Memtrade: A Disaggregated-Memory Marketplace for Public Clouds

Hasan Al Maruf∗, Yuhong Zhong†, Hongyi Wang†, Mosharaf Chowdhury∗, Asaf Cidon†, Carl Waldspurger‡

University of Michigan∗  Columbia University†  Carl Waldspurger Consulting‡

Abstract
We present Memtrade, the first memory disaggregation system for public clouds. Public clouds introduce a set of unique challenges for resource disaggregation across different tenants, including security, isolation and pricing. Memtrade allows producer virtual machines (VMs) to lease both their unallocated memory and allocated-but-idle application memory to remote consumer VMs for a limited period of time. Memtrade does not require any modifications to host-level system software or support from the cloud provider. It harvests producer memory using an application-aware control loop to form a distributed transient remote memory pool with minimal performance impact; it employs a broker to match producers with consumers while satisfying performance constraints; and it exposes the matched memory to consumers as a secure KV cache. Our evaluation using real-world cluster traces shows that Memtrade provides significant performance benefit for consumers (improving average read latency up to 2.8x) while preserving confidentiality and integrity, with little impact on producer applications (degrading performance by less than 2.1%).

1 Introduction
Cloud resources are increasingly being offered in an elastic and disaggregated manner. Examples include serverless computing [8, 13] and disaggregated storage [5, 66, 75, 76, 104] that scale rapidly and adapt to highly dynamic workloads [2, 77, 78, 80, 87].

Memory, however, is still largely provisioned statically, especially in public cloud environments. In public clouds, a user launching a new VM typically selects from a set of static, pre-configured instance types, each with a fixed number of cores and a fixed amount of DRAM [4, 27, 36]. Although some platforms allow users to customize the amount of virtual CPU and DRAM [17], the amount remains static throughout the lifetime of the instance. Even in serverless frameworks, which offer elasticity and auto-scaling, a function has a static limit on its allocation of CPU and memory [9].

At the same time, long-running applications deployed on both public and private clouds are commonly highly over-provisioned relative to their typical memory usage. For example, cluster-wide memory utilization in Google, Alibaba, and Facebook datacenters hovers around 40%–60% [68, 92, 94, 98]. Large-scale analytics service providers that run on public clouds, such as Snowflake, fare even worse – on average 70%–80% of their memory remains unutilized [104]. Moreover, in many real-world deployments, workloads rarely use all of their allocated memory all of the time. Often, an application allocates a large amount of memory but accesses it infrequently (§2.2). For example, in Google’s datacenters, up to 61% of allocated memory remains idle [79]. Since DRAM is a significant driver of infrastructure cost and power consumption [19, 62, 63], excessive underutilization leads to high capital and operating expenditures, as well as wasted energy (and carbon emissions). Although recent memory-disaggregation systems address this problem by satisfying an application’s excess memory demand from an underutilized server [43, 47, 68, 79, 86, 93], existing frameworks are designed for private datacenters.

In this paper, we harvest both unallocated and allocated-but-idle application memory to enable memory disaggregation in public clouds. We propose a new memory consumption model that allows over-provisioned and/or idle applications (producers) to offer excess idle memory to memory-intensive applications (consumers) that are willing to pay for additional memory for a limited period of time at an attractive price, via a trusted third-party (broker). Participation is voluntary, and either party can leave at any time. Practical realization of this vision must address following challenges:

1) Immediately Deployable. Our goal is that Memtrade is immediately deployable on existing public clouds. Prior frameworks depend on host kernel or hypervisor modifications [43, 47, 68, 79, 86, 98]. In a public cloud setting this would require the operator to manage the memory disaggregation service, since a tenant cannot modify host-level system software. In addition, prior work assumes the latest networking hardware and protocols (e.g., RDMA) [43, 68, 79, 86, 93, 98]; availability of these features in public clouds is limited, restricting adoption.
(2) Efficient Harvesting. Memory harvesting needs to be lightweight, transparent and easily deployable without impacting performance. Most prior work includes only a VM’s unallocated memory in the remote memory pool. Leveraging idle application-level memory – allocated to an application but later unused or accessed infrequently – significantly enhances disaggregated memory capacity. This is especially challenging in public clouds, where a third-party provider has limited visibility of tenant workloads, and workloads may shift at any time. Existing cold page detection-based [40, 79] proactive page reclamation techniques need significant CPU and memory resources, along with host kernel or hypervisor modifications.

(3) Performant and Secure Consumption. To ensure producerside performance, Memtrade must return a producer’s harvested memory seamlessly when needed. Memory offered to consumers may also disappear due to a sudden burst in the producer’s own demand for memory, or if a producer disappears unexpectedly. Memtrade needs to manage this unavailability to provide a high-performance memory interface. Furthermore, in public clouds, an application’s memory may reside in a remote VM that belongs to a different organization, which may expose or corrupt the memory at any time. Existing frameworks lack data confidentiality and integrity, and provide poor client accountability for CPU bypass operations [101], restricting their adoption in public clouds.

(4) Incentivization and Resource Matching. Unlike prior work, which assumes cooperative applications, in a public cloud setting we need to create a market where producers and consumers have monetary incentives to participate. Producers must be compensated for leasing memory, and the price must be attractive to consumers compared to alternatives (e.g., existing in-memory caching services or spot instances). In addition, producers have varied availability and bursty workload demands, while consumers may have their own preferences regarding remote memory availability, fragmentation, network overhead, and application-level performance, all which must be considered when matching producers to consumers.

We design and develop Memtrade, an immediately-deployable realization of memory disaggregation in public clouds that addresses these challenges without any host kernel or hypervisor modifications. Memtrade employs a harvester in each producer VM to monitor its application-level performance and adaptively control resource consumption by dynamically setting the application’s Linux control group (cgroup) limits. The harvester uses an adaptive control loop that decides when to harvest from and when to return memory to the producer.

To prevent performance degradation in memory-sensitive applications, we design a novel in-memory swap space, Silo, which serves as a temporary victim cache for harvested pages. In the case of a sudden loss of performance, the harvester proactively prefetched previously-harvested pages back into memory. The combination of these mechanisms allows Memtrade to harvest idle pages with low impact to producer workload performance and offer them to consumers. Consumers of Memtrade can access the harvested memory through a key-value (KV) cache or a swap interface, with cryptographic protections for the confidentiality and integrity of data stored in the untrusted producer VM.

To maximize cluster-wide utilization, Memtrade employs a broker – a central coordinator that manages the disaggregated-memory market and matches producers and consumers based on their supply and demand, and helps facilitate their direct communication. The broker sets the price per unit of remote memory and is incentivized by receiving a cut of monetary transactions. Although we focus primarily on virtualized public clouds, Memtrade can be deployed in other settings, such as private datacenters and containerized clouds. We plan to open-source Memtrade.

Overall, we make the following research contributions:

• We introduce Memtrade, the first end-to-end system that enables memory disaggregation in public clouds (§3). Memtrade is easily-deployable and does not require any support from the cloud provider.

• We design a system to identify and harvest idle memory with minimal overhead and negligible performance impact (§4), which uses Silo – a novel in-memory victim cache for swapped-out pages to reduce performance loss during harvesting an application’s idle memory.

• We design a broker that arbitrates between consumers and producers, enables their direct communication and implements a placement policy based on consumer preferences, fragmentation, and producer availability (§5).

• Memtrade improves consumer average latency by up to 2.8×, while impacting producer latency by less than 2.1% (§7), and significantly increases memory utilization (up to 97.9%). We are the first to evaluate pricing strategies for resource disaggregation in public clouds (§7.4).

2 Background and Motivation

2.1 Memory Disaggregation

Memory disaggregation exposes capacity available in remote hosts as a pool of memory shared among many machines. It is often implemented logically by leveraging unallocated memory in remote machines via well-known abstractions, such as files [43], remote memory paging [47, 65, 68, 81], distributed OS virtual memory management [98] and the C++ Standard Library data structures [93]. Existing frameworks
require specialized kernels, hypervisors or hardware that might not be available in public clouds. Prior works focus on private-cloud use cases [43, 47, 68, 79, 93] and do not consider the transient nature of public-cloud remote memory, nor the isolation and security challenges when consumers and producers belong to different organizations.

2.2 Resource Underutilization in Cloud Computing

Underutilized Resources. Due to over-provisioning, a significant portion of resources remains idle in private and public clouds that run a diverse mix of workloads. To demonstrate this, we analyze production traces of Google [22], Alibaba [1], and Snowflake [104] clusters for periods of 29 days, 36 hours, and 14 days, respectively (Figure 1). In Google’s cluster, averaging over one-hour windows, memory usage never exceeds 50% of cluster capacity. In Alibaba’s cluster, at least 30% of the total memory capacity always remains unused. Even worse, in Snowflake’s cluster, which runs on public clouds, 80% of memory is unutilized on average.

However, the existence of idle memory is not sufficient for providing remote memory access; in the absence of dedicated hardware such as RDMA, it also requires additional CPU and network-bandwidth both at the consumer and the producer. Fortunately, the production traces also show that a significant portion of these resources are underutilized. Approximately 50–85% of overall cluster CPU capacity remains unused in all of these traces; Alibaba and Snowflake traces, which include bandwidth usage, show that 50–75% of network capacity remains idle.

Availability of Unallocated and Idle Memory. Another important consideration is whether unutilized memory remains available for sufficiently long periods of time to enable other applications to access it productively. Figure 2a shows that 99% of the unallocated memory in the Google cluster remains available for at least an hour. Beyond unallocated memory, which constitutes 40% of the memory in the Google traces, a significant pool of memory is allocated to applications but remains idle [47]. Figure 2b shows that an additional 8% of total memory is application memory that is not touched for an hour or more. In public clouds, beyond unallocated

![Figure 1: Cluster resources remain significantly unallocated in (a) Google (bandwidth not reported), (b) Alibaba, and (c) Snowflake.](image1)

![Figure 2: (a) Unallocated memory remains available for long periods, but (b) idle memory pages are reused quickly.](image2)

![Figure 3: Performance drop while harvesting different amounts of memory for (a) Zipfian trace on Redis, and (b) XGBoost training.](image3)

where many tenants are over-provisioned, the proportion of application idle memory may be much higher [104].

Uses for Transient Remote Memory. Transient remote memory seems attractive for numerous uses in many environments. KV caches are widely used in cloud applications [38, 49, 51, 57, 88, 111], and many service providers offer popular in-memory cache-as-a-service systems [6, 12, 28, 31]. Similarly, transient memory can be used for filesystem-as-a-service [114] in serverless computing. Application developers routinely deploy remote caches in front of persistent storage systems, and in-memory caches are a key driver of memory consumption in clouds [49, 88].

2.3 Disaggregation Challenges in Public Clouds

Harvesting Application Memory. Beyond unallocated memory, a large amount of potentially-idle memory is allocated to user VMs. In many cases, harvesting such idle memory has only minimal performance impacts. However, harvesting too aggressively can easily result in severe performance degradation, or even crash applications. Figure 3 shows the performance degradation while harvesting memory from two applications. We can harvest a substantial amount of memory from each without much performance loss. However, performance can quickly fall off a cliff, and dynamic application load changes necessitate adaptive harvesting decisions in real-time.

To reclaim an application’s idle memory, existing solutions use kernel modifications [40, 79] to determine the age of pages mapped by the application. Such an approach is
difficult to deploy in public clouds, where each user controls its own kernel distribution. Moreover, continuous page tracking can consume significant CPU and memory and require elevated permissions from the host kernel [25].

Transience of Remote Memory. Each producer and consumer have their own respective supply and demand characteristics. At the same time, producers may disappear at any time, and the amount of unallocated and idle memory that can be harvested safely from an application varies over time. Given the remote I/O cost, too much churn in memory availability may deteriorate a consumer’s performance.

Security. VMs that do not belong to the same organization in the public cloud are completely untrusted. Since consumer data residing in remote memory may be read or corrupted due to accidents or malicious behavior, its confidentiality and integrity must be protected. Producer applications must also be protected from malicious remote memory operations, and the impact of overly-aggressive or malicious consumers on producers must be limited.

3 Memtrade: Overview

Memtrade is a system that realizes memory disaggregation in public clouds. It consists of three core components (Figure 4): (i) producers, which expose their harvested idle memory to the disaggregated-memory market (§4); (ii) the broker, which pairs producers with consumers while optimizing cluster-wide objectives, such as maximizing resource utilization (§5); and (iii) consumers, which request remote-memory allocations based on their demand and desired performance characteristics (§6). This section provides an overview of these components and their interactions; more details appear in subsequent sections.

Producers. A producer employs a collection of processes to harvest idle memory within a VM, making it available to the disaggregated-memory market. A producer voluntarily participates in the market by first registering with the broker. Next, the producer monitors its resource usage and application-level performance metrics, periodically notifying the broker about its resource availability. The producer harvests memory slowly until it detects a possible performance degradation, causing it to back off and enter recovery mode. During recovery, memory is returned to the producer application proactively until its original performance is restored. Once the producer determines that it is safe to resume harvesting, it transitions back to harvesting mode.

When the broker matches a consumer’s remote memory request to the producer, it is notified with the consumer’s connection credentials and the amount of requested memory. The producer then exposes harvested memory through fixed-sized slabs dedicated to that consumer. A producer may stop participating at any time by deregistering with the broker.

Broker. The broker arbitrates between producers and consumers, matching supply and demand for harvested remote memory while considering consumer preferences and constraints. While Memtrade supports untrusted producers and consumers from diverse tenants, its logically-centralized broker component should be run by a trusted third party – such as a caching-as-a-service provider [28, 31] or the public cloud operator. The broker facilitates the direct connection between the consumer and producer using virtual private cloud interconnection mechanisms [11, 21]. The broker decides on the per-unit remote memory price for a given lease time in the disaggregated system, based in part on monitoring the current price of spot instances offered in the same public cloud. Appropriate pricing provides incentives for both producers and consumers to participate in the market; the broker receives a cut of the monetary transactions it brokers as commission.

To improve the availability of transient remote memory, the broker relies on historical resource usage information for producers to predict their future availability. It additionally considers producer reputations, based on the frequency of any prior broken leases, in order to reduce occurrences of unexpected remote memory revocations. Finally, it assigns producers to consumers in a manner that maximizes the overall cluster-wide resource utilization.

Consumers. A consumer voluntarily participates in the disaggregated-memory market by registering its connection credentials with the broker. Once approved by the broker, the consumer can submit a remote memory request by specifying its required remote memory, lease time, and preferences. After matching the request with one or more producers, the broker sends a message to the consumer with connection credentials for the assigned producer(s).
Algorithm 1 Harvester Pseudocode

1: procedure DoHarvest
2: Decrease cgroup memory limit by ChunkSize
3: 
4: procedure DoRecovery
5: while RecoveryPeriod not elapsed do
6: Disable cgroup memory limit
7: procedure RunHarvester
8: for each performance monitor epoch do
9: if no page-in then
10: Add performance data point to baseline estimator
11: Generate baseline performance distribution
12: if performance drop detected then
13: DoRecovery()
14: else
15: DoHarvest()
16: if severe performance drop detected then
17: Prefetch from disk

The consumer then communicates directly with assigned producers through a simple KV cache GET / PUT / DELETE interface to access remote memory. We also implement a transparent remote-paging interface for the consumer. However, since memory will be occasionally evicted by producers, and a swap interface assumes data is stored persistently, we do not focus on this interface. Conveniently, applications using caches assume that data is not persistent, and may be evicted asynchronously. The confidentiality and integrity of consumer data stored in producer memory is ensured cryptographically in a transparent manner (§6.1).

4 Producer

The producer consists of two key components: the harvester, which employs a control loop to harvest application memory, and the manager, which exposes harvested memory to consumers as remote memory. The producer does not require modifying host-level software, facilitating deployment in existing public clouds. Our current producer implementation only supports Linux VMs. The harvester coordinates with a loadable kernel module within the VM to make harvesting decisions, without recompling the guest kernel.

The harvester runs producer applications within a Linux control group (cgroup) [14] to monitor and limit the VM’s consumption of resources, including DRAM and CPU; network bandwidth is managed by a custom traffic shaper (§4.2). Based on application performance, the harvester decides whether to harvest more memory or release already-harvested memory. Besides unallocated memory which is immediately available for consumers, the harvester can increase the free memory within the VM by reducing the resident set size (RSS) of the application. In harvesting mode, the cgroup limit is decreased incrementally to reclaim memory in relatively small chunks; the default ChunkSize is 64 MB. If a performance drop is detected, the harvester stops harvesting and enters recovery mode, disabling the cgroup memory limit and allowing the application to fully recover.

Because directly reclaiming memory from an application address space can result in performance cliffs if hot pages are swapped to disk, we introduce Silo, a novel in-memory region that serves as a temporary buffer, or victim cache, holding harvested pages before they are made available as remote memory. Silo allows the harvester to return recently-reclaimed pages to applications efficiently. In addition, when it detects a significant performance drop due to unexpected load, Silo proactively prefetches swapped-out pages from disk, which helps mitigate performance cliffs. Algorithm 1 presents a high-level sketch of the harvester’s behavior.

The manager exposes the harvested memory via a key-value cache GET / PUT / DELETE interface, by simply running a Redis server for each consumer. A key challenge for the manager is handling the scenario where the harvester needs to evict memory. We leverage the existing Redis LRU cache-eviction policy, which helps reduce the impact on consumers when the producer suddenly needs more memory.

4.1 Adaptive Harvesting of Remote Memory

Monitoring Application Performance. The harvester provides an interface for applications to periodically report their performance, with a metric such as latency or throughput. Without loss of generality, our description uses a performance metric where higher values are better. Many applications already expose performance metrics that the harvester can leverage. Otherwise, the harvester uses the swapped-in page count (promotion rate) as a proxy for performance [79].

Estimating the Baseline. To determine whether the memory limit should be decreased or increased, the harvester compares the current application performance metric to baseline values observed without memory harvesting. Of
course, measuring performance without memory harvesting is difficult while the producer is actively reclaiming memory. To estimate the baseline performance without harvesting, we use statistics for swap-in events. When there are no swap-in events, the application has enough memory to run its workload. Therefore, the harvester includes the performance metric collected during these times as a baseline. An efficient AVL-tree data structure is used to track these points, which are discarded after an expiration time. Our current implementation adds a new data point every second, which expires after a 6-hour \( \text{WindowSize} \). We found this yielded good performance estimates; shorter data-collection intervals or longer expiration times could further improve estimates, at the cost of higher resource consumption \( (\S 7.1) \).

**Detecting Performance Drops.** To decide if it can safely reduce the cgroup memory limit, the harvester checks whether performance has degraded more than expected from its estimated baseline performance. Similar to baseline estimation, the harvester maintains another AVL tree to track application performance values over the same period.

After each performance-monitoring epoch, it calculates the 99th percentile \( (p99) \) of the recent performance distribution. The harvester assumes performance has dropped if the recent \( p99 \) is worse than baseline \( p99 \) by \( \text{P99Threshold} \) (by default, 1%), and it stops reducing the cgroup size, entering a recovery state. It then releases harvested memory adaptively to minimize the performance drop. Different percentiles or additional criteria can be used to detect performance drops.

**Effective Harvesting with Silo.** The harvester reclaim memory until a performance drop is detected. However, some workloads are extremely sensitive, and losing even a small amount of hot memory can result in severe performance degradation. Also, because the harvester adjusts the application memory size via a cgroup, it relies on the Linux kernel’s Page Frame Reclamation Algorithm (PFRA) to make decisions. Unfortunately, PFRA is not perfect and sometimes reclaims hot pages, even with an appropriate memory limit.

To address these problems, we design **Silo**, a novel in-memory area for temporarily storing swapped-out pages. We implement Silo as a loadable kernel module that is a backend for the Linux frontswap interface \( [20] \). The guest kernel swaps pages to Silo instead of disk, thus reducing the cost of swapping (Figure 5a). If a page in Silo is not accessed for a configurable \( \text{CoolingPeriod} \) (by default, 5 minutes), it is evicted to disk. Otherwise, an access causes it to be efficiently mapped back into the application’s address space (Figure 5b). In effect, Silo is an in-memory victim cache, preventing hot pages from being swapped to disk. Figure 6 shows that Silo can prevent performance cliffs, allowing the harvester to avoid significant performance degradation.

**Handling Workload Bursts.** Simply disabling the cgroup memory limit may not prevent performance drops in the face of sudden bursts. Memtrade addresses this issue by prefetching previously-reclaimed pages, proactively swapping them in from disk. If the current performance is worse than all the recorded baseline data points for consecutive epochs, the harvester instructs Silo to prefetch \( \text{ChunkSize} \) of the most recently swapped-out pages (Figure 5c). Producers with a low tolerance for performance degradation and compressible data could alternatively use a compressed RAM disk \( [39] \) instead of a disk-based swap device. This would provide more rapid recovery, trading off total harvestable memory.

### 4.2 Exposing Remote Memory to Consumers

The manager communicates with the broker to report resource availability, and it exposes a KV interface to the consumer. The entire harvested memory space is logically partitioned into fixed-size slabs; a slab (by default, 64 MB) is the granularity at which memory is leased to consumers. Different slabs from the same producer can be mapped to multiple consumers for performance and load balancing. Upon receiving an assignment message from the broker, the manager can instantly create a lightweight producer store in the producer VM, dedicated to serving remote memory for that consumer.

In Memtrade, the producer store is implemented by running a Redis \( [30] \) server within a cgroup in the producer VM, providing a familiar KV cache interface to consumers. Since
an empty Redis server consumes only 3 MB of memory and negligible CPU, for simplicity, the manager runs a separate producer store for each consumer. The producer can limit the maximum CPU used by producer stores via cgroup controls. However, producer-side CPU consumption is typically modest; YCSB on Redis uses 3.1% of a core on average.

When the lease period expires, before terminating the Redis server, the manager checks with the broker to determine if the consumer wants to extend its lease (at the current market price). Otherwise, the producer store is terminated and its memory slabs are returned to the remote memory pool.

**Network Rate Limiter.** The manager limits the amount of network bandwidth used by each consumer. We implemented a standard token-bucket algorithm [74] to limit consumer bandwidth. The manager periodically adds tokens to each consumer bucket, in proportion to its allotted bandwidth specified in the consumer request for remote memory. Before serving a request, the producer store first queries the manager to check the consumer’s available token count; if the I/O size exceeds the number of available tokens, it refuses to execute the request and notifies the consumer.

**Eviction.** The size of a producer store is determined by the amount of memory leased by each consumer. Once a producer store is full, it uses the default Redis eviction policy, a probabilistic LRU approximation [91]. If the consumer memory bursts, the manager must release memory back to the producer rapidly. In this scenario, the harvester asks the manager to reclaim an aggregate amount of remote memory allocated to consumers. The manager then generates eviction requests proportional to the corresponding producer store sizes and employs the approximate-LRU-based eviction for each producer store.

**Defragmentation.** The size of KV pairs may be smaller than the OS page size [52, 56, 88], which means that an application-level eviction will not necessarily free up the underlying OS page if other data in the same page has not been evicted. Fortunately, Redis supports memory defragmentation, which the producer store uses to compact memory.

5 Broker

The Memtrade broker is a trusted third-party that facilitates transactions between producers and consumers. It can be operated by the cloud provider, or by another company that runs the market as a service, similar to existing caching-as-a-service providers [28, 31]. Producers and consumers participate in the disaggregated market voluntarily, by registering their respective credentials with the broker. Each producer periodically sends its resource utilization metrics to the broker, which uses the resulting historical time series to predict future remote-memory availability over requested lease periods. Consumers request remote memory by sending allocation requests to the broker with the desired number of slabs and lease time, along with other preferences such as acceptable latency and bandwidth. The broker connects producers and consumers that may reside in separate virtual private clouds (VPCs) via existing high-bandwidth peering services [21, 37]. The broker maps consumer requests to producer slabs using an assignment algorithm that satisfies consumer preferences, while minimizing producer overhead and ensuring system-wide wellness objectives (e.g., load balancing and utilization).

Our current design runs the broker on a single node and can handle a market with thousands of participating VMs ($7.2$). Since consumers communicate directly with assigned producers until their leases expire, even if the broker is temporarily unavailable, the system can still continue to operate normally, except for the allocation of new remote memory. For higher availability, the broker state could be replicated using distributed consensus, e.g., leveraging Raft [18, 90] or ZooKeeper [72]. The Memtrade operator may also run several broker instances, each serving a disjoint set of consumers and producers (e.g., one broker per region or datacenter).

5.1 Availability Predictor

Remote memory is transient by nature and can be evicted at any time to protect the performance of producer applications. Hence, allocating remote memory without considering its availability may result in frequent evictions that degrade consumer performance. Fortunately, application memory usage often follows a predictable long-term pattern, such as exhibiting diurnal fluctuations [60]. The broker capitalizes on historical time series data for producer memory consumption, predicting the availability of offered remote memory using an Auto Regressive Integrated Moving Average (ARIMA) model [70]. Producers with completely unpredictable usage patterns are not suitable for Memtrade. ARIMA model parameters are tuned daily via a grid search over a hyperparameter space to minimize the mean squared error of the prediction.

5.2 Remote Memory Allocation

**Constraints and Assumptions.** While matching a consumer’s remote memory request, the broker tries to achieve the aforementioned goals under the following assumptions:

1. **Online requests:** Consumers submit remote memory requests in an online manner. During a placement decision, new or pending requests may be queued.
2. **Uncertain availability:** It is unknown exactly how long producer remote memory slabs will remain available.
3. **Partial allocation:** The broker may allocate fewer slabs than requested, as long as it satisfies the minimum amount specified by the consumer.
Placement Algorithm. When the broker receives an allocation request from a consumer, it checks whether at least one producer is expected to have at least one slab available for the entire lease duration (§5.1), at a price that would not exceed the consumer budget (§5.3). The broker calculates the placement cost of the requested slabs based on the current state of all potential producers with availability, as a weighted sum of the following metrics: number of slabs available at a given producer, predicted availability (based on ARIMA modeling), available bandwidth and CPU, network latency between the consumer and producer, and producer reputation (fraction of remote memory not prematurely evicted during past lease periods). A consumer may optionally specify weights for each of these placement desirability metrics with its request.

The broker selects the producer with the lowest placement cost, greedily assigning the number of slabs. If the producer cannot allocate the entire request, the broker selects the producer with the next-lowest cost and continues iteratively until there are no slabs left to allocate or no available producers. When fewer than the requested number are allocated, a request for the remaining slabs is appended to a queue. Pending requests are serviced in FIFO order until they are satisfied, or they are discarded after a specified timeout.

5.3 Remote Memory Pricing

Remote memory must be offered at a price that is attractive to both producers and consumers, providing incentives to participate in the disaggregated memory market. Considering the transient nature of harvested memory, any monetary incentive for leasing otherwise-wasted resources is beneficial to a producer, provided its own application-level performance is not impacted. This incentive can help the producer defray the expense of running its VM. A consumer must weigh the monetary cost of leasing remote memory against the cost of running a static or spot instance with larger memory capacity.

The broker sets a price for leasing a unit of remote memory (GB/hour) and makes it visible to all consumers. Various economic objectives could be optimized (e.g., total trading volume, total revenue of producers, etc.) We assume the broker optimizes the total revenue of producers by default, since this strategy maximizes the broker’s cut of the revenue.

From a consumer’s perspective, an alternative to Memtrade is running a separate spot instance and consuming its memory remotely [108]. Thus, to be economically viable to consumers, the price of remote memory in Memtrade should never exceed the corresponding spot instance price. For simplicity, the broker initially sets the price for each unit of remote memory to one quarter of the current market price for a spot instance, normalized by its size. This initial lower price makes remote memory attractive to consumers. Afterwards, the price is adjusted to approximate the maximal total producer revenue by searching for a better price locally. In each iteration, the broker considers the current market price \( p, p + \Delta p, \) and \( p - \Delta p \) as the candidates for the price in the next iteration, where \( \Delta p \) is the step size (by default, 0.002 cent/GB-hour). Then the broker chooses the one that generates the maximal total revenue for producers. Our pricing model yields good performance in real-world traces (§7.4). Of course, alternative price-adjustment mechanisms can be designed to achieve different economic objectives.

6 Consumer

A consumer uses remote memory. It first sends its remote memory demand to the broker, based on the current market price given by the broker and its expected performance benefit. After receiving an assignment from the broker, the consumer communicates with producers directly during the lease period. To ensure the confidentiality and integrity of its remote data, the consumer employs standard cryptographic methods during this communication. Rate-limiting techniques are used to protect producers from misbehaving or malicious consumers.

The consumer can use either a KV cache or a swap interface, which we built on top of Redis [30] and Infiniswap [68] clients, respectively. By default, Memtrade uses the key-value interface, because in contrast to swapping to disk, applications using a KV cache naturally assume cached data can disappear. We have also found the KV interface performs better than the swap interface (§7.3), due to the added overhead of going through the block layer when swapping. For the sake of brevity, we focus our description on the KV interface.

6.1 Confidentiality and Integrity

This section explains how the consumer ensures data confidentiality and integrity during its KV operations. The subscripts \( C \) and \( P \) are used to denote consumer-visible and producer-visible data, respectively.

PUT Operations. To perform a PUT, the consumer prepares a KV pair \((K_C, V_C)\) to be stored at a remote producer. First, the value \( V_C \) is encrypted using the consumer’s secret key and a fresh, randomly-generated initialization vector (IV). The IV is prepended to the resulting ciphertext, yielding the value \( V_P \) to be stored at the producer. Next, a secure hash \( H \) is generated for \( V_P \), to verify its integrity and defend against accidental or malicious corruption by the producer.

To avoid exposing the lookup key \( K_C \), the consumer substitutes a different key \( K_P \). Since \( K_P \) need only be unique, it can be generated efficiently by simply incrementing a counter for each new key stored at a producer. The producer storing the KV pair can be identified using an index \( P \) into a small table containing producer information.
The consumer stores the metadata tuple $M_C = (K_P, H, P_f)$ locally, associating it with $K_C$. While many implementations are possible, this can be accomplished conveniently by adding $(K_C, M_C)$ to a local KV store, where an entry serves as a proxy for obtaining the corresponding original value. Significantly, this approach also enables range queries, as all original keys are local.

**GET Operations.** To perform a GET, the consumer first performs a local lookup using $K_C$ to retrieve its associated metadata $M_C$, and sends a request to the producer using substitute key $K_P$. The consumer verifies that the value $V_P$ returned by the producer has the correct hash $H$: if verification fails, the corrupted value is discarded. The value $V_P$ is then decrypted using $IV$ with the consumer’s encryption key, yielding $V_C$.

**DELETE Operations.** To perform a consumer-side eviction, the consumer first removes the metadata tuple $M_C$ from its local store. It then sends an explicit DELETE request to the respective producer store so that the consumer and producer store contents remain synchronized.

**Metadata Overhead.** In our current prototype, each consumer uses a single secret key to encrypt all values. Encryption uses AES-128 in CBC mode, and hashing uses SHA-256, both standard constructions. By default, the integrity hash is truncated to 128 bits to save space. A 64-bit counter is employed to generate compact producer lookup keys. The resulting space overhead for the metadata $M_C$ corresponding to a single KV pair $(K_C, V_C)$ is 24 bytes; the $IV$ consumes an additional 16 bytes at the producer.

For applications where consumer data is not sensitive, value encryption and key substitution are unnecessary. Such an integrity-only mode requires only the integrity hash, reducing the metadata overhead to 16 bytes.

### 6.2 Purchasing Strategy

A consumer must determine a cost-effective amount of memory to lease to meet its application-level performance goals. In general, it may be difficult to estimate the monetary value of additional memory. However, when its application is a cache, lightweight sampling-based techniques [71, 105, 107] can estimate miss ratio curves (MRCs) accurately, yielding the expected performance benefit from a larger cache size.

The consumer estimates the value of additional cache space using the current *price-per-hit* from the known cost of running its VM, and its observed hit rate. The expected increase in hits is computed from its MRC, and valued based on the per-hit price. When remote memory is more valuable to the consumer than its cost at the current market price, it should be leased, yielding an economic consumer surplus.

### 7 Evaluation

We evaluate Memtrade on a CloudLab [16] cluster using both synthetic and real-world cluster traces.\(^1\) Our evaluation addresses the following questions:

- How effectively can memory be harvested? (§7.1)
- How well does the broker assign remote memory? (§7.2)
- What are Memtrade’s end-to-end benefits? (§7.3)
- How does pricing affect utility and utilization? (§7.4)

#### Experimental Setup.

Unless otherwise specified, we configure Memtrade as follows. The producer averages application-level latency over each second as its performance metric. We generate both the baseline performance distribution and the recent performance distribution from data points over the previous 6 hours (WindowSize). If the recent p99 drops below the baseline p99 by more than 1% (P99Threshold), it is considered a performance drop. Harvesting uses a 64 MB ChunkSize and a 5-minute CoolingPeriod. If a severe performance drop occurs for 3 consecutive epochs, Silo prefetches ChunkSize from disk.

Each physical server is configured with 192 GB DRAM, two Intel Xeon Silver 4114 processors with 20 cores (40 hyperthreads), and a 10Gb NIC. We use Intel DC S3520 SSDs and 7200 RPM SAS HDDs. We run the Xen hypervisor (v4.9.2) with Ubuntu 18.04 (kernel v4.15) as the guest OS.

#### Workloads.

Consumers run YCSB [59] on Redis [30]. Producers run the following applications and workloads:

- **Redis** running a Zipfian workload using a Zipfian constant of 0.7 with 95% reads and 5% updates.
- **memcached** and **MySQL** running MemCachier [28, 55] for 36 hours and 40 hours, respectively. We use 70 million SET operations to populate the memcached server, followed by 677 million queries for memcached and 135 million queries for MySQL.
- **XGBoost** [53] training an image classification model on images of cats and dogs [15] using CPU, with 500 steps.

\(^1\) Memtrade can be readily deployed on any major cloud provider. We run our evaluation in CloudLab since it is free.

|            | Total Harvested | Idle Harvested | Workload Harvested | Perf Loss |
|------------|-----------------|----------------|---------------------|-----------|
| **Redis**  | 3.8 GB          | 23.7%          | 17.4%               | 0.0%      |
| **memcached** | 8.0 GB        | 51.4%          | 14.6%               | 1.1%      |
| **MySQL**  | 4.2 GB          | 21.7%          | 7.0%                | 1.6%      |
| **XGBoost** | 18.3 GB         | 15.4%          | 17.8%               | 0.3%      |
| **Storm**  | 3.8 GB          | 1.1%           | 1.4%                | 0.0%      |
| **CloudSuite** | 3.6 GB       | 2.5%           | 15.3%               | 0.0%      |

Table 1: Total memory harvested (idle and unallocated), the percentage of memory harvested that was idle, the percentage of application-allocated memory that was harvested, and the performance loss of different workloads.


- **Storm** [33] running the Yahoo streaming workload [54] for 1.5 hours.
- **CloudSuite** [24] executing a web-serving benchmark with memcached as the cache and MySQL as the database, with 1000 users and 200 threads.

**VM Rightsizing.** To determine the VM size for each workload, we find the AWS instance type [3] with the minimal number of cores and memory that can fit the workload without affecting its baseline performance. We use configurations of M5n.Large (2 vCPU, 8 GB RAM) for Redis, M5n.2xLarge (8 vCPU, 32 GB RAM) for memcached and XGBoost, C6g.2xLarge (8 vCPU, 16 GB RAM) for MySQL, C6g.xLarge (4 vCPU, 8 GB RAM) for Storm, C6g.Large (2 vCPU, 4 GB RAM) for CloudSuite, and T2.xLarge (4 vCPU, 16 GB RAM) for consumer YCSB.

### 7.1 Harvester

**Effectiveness.** To observe the effectiveness of the harvester, we run the workloads with their respective producer configurations. For Redis, memcached, and MySQL, we use average latency to measure performance. Since XGBoost, Storm, and Cloudsuite do not provide any real-time performance metric, we use the promotion rate (number of swapped-in pages) as a proxy for performance.

We find that Memtrade can harvest significant amounts of memory, even from right-sized VMs (Table 1). Here, a notable portion of the total harvested memory is extracted from the application’s idle memory (on average, 1.1–51.4% across the entire workload) at a lower performance degradation cost of 0–1.6%. Also, a whole-machine, all-core analysis shows that the producer-side CPU and memory overheads due to the harvester were always less than 1%.

Figure 7 plots memory allocation over time for two representative workloads, and shows that for workloads such as MemCachier with varying access patterns (Figure 7a), the harvester dynamically adjusts the amount of harvested memory. For most workloads, the percentage of idle harvested memory is higher at the end of the run. Therefore, we expect that if we ran our workloads longer, the average percentage of idle harvested memory would only increase.

**Impact of Burst-Mitigation Techniques.** To observe the effectiveness of the harvester during workload bursts, we run YCSB on Redis using a Zipfian distribution (with constant 0.7). To create a workload burst, we abruptly shift it to a uniform distribution after one hour of the run. Figure 8 shows the average latency using different burst-mitigation approaches. When enabled, Silo prefetches harvested pages back into memory, which helps the application reduce its recovery time by 22.5% and 94.4% over SSD and HDD, respectively. A compressed RAM disk exhibits minimal performance degradation period during the workload burst (68.7% and 10.9% less recovery time over prefetching from SSD and HDD, respectively), at the cost of less harvested memory.

**Sensitivity Analysis.** We run YCSB over Redis with a Zipfian constant of 0.7 to understand the effect of each parameter on harvesting and producer performance. Each parameter is evaluated in an isolated experiment. Figure 9 reports the
experimental sensitivity results, using average performance to quantify degradation.

The Silo CoolingPeriod controls the aggressiveness of harvesting (Figure 9a). Setting it too high leads to less harvesting, while setting it too low causes performance drops that eventually also leads to less harvested memory.

Both the harvesting ChunkSize (Figure 9b) and the P99Threshold (Figure 9c) affect harvesting aggressiveness in a less pronounced way. The amount of harvested memory increases with more aggressive parameters, while the performance impact always remains below 1%. The performance-monitoring WindowSize does not significantly change either the harvested memory or performance (Figure 9d).

### 7.2 Broker Effectiveness

To evaluate the effectiveness of the broker, we simulate a disaggregated memory consumption scenario by replaying two days worth of traces from Google’s production cluster [22]. Machines with high memory demand – often exceeding the machine’s capacity – are treated as consumers. Machines with medium-level memory pressure (at least 40% memory consumption throughout the trace period) are marked as producers. When a consumer’s demand exceeds its memory capacity, we generate a remote memory request to the broker. We set the consumer memory capacity to 512 GB, the minimum remote memory slab size to 1 GB, and a minimum lease time of 10 minutes. In our simulation, 1400 consumers generate a total of 10.7 TB of remote memory requests within 48 hours. On the producer side, we simulate 100 machines.

On average, the broker needs to assign 18 GB of remote memory to the producers per minute. Our greedy placement algorithm can effectively place most requests. Even for a simulation where producers have only 64 GB DRAM, it can satisfy 76% of the requests (Figure 10a). With larger producers, the total number of allocations also increases. As expected, Memtrade increases cluster-wide utilization, by 38% (Figure 10b).

**Availability Predictor.** To estimate the availability of producer memory, we consider its average memory usage over the past five minutes to predict the next five minutes. ARIMA predictions are accurate when a producer has steady usage or follows some pattern; only 9% of the predicted usage exceeds the actual usage by 4%. On average, 4.59% of the allocated producer slabs get revoked before their lease expires.

### 7.3 Memtrade’s Overall Impact

**Encryption and Integrity Overheads.** To measure the overhead of Memtrade, we run the YCSB workload over Redis with 50% remote memory. Integrity hashing increases remote memory access latency by 24.3% (22.9%) at the median (p99). Hashing and key replacement cause 0.9% memory overhead for the consumer. Due to fragmentation in the producer VM, the consumer needs to consume 16.7% extra memory over the total size of actual KV pairs. Note that this fragmentation overhead would be same if the consumer had to store the KVs in its local memory.

Encryption and key substitution increase latency by another 19.8% (14.7%) at the median (p99). Due to padding, encryption increases the memory overhead by another 25.2%. Fragmentation in the producer VM causes 6.1% memory overhead. Note that for trusted producers, or for non-sensitive consumer data, encryption can be disabled.

**Application-Level Performance.** We run YCSB over Redis with different consumer VM configurations and security modes. The consumer memory size is configured such that Redis needs at least $x\%$ ($x \in \{0, 10, 30, 50, 100\}$) of its working set to be in remote Memtrade memory. If remote memory is not available, the I/O operation is performed using SSD.

For the 0% configuration, the entire workload fits in the consumer VM’s memory, and is fully served by its local Redis. Figure 11 shows that an application benefits from
using remote memory as additional cache instead of missing to disk. For the fully-secure KV cache interface, Memtrade improves average latency by 1.3–1.9×, and p99 latency by 1.5–2.1×. In the case of non-sensitive data with only integrity checks, Memtrade provides 1.45–2.3× and 2.1–2.7× better average and p99 latencies, respectively.

We also implemented a transparent swap-based consumer interface, built on top of Infiniswap [68]. When consuming remote memory via fully-secure remote paging, Memtrade’s performance drops due to hypervisor swapping overhead – average and p99 latency drop by 0.95–2.1× and 1.1–3.9×, respectively. However, given a faster swapping mechanism [86, 93] or faster network (e.g., RDMA), Memtrade swap is likely to provide a performance benefit to consumers.

Cluster Deployment. To measure the end-to-end benefit of Memtrade, we run 110 virtualized applications on CloudLab – 64 producer and 46 consumer VMs, randomly distributed across the cluster. Producers run the six workloads described earlier, while consumers run YCSB on Redis, configured with 10%, 30%, and 50% remote memory. The total consumer and producer memory footprints are 0.7 TB and 1.3 TB, respectively; our cluster has a total of 2.6 TB.

Table 2 shows that Memtrade benefits the consumers even in a cluster setting. Memtrade improves the average latency of consumer applications by 1.6–2.8×, while degrading the average producer latency by 0.0–2.1×.

7.4 Pricing Strategy
To study the impact of pricing strategy on the market, we simulate several pricing strategies with different objectives, such as maximizing the total trading volume, and maximizing the total revenue of producers. Our baseline simply sets the remote memory price to one quarter of the current spot-instance price (Figure 12b). We simulate 10,000 consumers that use Memtrade as an inexpensive cache. To estimate the expected performance benefit for consumers, we select 36 applications from the MemCachier trace, generate their MRCs (Figure 15 in the appendix for the interested), and randomly assign one to each consumer. For each consumer we allocate memory such that local memory serves at least 80% of its optimal hit ratio.

The strategies that maximize total trading volume (Figure 12c) and total producer revenue (Figure 12d) both adjust the market price dynamically to optimize their objectives. Significantly, when the remote-memory supply is sufficient, all three pricing strategies can improve the relative hit ratio for consumers by more than 16% on average (Figure 12e).

We also examine temporal market dynamics using a real-world trace to simulate a total supply of remote memory which varies over time. We use the idle memory statistics from the Google Cluster Trace 2019 – Cell C [23] to generate the total supply for each time slot, and assume one Google unit represents 5 GB of memory. For the spot instance price, we use the AWS historical price series of the spot instance type r3.large in the region us-east-2b [10]. Figure 13 plots the results. Consistent with the earlier pricing-strategy results in Figure 12, the max-trading-volume and max-revenue strategies effectively adjust the market price based on both supply and demand (Figure 13a). The behavior of all the three
pricing strategies with different economic objectives show similar levels of consistency (Figure 13b–13d).

We also examine a more realistic scenario where consumers consider the probability of being evicted when using MRCs to calculate their demand. If the eviction probability is 10%, the total revenue will decrease by 7.6% and 7.1% with the max-trading-volume strategy and the max-revenue strategy, respectively. Also, the cluster-wide utilization reductions corresponding to the max-trading-volume strategy and the max-revenue strategy are 0.0% and 5.8%.

In practice, the broker may have no prior knowledge regarding the impact of market price on consumer demand. In this case, we adjust the market price by searching for a better price locally with a predefined step size (0.002 cent/GB-hour). Figure 13e demonstrates the effectiveness of this approach using a simulation with the Google trace; the market price deviates from the optimal one by only 3.5% on average. Cluster-wide utilization increases from 56.8% to 97.9%, consumer hit ratios improve by a relative 18.2%, and the consumer’s cost of renting extra memory reduces by an average of 82.1% compared to using spot instances.

8 Related Work

Memory Disaggregation. Existing work on disaggregating datacenter resources [43, 44, 47, 65, 68, 69, 73, 76, 79, 82, 89, 93, 98] assume that memory is contained within the same organization and shared among multiple cooperative applications. Given the large amount of idle memory and diverse consumer applications and workloads, public clouds serve as a promising environment to exploit remote memory.

Public Cloud Spot Marketplaces. Amazon AWS, Microsoft Azure, and Google Cloud offer spot instances [32] – a marketplace for unutilized public cloud VMs that have not been reserved, but have been provisioned by the cloud provider. AWS allows customers to bid on spot instances while Azure and Google Cloud [29, 34] sell them at globally fixed prices. Prior research has explored the economic incentives for spot instances [41, 42, 50, 64, 67, 100, 102, 108, 110, 112, 113]. However, prior work used full spot instances to produce memory; Memtrade is more generic, enabling fine-grained consumption of excess memory from any instance type.

Single-Server Memory Management. Reclaiming idle memory from applications has been explored in many different contexts, e.g., physical memory allocation across processes by an OS [40, 58, 61], ballooning in hypervisors [96, 99, 106], transcendent memory for caching disk swap [83–85], etc. Our harvesting approach is related to application-level ballooning [95]. However, in most prior work, applications belong to the same organization while Memtrade harvests and grants memory across tenants. Multi-tenant memory sharing [42, 57, 64] has considered only single-server settings, limiting datacenter-wide adoption.

Resource Autoscaling and Instance Rightsizing. Cloud orchestration frameworks and schedulers [7, 26, 45, 97, 103] can automatically increase or decrease the number of instances based on the task arrival rate. However, users still need to statically determine the instance size before launching a task, which may lead to resource overprovisioning.

Instance rightsizing [35, 46, 48, 94, 109] automatically determines the instance size based on the resource consumption of a task. In existing solutions, the cloud provider is fully responsible for the resource reclamation and performance variability in the producer VMs. Memtrade is by design more conservative: producers can generate and reclaim the cache capacity at any time. Even with rightsizing, servers may have idle memory that can be harvested and offered to remote applications.

9 Concluding Remarks

We presented Memtrade, a readily deployable system for the realization of memory disaggregation in public clouds. With the rising popularity of serverless and disaggregated storage, we believe there will be increased demand for offering disaggregated computing resources in public clouds, and our work attempts to apply a similar approach to memory. This opens several interesting research directions for future work, including exploring whether other resources, such as CPU and persistent memory, can be offered in a similar manner via a disaggregated-resource market.

References

[1] Alibaba Cluster Trace 2018. https://github.com/alibaba/clusterdata/blob/master/cluster-trace-v2018/trace_2018.md.
[2] Amazon Aurora Serverless. https://aws.amazon.com/rds/aurora/serverless/.
[3] Amazon EC2 Instance Types. https://aws.amazon.com/ec2/instance-types/.
[4] Amazon EC2 Pricing. https://aws.amazon.com/ec2/pricing/on-demand/.
[5] Amazon Elastic Block Store. https://aws.amazon.com/ebs/.
[6] Amazon ElastiCache. https://aws.amazon.com/elasti cache/.
[7] Apache Hadoop NextGen MapReduce (YARN). http://goo.gl/eTGA.
[8] AWS Lambda. https://aws.amazon.com/lambda/.
[9] AWS Lambda Limits. https://docs.aws.amazon.com/lambda/latest/dg/limits.html.
[10] AWS Spot Instance Pricing History. https://docs.aws.amazon.com/AWSEC2/latest/UserGuide/using-spot-instances-history.html.
[11] AWS Transit Gateway. https://aws.amazon.com/transit-gateway/.
[12] Azure Cache for Redis. https://azure.microsoft.com/en-us/services/cache/.
[13] Azure Functions. https://azure.microsoft.com/en-us/services/functions/.
[14] Cgroups. https://www.kernel.org/doc/Documentation/cgroup-v1/cgroups.txt.
[15] Classification for Biospecies 3. https://www.kaggle.com/olgabelitskaya/tf-cats-vs-dogs/version/2.
[16] CloudLab. https://www.cloudlab.us/.
[17] Custom Machine Types. https://cloud.google.com/custom-machine-types/.
[18] etcd. https://github.com/etcd-io/etcd/.
[19] Facebook and Amazon are causing a memory shortage. https://www.networkworld.com/article/3247775/facebook-and-amazon-are-causing-a-memory-shortage.html.
[20] Frontswap. https://www.kernel.org/doc/html/latest/vm/frontswap.html.
[21] Global VNet Peering now generally available? https://azure.microsoft.com/en-us/blog/global-vnet-peering-now-generally-available/.
[22] Google Cluster Trace 2011. https://github.com/google/google-cluster-data/blob/master/ClusterData2011_2.md.
[23] Google Cluster Trace 2019. https://github.com/google/google-cluster-data/blob/master/ClusterData2019.md.
[24] Graph Analytics Benchmark in CloudSuite. http://parsa.epfl.ch/cloudsuite/graph.html.
[25] Idle Memory Tracking. https://www.kernel.org/doc/Documentation/cloudsuite/graph.html.
[26] Kubernetes. http://kubernetes.io.
[27] Linux Virtual Machines Pricing. https://azure.microsoft.com/en-us/pricing/details/virtual-machines/linux/.
[28] MemCachier. https://www.memcachier.com/.
[29] Preemptible VM Instances. https://cloud.google.com/compute/docs/instances/preemptible.
[30] Redis, an in-memory data structure store. https://redis.io.
[31] Redis Labs. https://redislabs.com/.
[32] Spot Instances. https://docs.aws.amazon.com/AWSEC2/latest/UserGuide/using-spot-instances.html.
[33] Storm: Distributed and fault-tolerant realtime computation. http://storm-project.net.
[34] Use low-priority VMs with Batch. https://docs.microsoft.com/en-us/azure/batch/batch-low-pri-vm.
[35] Vertical Pod Autoscaler. https://github.com/kubernetes/autoscaler/tree/master/vertical-pod-autoscaler.
[36] VM instances pricing. https://cloud.google.com/compute/vm-instance-pricing.
[37] What is VPC peering? https://docs.aws.amazon.com/vpc/latest/peering/what-is-vpc-peering.html.
[38] Who’s using Redis? https://redis.io/topics/whos-using-redis.
[39] zram. https://www.kernel.org/doc/Documentation/blockdev/zram.txt.
[40] N. Agarwal and T. F. Wenisch. Thermostat: Application-transparent page management for two-tiered main memory. SIGPLAN, 2017.
[41] O. Agmon Ben-Yehuda, M. Ben-Yehuda, A. Schuster, and D. Tsafrir. Deconstructing Amazon EC2 spot instance pricing. ACM Transactions on Economics and Computation, 2013.
[42] O. Agmon Ben-Yehuda, E. Posener, M. Ben-Yehuda, A. Schuster, and A. Mu’alem. Ginseng: Market-driven memory allocation. SIGPLAN, 2014.
[43] M. K. Aguiñera, N. Amit, I. Calciu, X. Degaullier, J. Gandhi, S. Novaković, A. Ramanathan, P. Subrahmanym, L. Suresh, K. Tati, R. VenkataSubramanian, and M. Wei. Remote regions: a simple abstraction for remote memory. In USENIX ATC, 2018.
[44] M. K. Aguiñera, N. Amit, I. Calciu, X. Degaullier, J. Gandhi, P. Subrahmanym, L. Suresh, K. Tati, R. VenkataSubramanian, and M. Wei. Remote memory in the age of fast networks. In SoCC, 2017.
[45] S. Alamro, M. Xu, T. Lan, and S. Subramaniam. CRED: Cloud rightsizing to meet execution deadlines and data locality. In 2016 IEEE 9th International Conference on Cloud Computing (CLOUD), 2016.
[46] O. Alipourfard, H. H. Liu, J. Chen, S. Venkataraman, M. Yu, and M. Zhang. CherryPick: Adaptively unearthing the best cloud configurations for big data analytics. In NSDI, 2017.
[47] E. Amaro, C. Branner-Augmon, Z. Luo, A. Ousterhout, M. K. Aguilera, A. Panda, S. Ratnasamy, and S. Shenker. Can far memory improve job throughput? In EuroSys, 2020.
[48] P. Ambati, I. Goiri, F. Frujeri, A. Gun, K. Wang, B. Dolan, B. Corell, S. Fasupuleti, T. Moscbroda, S. Elinkety, M. Fontoura, and R. Bianchini. Providing SLOs for resource-harvesting VMs in cloud platforms. In OSDI, 2020.
[49] B. Atikoglu, Y. Xu, E. Frachtenberg, S. Jiang, and M. Paleczny. Workload analysis of a large-scale key-value store. In SIGMETRICS, 2012.
[50] O. A. Ben-Yehuda, M. Ben-Yehuda, A. Schuster, and D. Tsafrir. The Resource-as-a-Service (RaaS) cloud. In HotCloud, 2012.
[51] B. Berg, D. S. Berger, S. McAllister, I. Grossof, S. Gunasekar, J. Lu, M. Uhal, J. Carrig, N. Beckmann, M. Harchol-Balter, and G. R. Ganger. The CacheLib caching engine: Design and experiences at scale. In OSDI, 2020.
[52] Z. Cao, S. Dong, S. Vemuri, and D. H. Du. Characterizing, modeling, and benchmarking RocksDB key-value workloads at Facebook. In FAST, 2020.
[53] T. Chen and C. Guerstein. XGBoost: A scalable tree boosting system. In SIGKDD, 2016.
[54] S. Chintapalli, D. Dagit, B. Evans, R. Farivar, T. Graves, M. Holderbaugh, Z. Liu, K. Nusbaum, K. Patil, B. J. Peng, et al. Benchmarking streaming computation engines: Storm, flink and spark streaming. In IPDPSW, 2016.
[55] A. Cidon, A. Eisenman, M. Alizadeh, and S. Katti. Dynacache: Dynamic cloud caching. In HotCloud, 2015.
[56] A. Cidon, A. Eisenman, M. Alizadeh, and S. Katti. Cliffhanger: Scaling performance cliffs in web memory caches. In NSDI, 2016.
[57] A. Cidon, D. Rushston, S. M. Rumble, and R. Stutsman. Memshare: a dynamic multi-tenant key-value cache. InUSENIX ATC, 2017.
[58] E. G. Coffman, Jr. and P. J. Denning. Operating Systems Theory. Prentice Hall Professional Technical Reference, 1973.
[59] B. Atikoglu, Y. Xu, E. Frachtenberg, S. Jiang, and M. Paleczny. Workload analysis of a large-scale key-value store. In SIGMETRICS, 2012.
S. Han, N. Egi, A. Panda, S. Ratnasamy, G. Shi, and S. Shenker. Network support for resource disaggregation in next-generation datacenters. In HotNets, 2013.

S. L. Ho and M. Xie. The use of ARIMA models for reliability forecasting and analysis. *Comput. Ind. Eng.*, 1998.

K. Katrinis, D. Syrivelis, D. Pnevmatikatos, G. Zervas, D. Theodoropoulos, I. Koutsooulos, K. Hasharoni, D. Raho, C. Pinto, F. Espina, S. Lopez-Buedo, Q. Chen, M. Nemirovsky, D. Roca, H. Klos, and T. Berends. Rack-scale disaggregated cloud data centers: The dReD-Box project vision. In DATE, 2016.

S. Han, N. Egi, A. Panda, S. Ratnasamy, G. Shi, and S. Shenker. Network support for resource disaggregation in next-generation datacenters. In HotNets, 2013.

S. L. Ho and M. Xie. The use of ARIMA models for reliability forecasting and analysis. *Comput. Ind. Eng.*, 1998.

K. Katrinis, D. Syrivelis, D. Pnevmatikatos, G. Zervas, D. Theodoropoulos, I. Koutsooulos, K. Hasharoni, D. Raho, C. Pinto, F. Espina, S. Lopez-Buedo, Q. Chen, M. Nemirovsky, D. Roca, H. Klos, and T. Berends. Rack-scale disaggregated cloud data centers: The dReD-Box project vision. In DATE, 2016.

S. K. Lim, J. Chang, T. Mudge, P. Ranganathan, S. K. Reinhardt, and T. F. Wenisch. Disaggregated memory for expansion and sharing in blade servers. *SIGARCH, 2009.*

D. Magenheimer. Transcendent memory on Xen. *Xen Summit, 2009.*

D. Magenheimer, C. Mason, D. McCracken, and K. Hackel. Paravirtualized paging. In WOV, 2008.

D. Magenheimer, C. Mason, D. McCracken, and K. Hackel. Transcendent memory and linux. In *Proceedings of the Linux Symposium, pages 191–200. Citeseer, 2009.*

H. A. Maruf and M. Chowdhury. Effectively Prefetching Remote Memory with Leap. *In USENIX ATC, 2020.*

I. Müller, R. F. Bruno, A. Klimovic, G. Alonso, J. Wilkes, and E. Sedlar. Serverless clusters: The missing piece for interactive batch applications? *In SPMA, 2020.*

R. Nishtala, H. Fugal, S. Grimm, M. Kwaitkowski, H. Lee, H. C. Li, R. McElory, M. Palczewy, D. Peek, P. Saab, D. Stafford, T. Tung, and Y. Venkataramani. Scaling memcache at Facebook. In *NSDI, 2013.*

V. Nitu, B. Teabe, A. Tchana, C. Isci, and D. Hagimont. Welcome to zombieland: Practical and energy-efficient memory disaggregation in a datacenter. In EuroSys, 2018.

D. Ongaro and J. Ousterhout. In search of an understandable consensus algorithm. *In USENIX ATC, 2014.*

K. Psounis, B. Brabham, and D. Engler. A randomized cache replacement scheme approximating LRU. In *Proceedings of the 34th Annual Conference on Information Sciences and Systems, March 2000.*

C. Reiss, A. Tumanov, G. R. Ganger, R. H. Katz, and M. A. Kozuch. Heterogeneity and dynamicity of clouds at scale: Google trace analysis. In SoCC, 2012.

Z. Ruan, M. Schwartzkopf, M. K. Agullera, and A. Belay. AIFM: High-performance, application-integrated far memory. In *ODS! 2020.*

R. Krazda, P. Findtensen, J. Swiderski, P. Zycz, B. Broniek, J. Kusmiercz, P. Nowak, B. Strack, P. Witusowski, S. Hand, and J. Wilkes. Autopilot: Workload autoscaling at Google. In *EuroSys, 2020.*

T.-I. Salomie, G. Alonso, T. Roscoe, and K. Elphinston. Application level ballooning for efficient server consolidation. In *EuroSys, 2013.*

J. H. Schopp, K. Fraser, and M. J. Silbermann. Resizing memory with balloons and hotplug. In *Proceedings of the Linux Symposium, volume 2, pages 313–319, 2006.*

M. Schwartzkopf, A. Konwinski, M. Abd-El-Malek, and J. Wilkes. Omega: Flexible, scalable schedulers for large compute clusters. In *EuroSys, 2013.*

Y. Shan, Y. Huang, Y. Chen, and Y. Zhang. LegoOS: A disseminated, distributed OS for hardware resource disaggregation. In *ODS!, 2018.*

P. Sharma, P. Kulkarni, and P. Shenoy. Per-VM page cache partitioning for cloud computing platforms. In *COMSNETS, 2016.*

S. Shastri, A. Rizk, and D. Irwin. Transient guarantees: Maximizing the value of idle cloud capacity. In *SC, 2016.*

A. K. Simpson, A. Szekeres, J. Nelson, and I. Zhang. Securing RDMA for high-performance datacenter storage systems. In *HotCloud, 2020.*

Y. Song, M. Zafer, and K.-W. Lee. Optimal bidding in spot instance market. In *2012 Proceedings IEEE Infocom, pages 190–198. IEEE, 2012.*

A. Verma, L. Pedrosa, M. Korupolu, D. Oppenheimer, E. Tune, and J. Wilkes. Large-scale cluster management at google with Borg. In *EuroSys, 2015.*

M. Vuppalaapati, J. Miron, R. Agarwal, D. Truong, A. Motivalli, and T. Cruanes. Building an elastic query engine on disaggregated storage. In *NSDI, 2020.*

C. Waldspurger, T. Saemundsson, I. Ahmed, and N. Park. Cache modeling and optimization using miniature simulations. In *USENIX ATC, 2017.*

C. A. Waldspurger. Memory resource management in VMware ESX server. In *ODS!, 2002.*

C. Waldspurger, N. Park, A. Garthwaite, and I. Ahmed. Efficient MRC construction with SHARDS. In *FAST, 2015.*

C. Wang, B. Urgaonkar, A. Gupta, G. Kesidis, and Q. Liang. Exploiting spot and burstable instances for improving the cost-efficacy of in-memory caches on the public cloud. In *EuroSys, 2017.*

Y. Wang, K. Arya, M. Kogias, M. Vanga, A. Bhandari, N. J. Yadwadkar, S. Sen, S. Elnikety, C. Kozyrakis, and R. Bianchini. SmartHarvest: Harvesting idle CPUs safely and efficiently in the cloud. In *EuroSys, 2021.*

H. Xu and B. Li. Dynamic cloud pricing for revenue maximization. *IEEE Transactions on Cloud Computing, 1(2):158–171, 2013.*

J. Yang, Y. Yue, and K. V. Rashmi. A large scale analysis of hundreds of in-memory cache clusters at Twitter. In *ODS!, 2020.*

Q. Zhang, Q. Zhu, and R. Boutaba. Dynamic resource allocation for spot markets in cloud computing environments. In *2011 Fourth IEEE International Conference on Utility and Cloud Computing, pages 178–185. IEEE, 2011.*

L. Zheng, C. Joe-Wong, C. W. Tan, M. Chiang, and X. Wang. How to bid the cloud. In *ACM SIGCOMM Computer Communication Review, volume 45, pages 71–84. ACM, 2015.*

Q. Zheng, K. Ren, G. Gibson, B. Settlemyer, and G. Grider. DeltaFS: exaccale file systems scale better without dedicated servers. In *PDSW, 2015.*
Figure 14: Unallocated represents the part of memory not allocated to the application; harvested means the portion of application’s memory which has been swapped to disk; Silo denotes the part of memory used by Silo to buffer reclaimed pages; RSS consists of application’s anonymous pages, mapped files, and page cache that are collected from the cgroup’s stats file.
Figure 15: Miss Ratio Curves of 36 MemCachier Applications