditure (OPEX) including their power usage over three years. We found an RDMA adapter costs $600 [7] and RDMA switch costs $318 [8] per machine and the operating cost is $52 over three years [33] – overall, the three-year TCO is $970 for each machine. We consider the standard machine configuration and pricing from Google Cloud Compute [4], Amazon EC2 [2], and Microsoft Azure [2] to build revenue models and calculate the TCO savings for 30% of leveraged memory for each machine (Table 4). For example, in Google Cloud, the savings of disaggregation over three years using Hydra is (($5.18*30*36)/1.25-$970)/($1553*36)*100% = 6.3%.

8 RELATED WORK

Memory Disaggregation Systems. In last few decades, many software systems tried to leverage remote machine’s memory for paging [1, 22, 26, 28, 33, 34, 40, 42, 46, 50, 58], for a global virtual memory abstraction [10, 27, 38], and to create distributed data stores [25, 37, 43, 52]. There are also proposals for hardware-based remote access to disaggregated memory using PCIe interconnects [44] and extended NUMA fabric [51]. Table 5 compares a selected few across key characteristics.

Fault-Tolerant Memory Disaggregation. Prior work on memory disaggregation focused primarily on fault tolerance [16, 28], and even that was primarily limited to theoretical analysis. To the best of our knowledge, Remote Memory Pager [46] is the earliest implementation of fault-tolerant remote memory paging using replication and parity. However, all were limited to single server-client scenarios without considering scalability concerns, and online recovery was prohibitive due to slow networks and high decoding latency. Hydra demonstrates the feasibility of single µs latency for erasure-coded, disaggregated cluster memory.

Erasure Coding in Storage. Erasure coding has been widely employed in RAID systems to achieve space-efficient fault tolerance [59, 68]. Recent large-scale clusters leverage erasure coding for storing cold data in a space-efficient manner to achieve fault-tolerance [34, 49, 63]. EC-Cache [56] in an erasure-coded in-memory cache for 1MB or larger objects,

### Table 3: Latencies for VoltDB and Memcached workloads (ETC and SYS) for SSD backup, Hydra (HYD) and replication (REP) in the cluster experiment.

| Latency (ms) | 50th | 99th |
|-------------|------|------|
| VoltDB | 60   | 179  |
| Memcached ETC/SYS | 64   | 217  |
| Power Graph | 69   | 286  |
| GraphX | 70   | 70   |
| Hydra | 111  | 116  |
| Replication | 117  | 114  |

### Table 4: Revenue model and TCO savings over three years for each machine with 30% unused memory on average.

| Monthly Pricing | Google | Amazon | Microsoft |
|-----------------|--------|--------|-----------|
| Standard machine | $1,553 | $2,211 | $2,242 |
| 1% memory | $5.18 | $9.21 | $5.92 |
| Hydra | 6.3% | 8.8% | 5.1% |
| Replication | 3.3% | 5.0% | 2.8% |

Figure 18: Median completion times (i.e., throughput) of 250 containers on a 50-machine cluster.
Table 5: Selected proposals on leveraging remote memory over the years.

| System                  | Year | Deployability | Fault Tolerance               | Load Balancing         | Latency Tolerance |
|-------------------------|------|---------------|--------------------------------|------------------------|-------------------|
| Global Memory [27]      | '95  | OS Change     | Local Disk                     | Global Manager         | None              |
| Memory Pager [46]       | '96  | Unmodified    | Replication/RAID               | None                   | None              |
| Network RAM [16]        | '98  | None          | Local Disk/Replication/RAID    | None                   | None              |
| HPBD [42]               | '05  | Unmodified    | None                           | None                   | None              |
| Memory Blade [44]       | '09  | HW Change     | Reprovision                    | None                   | None              |
| RamCloud [52]           | '10  | App. Change   | Remote Disks                   | Randomization          | None              |
| FaRM [25]               | '14  | App. Change   | Replication                    | Central Coordinator    | None              |
| Infiniswap [33]         | '17  | Unmodified    | Local Disk                     | (Coarse) Power of Choices | None              |
| Remote Regions [13]     | '18  | App. Change   | None                           | Central Manager        | None              |
| LegoOS [60]             | '18  | OS Change     | Remote Disk                    | None                   | None              |
| Compressed Far Memory [40]| 19  | OS Change     | None                           | None                   | None              |
| Hydra [19]              |      | Unmodified    | Erasure Coding                 | (Fine) Power of Choices | Late Binding      |

but its scalability is limited due to communication overhead. In contrast, Hydra achieves resilient disaggregated cluster memory with single $\mu$s page access latency while maintaining all the other benefits of erasure codes.

9 CONCLUSION

The confluence of increasing memory demand and slowdown in technology scaling has increased the memory TCO of datacenters. Memory disaggregation is a promising far memory solution, but its deployment is hindered by increased application failure domains and susceptibility to stragglers [14, 20, 40]. Designing resilient memory disaggregation faces the classic performance-vs-efficiency tradeoff, where existing solutions either settle for high latency or high memory overhead.

We have shown how to carefully leverage online erasure coding to achieve single $\mu$s latency required for effective memory disaggregation without sacrificing the benefits of erasure coding. We have demonstrated that Hydra achieves the best of both worlds: it improves the latency and throughput of memory-intensive applications by up to 64.78× and 20.61×, respectively, over the state-of-the-art disk backup-based solution; and it provides similar performance to that of in-memory replication with 1.6× lower memory overhead, leading to TCO gains. In summary, Hydra demonstrates that erasure codes can be made practical for disaggregated cluster memory.
REFERENCES

[1] Accelio based network block device. https://github.com/accelio/NBDX.

[2] Amazon EC2 Pricing. https://aws.amazon.com/ec2/pricing. Accessed: 2019-08-05.

[3] Fio - Flexible I/O Tester. https://github.com/axboe/fio.

[4] Google Compute Engine Pricing. https://cloud.google.com/compute/pricing. Accessed: 2019-08-05.

[5] Hard Drive Annualized Failure Rates 2013-2017. https://www.backblaze.com/blog/hard-drive-failure-rates-q1-2017/.

[6] Intel Intelligent Storage Acceleration Library (Intel ISA-L). https://software.intel.com/en-us/storage/ISA-L.

[7] Mellanox InfiniBand Adapter Cards. https://www.mellanoxstore.com/categories/adapters/infiniband-and-vpi-adapter-cards.html.

[8] Mellanox Switches. https://www.mellanoxstore.com/categories/switches/infiniband-and-vpi-switch-systems.html.

[9] Memcached - A distributed memory object caching system. http://memcached.org.

[10] The Versatile SMP (vSMP) Architecture. http://www.scalemp.com/technlogy/versatile-smp-vsmarchitecture/.

[11] TPC Benchmark C (TPC-C). http://www.tpc.org/tpcc/.

[12] VoltDB. https://github.com/VoltDB/voltdb.

[13] VoltDB. https://github.com/VoltDB/voltdb.

[14] Amazon EC2 Pricing. https://aws.amazon.com/ec2/pricing. Accessed: 2019-08-05.

[15] Eric A. Anderson and Jeanna M. Neefe. 1994. An Exploration of Network RAM. Technical Report UCB/CSD-98-1000. EECS Department, University of California, Berkeley.

[16] Infiniband Trade Association. Infiniband architecture specification volume 1. https://www.oiforum.org/technical/files/dl/7859.

[17] Berk Atikoglu, Yuehai Xu, Eitan Frachtenberg, Song Jiang, and Mike Paleczny. 2012. Workload Analysis of a Large-scale Key-Value Store. In USENIX ATC.

[18] Marcos K. Aguilera, Nadav Amit, Irina Calciu, Xavier Deguillard, Jayneel Gandhi, Stanko Novakovic, Arun Ramanathan, Pratap Subrahmanyan, Lalith Suresh, Kiran Tati, Rajesh Venkatasubramanian, and Michael Wei. 2018. Remote regions: a simple abstraction for remote memory. In USENIX ATC.

[19] Mario A. M. Martínez, Michael F. Kaashoek, and Ronald C.裁ken. 2009. The Nature of Datacenter Traffic: Measurements and Analysis. In IMC.

[20] Juncheng Gu, Yuehai Xu, Churoo Park, Hongzhong Zheng, John Halbert, Kuljit Bains, S.Jang, and Joo Sun Choi. 2014. Co-architecting controllers and DRAM to enhance DRAM processing. In The Memory Forum.

[21] Steven K Reinhardt, and Thomas F Wenisch. 2009. Disaggregated memory for expansion and sharing in blade servers. In NSDI.

[22] Chinnmay Kulkarni, Aniraj Kesavan, Tian Zhang, Robert Ricci, and Ryan Stutsman. 2017. Rocksteady: Fast Migration for Low-latency In-memory Storage. In SOSP.

[23] Yoosik Kuperman, Joel Nider, Abel Gordon, and Dan Tsafrir. 2016. Paravirtual Remote I/O. In ASPLOS.

[24] Haewoon Kwak, Changhyun Lee, Hosung Park, and Sue Moon. 2010. What is Twitter, a social network or a news media?. In WWW.

[25] Doron Gesher, Amin Vahdat, Yaogong Wang, David Wetherall, and David Ghobadi. A Minidisk: Using remote memory on heterogeneous NOWs. University of Washington.

[26] Rishiyur Nikhil, and Robert Stets. 1999. Cashmere-VLM: Remote memory paging for software distributed shared memory. In IPPS/SPDP.

[27] Michael J Feeley, William E Morgan, EP Pighin, Anna R Karlin, Henry M Levy, and Chandramohan A Thekkath. 1995. Implementing global memory management in a workstation cluster. In SOSP.

[28] Edward W. Felten and John Zahorjan. 1991. Issues in the implementation of a remote memory paging system. Technical Report 91-03-09. University of Washington.

[29] Michael D. Flouris and Evangelos P. Markatos. 1999. The network RamiDisk: Using remote memory on heterogeneous NOWs. Journal of Cluster Computing 2, 4 (1999), 281–295.

[30] Srikant Kandula, Sudipta Sengupta, Albert Greenberg, Parveen Patel, and Ronnie Chadik. 2009. The Nature of Datacenter Traffic: Measurements and Analysis. In IMC.

[31] Parikshit Gopalan, Jin Li, and Sergey Yekhanin. 2012. Erasure Coding in Windows Azure Storage. In USENIX ATC.

[32] Jayneel Gandhi, Stanko Novakovic, Arun Ramanathan, Pratap Subrahmanyan, Lalith Suresh, Kiran Tati, Rajesh Venkatasubramanian, and Michael Wei. 2018. Remote regions: a simple abstraction for remote memory. In USENIX ATC.

[33] Jeffrey Dean and Luiz André Barroso. 2013. The tail at scale. ACM 56, 2 (2013), 74–80.

[34] Asaf Cidon, Stephen M Rumble, Ryan Stutsman, Sachin Katti, John Osterhout, and Mendel Rosenblum. 2013. Copies: Reducing the Frequency of Data Loss in Cloud Storage. In USENIX ATC.

[35] Aleksandar Dragoevic, Dushyant Narayanan, Orion Hodson, and Miguel Castro. 2014. FaRM: Fast Remote Memory. In NSDI.

[36] Sunil Gupta, Tanuj Gajbhiye, and Amol Subramanian. 2015. DISQ: Disaggregated memory for expansion and sharing in blade servers. In ISCA.

[37] Kevin Lim, Jichuan Chang, Trevor Mudge, Parthasarathy Ranganathan, Steven K Reinhardt, and Thomas F Wenisch. 2009. Disaggregated memory for expansion and sharing in blade servers. In ISCA.

[38] Kevin Lim, Yoshiho Turner, Jose Renato Santos, Alvin AuYoung, Jichuan Chang, Parthasarathy Ranganathan, and Thomas F Wenisch. 2012. System-level implications of disaggregated memory. In HPCA.

[39] Evangelos P Markatos and George Dramitinos. 1996. Implementation of global memory management in a workstation cluster. In SOSP.

[40] Radhika Mittal, Nandita Dukkipati, Emily Blem, Hassan Wassel, Monia Ghobadi, Amin Vahdat, Yaqoong Wang, David Wetherall, and David Zats. 2015. TIMELY: RTT-based Congestion Control for the Datacenter.
In SIGCOMM.

[48] Jeffrey C Mogul and John Wilkes. 2019. Nines are Not Enough: Meaningful Metrics for Clouds. In HotOS.

[49] Subramanian Muralidhar, Wyatt Lloyd, Southern California, Sabyasachi Roy, Cory Hill, Ernest Lin, Weiwen Liu, Satadru Pan, Subramanian Muralidhar, Wyatt Lloyd, Sabyasachi Roy, Cory Hill, Ernest Lin, Weiwen Liu, Satadru Pan, Shiva Shankar, Viswanath Sivakumar, Linpeng Tang, and Sanjeev Kumar. 2014. Facebook’s Warm BLOB Storage System. In OSDI.

[50] Tia Newhall, Sean Finney, Kuzman Ganchev, and Michael Spiegel. 2003. Nswap: A network swapping module for Linux clusters. In Euro-Par.

[51] Stanko Novakovic, Alexandros Daglis, Edouard Bugnion, Babak Falsafi, and Boris Grot. 2014. Scale-out NUMA. In ASPLOS.

[52] Diego Ongaro, Stephen M Rumble, Ryan Stutsman, John Ousterhout, and Mendel Rosenblum. 2011. Fast Crash Recovery in RAMCloud. In SOSP.

[53] John Ousterhout, Parag Agrawal, David Erickson, Christos Kozyrakis, Jacob Leverich, David Mazieres, Subhasish Mitra, Aravind Narayanan, Guru Parulkar, Mendel Rosenblum, Stephen M. Rumble, Eric Stratmann, and Ryan Stutsman. 2010. The Case for RAMClouds: Scalable High Performance Storage Entirely in DRAM. SIGOPS OSR 43, 4 (2010).

[54] Gahyun Park. 2011. Brief announcement: A generalization of multiple choice balls-into-bins. In PODC.

[55] Parthasarathy Ranganathan. 2017. More Moore: Thinking outside the (server) box. In Keynote at ISCA.

[56] K V Rashmi, Mosharaf Chowdhury, Jack Kosaian, Ion Stoica, and Kannan Ramchandran. 2016. EC-Cache: Load-Balanced, Low-Latency Cluster Caching with Online Erasure Coding. In OSDI.

[57] I. Reed and G. Solomon. 1960. Polynomial Codes Over Certain Finite Fields. J. Soc. Industr. Appl. Math. 8, 2 (1960), 300–304.

[58] Ahmad Samih, Ren Wang, Christian Maciocco, Tsung-Yuan Charlie Tai, Ronghui Duan, Jiangang Duan, and Yan Solihin. 2012. Evaluating dynamics and bottlenecks of memory collaboration in cluster systems. In CCGrid.

[59] Maheswaran Sathiamoorthy, Megasthenis Asteris, Dimitris S. Papailiopoulos, Alexandros G. Dimakis, Ramkumar Vadali, Scott Chen, and Dhruba Borthakur. 2013. XORing Elephants: Novel Erasure Codes for Big Data. In VLDB.

[60] Yizhou Shan, Yutong Huang, Yilun Chen, and Yiyeng Zhang. 2018. LegoOS: A Disseminated, Distributed OS for Hardware Resource Dis-aggregation. In OSDI.

[61] Shivaram Venkataraman, Aurojit Panda, Ganesh Ananthnarayanan, Michael J. Franklin, and Ion Stoica. 2014. The Power of Choice in Data-Aware Cluster Scheduling. In OSDI.

[62] Abhishek Verma, Luis Pedrosa, Madhukar Korupolu, David Oppenheim, Eric Tune, and John Wilkes. 2015. Large-scale cluster management at Google with Borg. In EuroSys.

[63] Sage A. Weil, Scott A. Brandt, Ethan L. Miller, Darrell D. E. Long, and Carlos Maltzahn. 2006. Ceph: A Scalable, High-performance Distributed File System. In OSDI.

[64] Matt M. T. Yu, Helen H. W. Chan, and Patrick P. C. Lee. 2017. Erasure Coding for Small Objects in In-memory KV Storage. In SYSTOR.

[65] Heng Zhang, Mingkai Dong, and Haibo Chen. 2016. Efficient and Available In-memory KV-Store with Hybrid Erasure Coding and Replication. In FAST.

[66] Qi Zhang, Mohamed Fateh Zhani, Shuo Zhang, Quanyan Zhu, Raouf Boutaba, and Joseph L. Hellerstein. 2012. Dynamic energy-aware capacity provisioning for cloud computing environments. In ICAC.

[67] Yiwen Zhang, Juncheng Gu, Youngmoon Lee, Mosharaf Chowdhury, and Kang G. Shin. 2017. Performance Isolation Anomalies in RDMA. In KBNets.

[68] Zhe Zhang, Zmey Deshpande, Xiaosong Ma, Eno Thereska, and Dushyanth Narayanan. 2010. Does erasure coding have a role to play in my data center? Technical Report May. Microsoft Research Technical Report MSR-TR-2010-52, May 2010.