Memshare: a Dynamic Multi-tenant Memory Key-value Cache

Asaf Cidon\(^1\), Daniel Rushton\(^2\), Stephen M Rumble\(^3\), and Ryan Stutsman\(^2\)

\(^1\)Stanford University
\(^2\)University of Utah
\(^3\)Google Inc

Abstract

Web application performance is heavily reliant on the hit rate of memory-based caches. Current DRAM-based web caches statically partition their memory across multiple applications sharing the cache. This causes underutilization of memory which negatively impacts cache hit rates. We present Memshare, a novel web memory cache that dynamically manages memory across applications. Memshare provides a resource sharing model that guarantees private memory to different applications while dynamically allocating the remaining shared memory to optimize overall hit rate. Today’s high cost of DRAM storage and the availability of high performance CPU and memory bandwidth, make web caches memory capacity bound. Memshare’s log-structured design allows it to provide significantly higher hit rates and dynamically partition memory among applications at the expense of increased CPU and memory bandwidth consumption. In addition, Memshare allows applications to use their own eviction policy for their objects, independent of other applications. We implemented Memshare and ran it on a week-long trace from a commercial memcached provider. We demonstrate that Memshare increases the combined hit rate of the applications in the trace by an 6.1\% (from 84.7\% hit rate to 90.8\% hit rate) and reduces the total number of misses by 39.7\% without affecting system throughput or latency. Even for single-tenant applications, Memshare increases the average hit rate of the current state-of-the-art memory cache by an additional 2.7\% on our real-world trace.

1 Introduction

DRAM-based caches have become essential for reducing application latency and absorbing massive database request loads in web applications. Facebook has dozens of applications that access hundreds of terabytes of data stored in memcached\(^1\) in-memory caches\(^5\). Smaller companies are using outsourced multi-tenant in-memory caches to cost-effectively boost SQL database performance.

High access rates and slow backend database performance mean that reducing the miss rate directly translates to significant end-to-end application performance. For example, one Facebook memcached pool achieves a 98.2\% hit rate\(^8\). With an average cache latency of 200 $\mu$s and MySQL access times of 10 ms, increasing the hit rate to 99.0\% (a miss reduction of 44\%) reduces latency by over 20\% (from 376 $\mu$s to 298 $\mu$s) and reduces database read load by 1.8\times. The end-to-end speedup is even greater for user queries, which often wait on hundreds of reads\(^3\).

Today, operators naively divide memory statically across applications. For example, Facebook, which manages its own data centers and cache clusters\(^8\), physically partitions machines into separate cache pools for isolation. Similarly, Memcachier\(^3\)\(^15\), which supplies a cache-as-a-service for hundreds of customers, statically designates a portion of each cache server’s memory for a specific customer.

Static partitioning achieves strong isolation, but is inefficient when applications under utilize their memory while others are short of resources. Moreover, it is difficult for cache operators to decide how much memory should be allocated to each application over time. Ideally, a web cache should automatically learn and assign the optimal memory partitions for each application based on their changing working sets; if an application needs a short term memory boost, it should be able to borrow memory from one that needs it less.

To this end, we design Memshare, a novel multi-tenant DRAM cache that improves cache hit rates by exploiting shared and idle memory resources while providing performance isolation guarantees. To facilitate dynamic partitioning of memory among applications, Memshare stores each application’s objects in a segmented in-memory log. Memshare uses an arbiter to dynamically decide which applications require more memory and which applications are over-provisioned, and it uses a cleaner to evict objects based on their rank and to compact memory to eliminate fragmentation. Memshare
enables resource sharing for varying sharing models. This paper makes two main contributions:

1. Memshare is the first multi-tenant web memory cache that provides isolation guarantees, similar to applications’ private memory allocation, while optimally utilizing shared and idle memory. Memshare achieves this with a novel sharing model for caches that relies on dynamic and automatic profiling and adaptive memory reallocation to boost overall hit rate.

2. Memshare uniquely enforces isolation through a log-structured design with application-aware cleaning while retaining fungibility of memory between applications that have objects of different sizes. Due to its memory efficient design, Memshare achieves significantly higher hit rates than the state-of-the-art memory cache, both in multi-tenant environments and in single-tenant environments.

In Memshare, each application specifies a minimum amount of private memory, and the remaining shared memory is used flexibly to maximize hit rate. Memshare maximizes the hit rate by estimating the current hit rate gradient of each application and awarding memory to the application that would benefit from it the most. This enables cache providers to significantly increase hit rates with fewer memory resources while insulating individual applications from slowdowns due to sharing. Operators can also run all applications without private memory shares, in which case Memshare will automatically determine an effective allocation for each application that balances overall hit rate. Even when all memory is partitioned among applications, Memshare can increase overall system efficiency without affecting performance isolation by allowing idle memory to be reused between applications.

For all sharing models, Memshare lets applications specify their preferred eviction policy (e.g., LRU, LFU, Segmented LRU). The eviction policy is expressed using a ranking function. For example, in order to implement LRU, objects are ranked based on the timestamp of their last access. To implement LFU, objects are ranked based on their access frequency.

Existing memory caches cannot support these properties; they typically use a slab allocator, where objects of different sizes are assigned to slab classes and eviction is done independently on a class-by-class basis. This greatly limits the ability to reassign memory from one application to another or reassign memory between objects of different size.

Memshare replaces the slab allocator with a novel log-structured allocator that makes memory fungible between objects of different sizes and applications. The main drawback of the log-structured allocator is that in order to reassign memory, it continuously repacks memory contents, which increases CPU and memory bandwidth utilization. However, trading off increased hit rates with higher CPU and memory bandwidth utilization is an attractive option, since web memory caches are typically memory capacity bound and not CPU bound. For example, in a week-long trace from Memcached, cache inserts result in less than 0.0001% memory bandwidth utilization and similarly negligible CPU overhead. CPU and memory bandwidth should be viewed as under utilized resources that can be leveraged to increase the cache efficiency, which motivates the use of a log-structured design for memory caches.

More evidence comes from Nathan Bronson from the data infrastructure team at Facebook: “Memcached shares a RAM-heavy server configuration with other services that have more demanding CPU requirements, so in practice memcached is never CPU-bound in our data centers. Increasing CPU to improve the hit rate would be a good trade off.” Even under the worst case scenario of high CPU load, Memshare’s cleaner can dynamically shed load by giving up eviction policy accuracy. In practice, it can strongly enforce global eviction policies like LRU with minimal CPU load.

We implement Memshare and analyze its performance by running a week-long trace from Memcached, a multi-tenant memcached service. We show that Memshare adds 6.1% to the overall cache hit rate compared to memcached. We demonstrate that this miss reduction does not affect overall system throughput for real workloads, since CPU and memory bandwidth are significantly under utilized. Our experiments show that Memshare achieves its superior hit rates and consuming less than 10 MB/s of memory bandwidth, even under aggressive settings. This represents only about 0.01% of the memory bandwidth of a single CPU socket. We demonstrate that in the case of a single-tenant application running in the cache, Memshare increases the number of hits by extra 2.37% compared to Cliffhanger, the state-of-the-art single-tenant cache. In conclusion, to the best of our knowledge, Memshare achieves significantly higher average hit rates both for multi-tenant and single-tenant applications than any other memory cache.

2 Motivation

Memory-based web caches have become an essential part of the infrastructure of web applications. Companies like Facebook, Twitter, Dropbox, and Box maintain clusters of thousands of dedicated servers that run web caches like memcached that serve a wide variety of real-time and batch applications. Smaller companies utilize caching-as-a-service providers such as Elasticache, Redis Labs and Memcached. These multi-tenant cache providers may split a single server’s
memory among dozens or hundreds of applications.

Today, cache providers partition the memory space statically across multiple applications sharing the same cache server. For example, Facebook, which manages its own cache clusters, partitions its applications to a handful of pools [34, 8]. These pools are clusters of memcached servers that cache objects with similar QoS requirements. The choice of which applications are allocated into each pool is manual. Caching-as-a-service providers such as Memcached [4, 15] allow their customers to purchase a certain amount of memory. Each application is statically allocated memory on several memcached servers, and these servers maintain a separate eviction queue for each application.

### 2.1 Partitioned vs Shared

We compare two different resource sharing schemes with memcached: the static partitioning used by Memcached, and a greedy shared memory policy, both using memcached’s slab allocator with LRU. In the static partitioning, we run applications just as they run in our commercial Memcached trace; each is given isolated access to the same amount of memory it had in the trace. In the shared policy, applications share all memory, and their objects share eviction queues. An incoming object from any application evicts objects from the tail of the shared per-class eviction queues, regardless of which application’s objects are disposed. We use a motivating example of three different applications (3, 5 and 7) selected from a week-long trace of memcached traffic running on Memcached. These applications suffer from bursts of requests, so they clearly demonstrate the trade-offs between the partitioned and shared memory policies.

Table 1 shows the average hit rates over a week of the three applications in both configurations. Figure 1 depicts the average miss rate and cache occupancy over an entire week. The shared policy gives a superior overall hit rate; however, it comes at the expense of a 1% drop in application 3’s hit rate. This would result in 43% higher database load and increased latencies for that application. Notice that the figure shows that the greedy scheme significantly changes the memory allocation between the applications; application 3 loses about half its memory, while application 7 doubles its share.

![Figure 1: Miss rate and cache occupancy of Memcached's partitioned and shared policies over time.](image)

**Table 1:** Average hit rate of Memcached’s partitioned and shared policy over a week.

| Application | Partitioned Hit Rate | Shared Hit Rate |
|-------------|-----------------------|-----------------|
| 3           | 97.6%                 | 96.6%           |
| 5           | 98.8%                 | 99.1%           |
| 7           | 30.1%                 | 39.2%           |
| Combined    | 87.8%                 | 88.8%           |
evict 1 MB full of small objects, some of which may be hot as well as cold items; memcached tracks LRU rank via an explicit list, which doesn’t relate to how objects are physically grouped within slabs. Second, the newly allocated 1 MB memory for application 3 could only be used for a single object size. So for example, application 3 would only be able to use it for objects of size 256-512 byte or objects between 512-1024 bytes. If it needed to be allocated more memory for objects of both sizes, it would need application 1 to evict yet another slab. Ideally, the cache should be able to evict only the bottom ranked items from application 1, based on application 1’s eviction policy, which have a total size of 4 KB.

This motivates a new design for a multi-tenant cache memory allocator, which can dynamically move variable amounts of memory among applications, while preserving applications’ eviction policy and priorities.

3 Design

This section presents the design of Memshare Memshare is a lookaside cache server that supports the memcached API. When the cache is full, its goal is to evict stale objects to make room for fresh values. Memshare dynamically and automatically assigns a portion of the cache to each application, while monitoring how effectively each application uses its share, and it reapportions memory to improve hit rates.

Memshare is split into two key components. First, Memshare’s arbiter must determine how much memory should be assigned to each application (its targetMem). Second, Memshare’s cleaner implements these assignments by prioritizing eviction from applications that are using too much cache space.

3.1 The Cleaner and Arbiter

Memshare’s in-memory cleaner fluidly reallocates memory among applications. The cleaner finds and evicts the least useful items for any application from anywhere in memory, and it coalesces the resulting free space so that it can be used to host any object from any application of any size. This coalescing also provides fast allocation and high memory utilization.

All items in Memshare are stored in a segmented in-memory log (Figure 2). New items are allocated contiguously from the same active head segment, which starts empty and fills front-to-back. Once an item has been appended to the log, the hash table entry for its key is pointed to its new location in the log. Unlike slab allocator systems like memcached, Memshare’s segments stores objects of all sizes from all applications; they are all freely intermixed. By default, segments are 1 MB; when the head segment is full, an empty “free” segment is chosen as head.

When the system is running low on free segments (< 1% of total DRAM), it begins to run the cleaner in the background, in parallel with handling normal requests. The cleaner frees space in two steps. First, it evicts objects that belong to an application that is using too much cache memory. Second, it compacts free space together into whole free segments by moving objects in memory. Keeping a small pool of free segments allows the system to tolerate bursts of writes without blocking on cleaning.

Memshare relies on its arbiter to choose which objects the cleaner should prefer for eviction. To this end we define the need of each application as its need for memory:

\[
\text{need(app)} = \frac{\text{targetMem(app)}}{\text{actualMem(app)}}
\]

Where actualMem is the actual number of bytes currently storing objects belonging to the application, and targetMem is the number of bytes that the application is supposed to be allocated. In the case of partitioned resource allocation targetMem is constant. If the need of an application is above 1 , it means it needs to be allocated more memory. Similarly, if the need is below 1 , it is consuming more memory than it is supposed to have.

The arbiter ranks applications according to their need for memory, and the cleaner prefers to clean from segments that contain more data from the applications that have the lowest need. Items in a segment being cleaned are considered one-by-one; some are saved and others are evicted.

Cleaning is composed of “passes”. Each pass takes \( n \) distinct segments and outputs at most \( n - 1 \) new distinct segments, freeing up at least one empty segment. This is done by writing back the most essential objects into the \( n - 1 \) output segments. The writing is done contiguously so that free space, caused by obsolete objects that were overwritten, is also eliminated. \( n \) is a system parameter that is discussed in Section 6. Note that multiple passes can run in parallel.

In each pass, Memshare selects a fraction of the segments for cleaning randomly and a fraction based on which segments have the most data from applications with the lowest need. This directs the cleaner to choose more segments occupied by applications that are using more than their fair share. Random selection helps to avoid pathologies. For example, if segments were only
Algorithm 1 Memory relocation

1: function CLEANMEMORY(segments, n)
2:    relocated = 0
3:    residual = (n - 1) · segmentSize
4:    while relocated < residual do
5:        app = arbiter.maxNeed()
6:        object = maxRank(segments, app)
7:        segments.remove(object)
8:        if object.size ≤ residual - relocated then
9:            relocated = relocated + object.size
10:       else
11:           relocated = relocated + object.size
12:        end if
13:    end while
14: end function

Figure 3: Memshare relocates objects from n segments to n−1 segments. The the arbiter first chooses the application with the highest need, and the cleaner relocates the object with the highest rank among the objects of that application.

The performance of Memshare involves a trade off between the accuracy of the eviction policy, determined by the parameter n and the rate of updates to the cache. n is limited by the rate of updates to the cache. The higher the rate of updates, the faster the cleaner must be to free up enough memory to keep up with the updates. Section 6 evaluates this cost and finds for our trace the cleaning cost is less than 0.01% utilization for single modern CPU socket. Even so, the cleaner can be made faster and cheaper by decreasing n; decreasing n reduces the amount of the data the cleaner will rewrite to reclaim a segment worth of free space. This also results in the eviction of items that are ranked higher by their respective applications, so the accuracy of the eviction policy decreases. In our design, n can be dynamically adjusted based on the rate of updates to the memory cache. Note that memory cache workloads typically have a low update rate (less than 3%) [34].

The last segment out of the n−1 segments produced by the cleaning pass may be under utilized, because of many dead items in the original n segments. One of the interesting properties of the cleaner, is that the n−1 segments are sorted based on need and rank. Therefore, a
further optimization of the cleaner is to delete the last segment in case its utilization is low (e.g., under 50%), since it contains the lowest rank and need objects of the \( n - 1 \) segments.

### 4 Memshare’s Sharing Model

Memshare provides a resource allocation policy that provides both a minimum amount of private memory for each application, and assigns the rest of the cache’s shared memory to the application that would benefit from it the most in terms of hit rate. Each application is allocated a certain amount of private guaranteed memory (\( \text{privateMem} \)). Any remaining memory on the server is shared among the different applications, and we refer to it as \( \text{sharedMem} \). At each point in time, Memshare has a target amount of memory it is trying to allocate to each application, \( \text{targetMem} \). In the case of statically partitioned memory, \( \text{sharedMem} \) is zero, and \( \text{targetMem} \) is always equal to \( \text{privateMem} \) for each application.

\( \text{targetMem} \) defines its application’s fair share. Therefore, the resource allocation policy needs to ensure that each application’s \( \text{targetMem} \) does not drop below its \( \text{privateMem} \), and that the remaining \( \text{sharedMem} \) is distributed among each application in a way that maximizes some performance goal such as the maximum overall hit rate.

In maximizing the overall hit rate among the difference applications, we can estimate each application’s hit rate curve, which is the hit rate it would achieve for a given amount of memory. If we know one of the application’s hit rate curves, we can allocate memory to the applications that would achieve the highest number of hits \( [15] \). However, estimating the entire hit rate curve for each application running on the cache can be expensive and inaccurate \( [16] \).

Instead of estimating the entire hit rate curves, we estimate the local hit rate curve gradient, by leveraging shadow queues. A shadow queue is an extension of the cache that does not store the values of the items, only the keys. Each application has its own shadow queue. Objects are evicted from the cache into the shadow queue. For example, assume a certain application has 10,000 objects stored in the cache, and it has a shadow queue that stores the keys of 1,000 objects. When a request misses the eviction queue but hits the application’s shadow queue, it means that if the application was allocated space for another 1,000 objects, the request would have been a hit. The rate of hits in the shadow queue provides a local approximation of an application’s hit rate curve gradient \( [16] \). Therefore, the application with the highest rate of hits in its shadow queue would provide the highest number of hits if its memory was incrementally increased.

Algorithm 2 depicts how we decide to set the \( \text{targetMem} \). Each application is initially assigned a proportion of \( \text{sharedMem} \). When a request enters the cache, if it is a miss, we check to see if its key is stored in its application’s shadow queue, i.e., if the request hit the application’s shadow queue. If there was a shadow queue hit, that application is assigned a credit. A credit represents a certain amount of memory (e.g., 64 KB) from the total pool of shared memory. The algorithm takes away a credit at random from an application. \( \text{pickRandom} \) is a function that randomly chooses an object from a list. We will show below how the cleaner utilizes \( \text{targetMem} \) to choose which applications to evict objects from. \( \text{appList} \) is a list of all applications in the cache and \( \text{cache} \) is a list of all objects in the cache.

Table 2 compares Memshare with the statically partitioned scheme used by Memcached. We ran Memshare when 50% of the memory that was allocated in the original Memcached trace of each application is used as private memory and the rest is allocated as shared memory. Memshare provide near-equal or greater hit rate than the partitioned memcached policy. Even though 50% of its memory is reserved, Memshare also achieves a higher overall hit rate (89.2%) than the greedy shared memory scheme (88.8%).

Table 3 and Figure 4 further explore the trade off be-

| App | Partitioned Hit Rate | Memshare 50% Hit Rate |
|-----|----------------------|-----------------------|
| 3   | 97.6%                | 99.4%                 |
| 5   | 98.8%                | 98.8%                 |
| 7   | 30.1%                | 34.5%                 |
| Combined | 87.8% | 89.2% |

Table 2: Average hit rate of Memshare with 50% private memory compared to the partitioned policy.

Algorithm 2: Shared memory: set target memory

1: function SETTARGET(request, application)
2: \( \text{if request} \not\in \text{cache AND request} \in \text{application.shadowQueue then} \)
3: \( \text{candidateApps} = \{\} \)
4: for \( app \in \text{appList} \) do
5: \( \text{if app.sharedMem} \geq \text{credit then} \)
6: \( \text{candidateApps} = \text{candidateApps} + \{app\} \)
7: end if
8: end for
9: \( \text{pick} = \text{pickRandom(candidateApps)} \)
10: \( \text{application.sharedMem} = \text{application.sharedMem} + \text{credit} \)
11: \( \text{pick.sharedMem} = \text{pick.sharedMem} - \text{credit} \)
12: end if
13: for \( app \in \text{appList} \) do
14: \( \text{app.targetMem} = \text{app.privateMem} + \text{app.sharedMem} \)
15: end for
16: end function

Objects are evicted from the cache into the shadow queues. Each application has its own shadow queue. A shadow queue is an extension of the cache that does not store the values of the items, only the keys. Each application is initially assigned a proportion of \( \text{sharedMem} \). A credit represents a certain amount of memory (e.g., 64 KB) from the total pool of shared memory. The algorithm takes away a credit at random from an application. \( \text{pickRandom} \) is a function that randomly chooses an object from a list. We will show below how the cleaner utilizes \( \text{targetMem} \) to choose which applications to evict objects from. \( \text{appList} \) is a list of all applications in the cache and \( \text{cache} \) is a list of all objects in the cache.
Figure 4: Comparison of Memshare’s memory consumption and the rate of shadow queue hits with different amounts of memory reserved for applications 3, 5 and 7. Memshare assigns more shared memory to applications that have a high rate of shadow queue hits.

| Private Memory | Total Hit Rate |
|----------------|---------------|
| 0%             | 89.4%         |
| 25%            | 89.4%         |
| 50%            | 89.2%         |
| 75%            | 89.0%         |
| 100%           | 88.8%         |

Table 3: Comparison of Memshare’s total hit rate with different amounts of private memory for applications 3, 5, and 7.

Table 4: Assigning different credit sizes to each application allows cache operators to prioritize among applications.

| App | Credit Size | Hit Rate | Credit Size | Hit Rate |
|-----|-------------|----------|-------------|----------|
| 3   | 64 KB       | 99.4%    | 64 KB       | 99.5%    |
| 5   | 128 KB      | 98.5%    | 64 KB       | 98.6%    |
| 7   | 192 KB      | 33.4%    | 64 KB       | 32.3%    |

4.1 Prioritizing Shared Memory Allocation Among Applications

Cache providers may want to guarantee that when certain applications have bursts of requests, they would get a higher priority than other applications. In order to accommodate this requirement, Memshare enables cache operators to assign different shadow queue credit sizes to different applications. This guarantees that if a certain application has a higher credit size than other applications, when it requires a larger amount of memory due to a burst of activity, it will be able to expand its memory footprint faster than other applications.

Table 4 demonstrates how assigning different weights to different applications affects their overall hit rate. In this example, application 7 achieves a higher relative hit rate, since it receives larger credits in the case of a shadow queue hit.

4.2 Increasing System Efficiency for Private Memory

Shared memory is ideal for environments such as Facebook or other large web-scale providers, where multiple cooperative applications utilize a shared caching layer, and the operator wants to provide the best possible overall performance, while providing minimum guarantees to each application.

However, in some environments, applications are inherently selfish and would like to maximize their private memory, but the cache operator still has an incentive to optimize for the highest possible utilization of memory. If certain applications are under utilizing their private memory, their resources can be re-assigned without negative impact to their performance.

We present a solution for re-assigning idle memory among applications that leverages the simple idea of an idle memory tax [48], where memory that has not been accessed for a long time can be re-assigned.

The only difference between Memshare’s shared
Algorithm 3 Idle tax: set target memory

1: function SET_TARGET(app, taxRate, idleTime)
2:     idleMem = 0
3:     for object ∈ app do
4:         if object.timestamp < currentTime - idleTime then
5:             idleMem += object.size
6:     end if
7:     end for
8:     activeFraction = 1 - idleMem / app.actualMem
9:     τ = 1 - activeFraction * taxRate / (1 - taxRate)
10:    app.targetMem = idleMem + (app.privateMem / τ)
11: end function

| App | Memcached | Partitioned | Idle Tax |
|-----|----------|-------------|----------|
| 3   | 97.6%    | 99.4%       |          |
| 5   | 98.8%    | 98.6%       |          |
| 7   | 30.1%    | 31.3%       |          |

Combined 87.8% 88.8%

Table 5: Average hit rate of Memshare’s idle tax policy.

memory allocation and the idle tax policy, is in how
the arbiter sets each application’s targetMem. Algorithm 3 describes how the arbiter computes the targetMem for each application in this scenario. In the algorithm, taxRate is a number between 0 and 1, which defines what portion of each application’s memory can be reclaimed by other applications if it is idle. If taxRate is set to 1, all of the application’s memory can be reclaimed by other applications if the memory is idle (and its targetMem will be equal to 0). If taxRate is equal to 0, the idle tax cache policy is effectively the same as partitioned allocation. The algorithm defines idle memory as memory that has not been accessed by a time interval greater than idleTime. The arbiter keeps track of what fraction of each application’s memory is idle, and it sets the targetMem based on what fraction of each application is idle and on the tax rate.

In this algorithm, targetMem can never be higher than privateMem. Therefore, if multiple applications do not have any idle memory, and they are competing for additional memory, the resources will be allocated to them on a fair share based on their privateMem. For example, if two applications are contending for 10 MB of free memory, and one of them has a targetMem of 5 MB, and the other one has a targetMem of 1 MB, the remaining 10 MB will be split in a 5:1 ratio (8 MB and 2 MB).

Table 5 depicts the hit rate Memshare’s idle tax algorithm using a tax rate of 50% and a 5 hour idle time. In the three application example, the overall hit rate is increased, because the idle tax cache policy favors objects that have been accessed recently. Even though application 5’s memory suffers a slight decrease, because some of its idle objects were accessed after more than 5 hours, this decrease is much more tempered than in the case of greedy shared memory.

4.3 Automatically Defining Private Memory

Memshare’s shared memory algorithm tries to optimally distribute shared memory across applications, while the idle tax algorithm taxes applications that are not actively using their private memory. These two approaches can be combined, for example, in the case where cache operators want to reserve a certain amount of space for an application, but are not sure how much memory to allocate to each application. In this case, they can run Memshare with the shared memory algorithm using private memory set to 0. After the algorithm runs for several hours, the cache operator can switch to the idle tax algorithm and set each application’s private memory to be equal to the average target memory of the shared cache algorithm.

5 Implementation

In this section, we describe the implementation of Memshare and how its various parts are synchronized. Memshare consists of three major modules written in C++ on top of memcached 1.4.24: the log, the arbiter and the cleaner. Memshare reuses most of memcached’s units without change including its hash table, basic transport, dispatch, and request processing.

5.1 The Log

The log replaces memcached’s slab allocator. It provides a basic alloc and free interface. On allocation, it returns a pointer to the requested number of bytes from the current “head” segment. If the request is too big to fit in the head segment, the log selects an empty segment as the new head and allocates from it.

Allocation of space for new objects and the change of a head segment are protected by a spinlock. Contention is not a concern since both operations are inexpensive: allocation increments an offset in the head segment and changing a head segment requires popping a new segment from a free list. If there were no free segments threads would block waiting for the cleaner to add new segments to the free list. In practice the free list is never empty (we describe the reason below).

5.2 The Arbiter

The arbiter tracks two key attributes for each application: the amount of space each application is occupying in the cache and its shadow LRU queue of recently evicted items. The SET request handler forwards each successful SET to the arbiter so the per-application bytes-in-use count can be increased. On evictions during cleaning passes, the arbiter decreases the per-application bytes-in-use count and inserts the evicted items’ into the application’s shadow queue. In practice, the shadow queue
only stores the 64-bit hash of each key and the length of each item that it contains, which makes it small and efficient. Hash collisions are almost non-existent and do no harm; they simply result in slight over-counting of shadow queue hits.

5.3 The Cleaner

The cleaner always tries to keep some amount of free memory available. By default, when the log notices less than 1% of memory is free it notifies the cleaner, which starts cleaning. It stops when at least 1% is free again. If the cleaner falls behind the rate at which service threads perform inserts, then it starts new threads and cleans in parallel. The cleaner can clean more aggressively, by reducing the number of segments for cleaning \( n \), or freeing up more segments in each cleaning pass. This trades eviction policy accuracy for reduced CPU load and memory bandwidth.

Cleaning passes must synchronize with each other and with normal request processing. A spin lock protects the list of full segments and the list of empty segments. They are both manipulated briefly at the start and end of each cleaning pass to choose segments to clean and to acquire or release free segments. In addition, the cleaner uses Memcached’s fine-grained bucket locks to synchronize hash table access. The cleaner accesses the hash table to determine item liveness, to evict items, and to update item locations when they are relocated.

The arbiter’s per-app bytes-in-use counts and shadow queues are protected by a spin lock, since they must be changed in response to evictions. Each cleaner pass aggregates the total number of bytes evicted from each application and it installs the change with a single lock acquisition to avoid the overhead of acquiring and releasing locks for every evicted item. The shadow queue is more challenging, since every evicted key needs to be installed in some application’s shadow queue. Normally, any GET that results in a miss should check the application’s shadow queue. So, blocking operations for the whole cleaning pass or even just for the whole duration needed to populate it with evicted keys would be prohibitive. Instead, the shadow queue is protected with a spin lock while it is being filled, but GET misses use a tryLock operation. If the tryLock fails, the shadow queue access is ignored.

The last point of synchronization is between GET operations and the cleaner. The cleaner never modifies the objects that it moves. Therefore, GET operations do not acquire the lock to the segment list and continue to access records during the cleaning pass. In rare schedules, this could result in a GET operation finding a reference in the hash table to a place in a segment that is cleaned before it is actually accessed. Memshare uses an epoch mechanism to make this safe. Each request/response cycle is tagged at its start with an epoch copied from a global epoch number. After a cleaning pass has removed all of the references from the hash table, it tags the segments with the global epoch number and then increments it. A segment is only reused when all requests in the system are from epochs later than the one it is tagged with.

5.4 Modularity

Memshare maintains a strong separation between the cleaner and the arbiter, even though eviction order is highly dynamic and requires tight communication between the modules. To do this, after a cleaning pass chooses segments, it notifies the arbiter which items are being cleaned. The arbiter ranks them and then calls back to the cleaner for each item that it would like to keep. If the relocation is successful the arbiter updates the item’s location in the hash table. Once the empty segments have been filled with relocated items, the arbiter removes the remaining entries from the hash table and updates per-application statistics and shadow queues. In this way, the cleaner is oblivious to applications, ranking, eviction policy, and the hash table. Its only task is efficient and parallel item relocation.

6 Evaluation

In this section we present the evaluation of Memshare on the Memcached traces and a set of microbenchmarks. To measure the end-to-end performance of Memshare, we ran the week-long Memcached trace on Memshare. Since the Memcached traces have a low load of requests, we also benchmarked our implementation using the YCSB [17] workload generator.

Our experiments run on 4-core 3.4 GHz Intel Xeon E3-1230 v5 (with 8 total hardware threads) and 32 GB of DDR4 DRAM at 2133 MHz. All experiments are compiled and run using the stock kernel, compiler, and libraries on Debian 8.4 AMD64.

6.1 End-to-end Performance

Our evaluation uses 1 MB segments and 100 candidate segments for cleaning. We ran the shared cache policy with 75% of each application’s original Memcached memory as private, and the rest as shared. For each application we used a shadow queue that represents 10 MB

| Policy          | Combined Hit Rate | Miss Reduction |
|-----------------|-------------------|----------------|
| memcached       | 84.66%            | 0.00%          |
| Cliffhanger     | 87.73%            | 20.00%         |
| Memshare Tax    | 89.92%            | 34.28%         |
| Memshare Shared | 90.75%            | 39.69%         |

Table 6: Combined hit rate of Memshare’s idle tax (50% tax) and shared memory policy (75% private) compared with Cliffhanger, which is the state-of-the-art slab-based cache and Memcached. The miss reduction column compares the miss rate of the different policies to memcached.
of objects. We ran the idle tax policy with a 50% tax rate and with all of the memory allocated to each application as private.

We tested the end-to-end performance of Memshare using all the major applications from the Memcachier trace with the shared memory and idle tax policies. Figure 5 presents the hit rate results and Table 6 presents the summary. The shared cache policy provides a higher overall combined hit rate increase, since it tries to maximize for overall hit rates.

For the shared memory policy, we experimented with using different credit sizes. When Memshare uses credit sizes that are too small, shared memory won’t be moved quickly enough between applications to maximize hit rate. When it uses credit sizes that are too high, the allocation of shared memory among applications will oscillate, which will cause excessive evictions. We found that for the Memcachier applications a credit size of 64 KB provides a good balance.

Table 7 presents the combined hit rate and cleaner memory bandwidth consumption of top 20 applications in Memcachier trace using Memshare with the shared memory policy with 75% private memory, and varying the number of segments in each cleaning pass.

| Segments (n) | Hit Rate | Memory Bandwidth (MB/s) |
|--------------|----------|-------------------------|
| 1            | 89.20%   | 0.04                    |
| 10           | 90.47%   | 2.14                    |
| 20           | 90.58%   | 2.86                    |
| 40           | 90.74%   | 4.61                    |
| 60           | 90.74%   | 6.17                    |
| 80           | 90.75%   | 7.65                    |
| 100          | 90.75%   | 9.17                    |

Table 7: Combined hit rate and memory bandwidth consumption of top 20 applications in Memcachier trace using Memshare with the shared memory policy with 75% private memory, and varying the number of segments in each cleaning pass.

Table 8: Average hit rate of the top 20 applications in the trace with Memshare with 100% private memory, compared with Cliffhanger and memcached. We run each application as a single tenant.

| Policy | Average Single Tenant Hit Rate |
|--------|--------------------------------|
| memcached | 88.3%                        |
| Cliffhanger | 93.1%                    |
| Memshare 100% Private | 95.5%                     |

Table 8: Average hit rate of the top 20 applications in the trace with Memshare with 100% private memory, compared with Cliffhanger and memcached. We run each application as a single tenant.

While consuming less than 0.01% of the memory bandwidth of a single modern CPU socket. Even at 100 candidate segments, the memory bandwidth of Memshare is less than 10 MB/s for the top 20 applications in the trace.

### 6.1.1 Single Tenant Hit Rate

In addition to providing multi-tenant guarantees, Memshare’s log structured design significantly improves hit rates on average for individual applications on a cache which uses a slab allocator. Table 8 compares the average hit rates between Memshare and two systems that utilize slab allocators: memcached and Cliffhanger. Within a single tenant application, Cliffhanger optimizes the amount of memory allocated to each slab to optimize for its overall hit rate. However, Memshare’s log structured design provides superior hit rates compared to Cliffhanger, because it allows memory to be allocated fluidly for objects of different sizes. In contrast, each time Cliffhanger moves memory from one slab class to another, it must evict an entire 1 MB of objects, including objects that may be hot. On average, Memshare with 100% private memory increases the hit rate by 7.13% compared to memcached and by 2.37% compared to Cliffhanger.

### 6.2 Microbenchmarks

Since the Memcachier traces do not result in a high CPU utilization, we also ran microbenchmarks of Memshare using the YCSB framework, which incurs significantly higher CPU and memory bandwidth utilization. The results show that Memshare incurs minimal
Latency

|           | GET Hit | GET Miss | SET   |
|-----------|---------|----------|-------|
| memcached | 21.44 µs| 21.8 µs  | 29.48 µs |
| Memshare  | 22.04 µs| 23.0 µs  | 23.62 µs |

Table 9: Average latencies of Memshare compared to memcached under an artificial workload that causes high CPU utilization. Memshare’s shadow queue lookup increases the latency in the case of GET cache misses.

| Op/s       | memcached 5% writes | Memshare 5% writes | memcached 100% writes | Memshare 100% writes |
|------------|----------------------|--------------------|-----------------------|----------------------|
|           | 705,968              | 690,332            | 540,325               | 519,277              |

Table 10: Average throughput of Memshare compared to memcached under a YCSB workload with 5% writes and 95% reads and under a workload with 100% writes.

6.2.1 Latency

Table 9 presents the average latency of Memshare compared to memcached when the cache is full and the cleaner is running. These numbers are taken with both the clients and cache server threads running on the same machine. Consequently, they represent a worst case; typical cache access times are dominated by the network software stack and round trip times [37]. Memshare’s GET hit latency is 2.7% higher than memcached. Memshare incurs a 5.5% latency overhead for GET misses, since it checks whether the key exists in the shadow queue. This extra overhead could be eliminated. Note that adding an overhead to a GET miss is typically insignificant, since the application needs to issue a database query, which takes tens to hundreds of milliseconds.

6.2.2 CPU and Throughput

Table 10 compares the throughput of Memshare with memcached under a YCSB workload with 5% writes and 95% reads and with a workload with 100% writes. On average, Memshare has a 2.2% lower throughput for the first workload and a 3.9% lower throughput under the punishing all writes workload.

Most of the throughput loss is due to Memshare’s cleaner. To quantify the throughput loss, we measured the CPU time spent by Memshare on different tasks. In the 5% write workload, Memshare spends 5.1% of the process’s CPU time on cleaning, and 1.1% of the process’s CPU time testing shadow queues on GET misses.

The 100% write workload is unrealistic (such a workload does not need a cache), but it highlights the worst case throughput cost for the hit rate improvements that Memshare gives. With a 100% write workload 12.8% of the process’s CPU time is spent on cleaning.

Overall, the small decrease in throughput of Memshare is well justified. In-memory caches are typically capacity-bound not throughput-bound, and they often operate under low loads [13, 14]. In particular, the Memcacheier trace introduces loads which are two orders of magnitude lower than the throughput of Memshare.

6.2.3 Memory Overhead and Utilization

Memshare has a small memory overhead. The shared memory policy uses shadow queues that store keys which represent 10 MB of objects. The memory overhead of the shadow queues depends on the size of the objects. For example, assuming objects are small on average (128 B), a shadow queue stores 81,920 keys. Only 8 B key hashes are kept, so key length isn’t a factor. In this case, the overhead is 81,920 · 8 B = 640 KB per application. The rest of the data structures used by Memshare have a negligible memory overhead.

As mentioned earlier, Memshare’s cleaning process does waste some space by keeping some segments pre-cleared. However, this free space only represents about 1% of the total cache space in our implementation. Even with idling a small fraction of memory, Memshare is still better than memcached’s slab allocator, since it eliminates the internal fragmentation that slab allocators suffer from. For example, in the trace, memcached’s fragmentation causes the cache to run at 70%-90% memory utilization.

7 Related Work

Our work is inspired by ideas from previous work on memory resource allocation and caching. Cliffhanger [16] introduced a technique to estimate the local gradient of hit rate curves in memory caches using shadow queues, for re-balancing slabs that belong to objects of different sizes. We applied a similar idea to assign memory among multiple applications. Compared to Cliffhanger, Memshare achieves significantly higher hit rates and can flexibly move memory across applications, because it uses a log-structured memory allocator rather than a slab allocator.

We were inspired by the idea of taxing idle memory from Carl Waldspurger’s work on ESX [48] and min-funding revocation [47]. In contrast to ESX, Memshare keeps track of the timestamps of the last access of all objects, so it is fairly simple to keep track of which objects are idle.

Our concept of a ranking function to rank the priorities
of the objects of each application was inspired by the concept of ranking functions introduced by Beckmann et al \cite{10}, as a flexible model for replacement policies for CPU caches.

RAMCloud \cite{40} and MICA \cite{31} have applied the ideas of log-structured file systems \cite{39,42,43,12,52} to DRAM-based caches. In addition, there are other examples of using log-structured caches in other contexts, such as a CDN photo cache \cite{46} and mobile device caches \cite{5}. Memshare uses a log-structured design similar to RAMCloud and MICA, but differs from them in several important ways. First, unlike these systems, Memshare addresses multi-tenant resource sharing. Second, both RAMCloud and MICA rely on a FIFO based approach for eviction, which typically suffers from lower hit rates than LRU. Memshare enables application developers to apply any eviction policy using their own ranking functions.

7.1 Resource Allocation and Sharing

FairRide \cite{38} provides a general framework for cache memory allocation and fairness, in particular when applications, processes or threads share data. While shared data among competing applications is common in certain scenarios, it is not common in key-value web caches in a data center setting. For example, in both Facebook and Memcached, different applications have their own unique key spaces, and they cannot access the same keys on memcached. For applications that do not share data, FairRide implements a memory partitioning policy in a distributed setup. Memshare, unlike FairRide, can efficiently utilize non-reserved and allocated idle memory to optimize the hit rate of applications and provide them with a memory boost in case of a burst of requests.

Mimir \cite{41} and Dynacache \cite{15} provide a framework for approximating the stack distance curves of web memory caches, in order to understand how much memory needs to be allocated to different applications. These systems are essentially offline optimizers, since an optimization solver that runs on historical data does not adapt when application workloads change on the fly. In addition, they do not provide a mechanism for allocating memory among different applications sharing the same cache. Mimir’s techniques can be combined with Memshare to help cache providers make offline decisions about cluster sizing.

Most previous efforts on cloud resource allocation, such as Moirai \cite{45}, Pisces \cite{44}, DRF \cite{20} and Choosy \cite{21} are focused on performance isolation and sharing in terms of requests per second (throughput), not in terms of cache hit rate which is the key ingredient in determining speedup in data center memory caches \cite{13}.

There have been several projects analyzing cache fairness and sharing in the context of multicore processors \cite{22,26,25}. In the context of multicore, fairness is viewed as a function of total system performance. Unlike CPU caches, DRAM-based web caches are typically separate from the compute and storage layer, so the end-to-end performance impact is unknown to the cache.

Ginseng \cite{7} and RaaS \cite{11,6} provide a framework for memory pricing and auctioning for outsourced clouds, but they only focus on pricing memory in the case where each application has its own dedicated memory cache server running on a VM. In contrast, Memshare enables multiple applications to share the same memory cache server, without the need to rely on VM isolation. This is the preferred deployment model for most web application providers (e.g., Facebook, Dropbox, Box).

7.2 Eviction Policies

Many eviction schemes can be used in conjunction with Memshare. For example, Greedy-Dual-Size-Frequency \cite{13} takes into account request sizes to replace LRU as a cache eviction algorithm for web proxy caches. Greedy-Dual-Wheel \cite{29} outperforms LRU by leveraging the knowledge of how long each request takes to be computed by the database. C-EVA \cite{9} computes the opportunity cost per byte for each object stored in a cache. Other eviction policies, like ARC \cite{33}, LRU-K \cite{35}, 2Q \cite{24}, LIRS \cite{23} and LFU \cite{28,27}, offer a combination of LRU and LFU.

7.3 Memory Cache Performance

MemC3 \cite{18} and work from Intel Labs \cite{40} improve the throughput of Memcached on multicore, by increasing concurrency and removing lock bottlenecks. While these systems significantly improve the throughput of Memcached, they do not improve overall hit rates. In the case of Facebook and Memcached, Memcached is memory capacity bound and not CPU bound \cite{13,15}.

8 Conclusions

Web cache memory hit rate is one of the most important factors in determining end-to-end web application performance. Current web memory caches statically partition memory across applications. This leaves room for significant improvement in increasing the hit rate of applications. We describe Memshare, a multi-tenant web memory cache that provides higher hit rates while maintaining private memory for each application. Memshare’s log-structured design provides a significant hit rate benefit over current caches that use slab allocation, both in the case of a multi-tenant and single-tenant memory cache. In addition, Memshare lets cache operators tune priorities and private memory across applications, and it allows applications to implement their own eviction policies.
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