PERFORMANCE PROFILING OF CACHE SYSTEMS AT SCALE

May 2014

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Master of Science in Computer Science

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Performance Profiling of Cache Systems at Scale

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Performance Profiling of Cache Systems at Scale

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Abstract

Large scale in-memory object caches such as memcached are widely used to accelerate popular web sites and to reduce the burden on backend databases. Operation and development teams tuning a cache tier would benefit from knowing answers to questions such as "how much total memory should be allocated to the cache tier?" and "what is the minimum cache size for a given hit rate?"

We propose a new lightweight online profiler, MIMIR, that hooks into the replacement policy of each cache server and periodically produces histograms of the overall cache hit rate as a function of memory size. It predicts smaller cache sizes with 99% accuracy on average at high performance. In order to predict the hit rate for larger cache sizes than the current allocation, the metadata for some evicted keys must be available. Keeping track of the metadata for all evicted keys is memory expensive and under intensive workloads will fill up the disk space quickly. We propose a new, fast and memory efficient method for storing a specific amount of evicted metadata with automatic flushing using Counting Filters, an extension of Bloom Filters to support removals. This method predicts the hit rate of a larger cache with 95% accuracy on average. Experiments on the profiler within memcached showed that dynamic hit rate histograms are produced with relatively low drop in throughput. Thus our evaluation suggests that online cache profiling can be a practical tool for improving provisioning of large caches.

Árangursvöktun á stórum flýtiminniskerfum

Trausti Sæmundsson

Maí 2014

Útdráttur

Stór flýtiminniskerfi eins og memcached eru notuð víða til þess að auka hraða á vinsælum vefsíðum og minnka álag á gagnagrunna. Kerfisstjórar myndu njóta góðs af því að hafa svör á reiðum höndum við spurningum líkt og "hversu mikið minni þarf fyrir flýtiminnisþjónustuna?" og "hver er lágmarksstærð á flýtiminni fyrir gefna nýtni?"

Við kynnum til sögunnar MÍMI. MÍMIR er ný vöktunarþjónustuna sem tengist við sérhvern flýtiminnisþjón og framleiðir nýtnigröf í rauntíma. Gröfin sýna nýtni þjónustunnar sé stærð hennar breytt. Nákvæmnin er yfir 99% að meðaltali fyrir minnkun á flýtiminniskerfinu og yfir 95% að meðaltali fyrir stækkun með litlum aukakostnaði. Til þess að spá fyrir um nýtni við stækkun á flýtimininskerfinu þyrfti að halda utan um fingrafar af eyddum gögnum sem getur þurft mikið af minni. Við kynnum nýja aðferð til þess að halda utan um takmarkað magn af fingraförum með sjálfvirkri eyðingu með svokölluðum teljarasíum (e. Counting Filters) sem er útgáfa af Bloom síum (e. Bloom Filters) sem styðja einnig eyðingu. Tilraunir á MÍMI sýna að rauntímamæling á flýtiminni sé hagnýt leið til þess að stilla af vélbúnað fyrir stórar flýtiminnisþjónustur.

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fyrir að leyfa mér að spila
Tetris í MS-DOS

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Some of the ideas and results described in this thesis appeared in the following publication:

Publications

Hjörtur Björnsson, Gregory Chockler, Trausti Sæmundsson, and Ýmir Vigfússon. "Dynamic performance profiling of cloud caches." In Proceedings of the 4th annual Symposium on Cloud Computing, p. 59. ACM, 2013.

The publication was a short paper (and a poster) describing the ideas behind the ROUNDER and STACKER algorithms (described in Section 3.3), with accuracy microbenchmark results and first results from the experimental evaluation in memcached. My contributions to this publication was to the design of ROUNDER and STACKER. I implemented ROUNDER and STACKER in Python and C, and ran all microbenchmarks and accuracy evaluations.

This thesis develops the algorithms further and presents additional performance evaluation. Aside from subsection 3.3.3, which contains an analytic optimality result, all of the ideas, algorithms and results in this thesis are my own.

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Chapter 1

Introduction

1.1 Cache Systems at Scale

Large-scale websites serve a great number of requests, many of which are identical. Serving each request by fetching data from a database causes contention and does not suffice under high load. Since these websites cannot scale with a database only, a new service called memcached was created. `Memcached` serves all data from main memory, thus responding faster than a database which has to touch disk. The typical use case for memcached is to store newly generaed pages so they need not to be re-rendered on every request. `Memcached` thus acts both as a memory speedup for databases and as a storage for those queries that require many CPU cycles to generate a response. The service thus simultaneously decreases response time and reduces load on the databases.

Owing to its benefits, memcached is popular all over the world and is used so heavily at Facebook that more than one billion requests per second are served directly from memcached. Caching systems, like memcached and Redis, have become a de facto standard as a layer between web servers and database back-ends. Using those caching systems, however, comes at a cost as they require an expensive resource: **main memory**.

Because a single computer cannot unilaterally handle significant load, many of today's companies invest explicitly in a special "caching" tier comprised of multiple cache servers, each of which has a large mount of main memory. Buying more cache servers increases the hit rate in the cache tier and can greatly reduce the load on the database backends preventing them from overloading. Cache servers are expensive and used in large numbers; Facebook, e.g., stored over 20TB of data in over 800 memcached servers

making it the world's heaviest memcached user already in 2008 [58]. Running at such a large scale makes it an important question to understand how many computers are required to satisfy service goals.

1.2 Automatic Scaling

To shield the databases properly from load, cache operators typically add more memcached servers *manually* or increase the memory on existing servers to ensure that the hit rate in the cache tier is high enough. Blindly adding servers without knowing exactly how many cache servers would be needed to achieve this goal can waste valuable resources.

We therefore address this allocation problem from the *automation* perspective and aim to help cache operators with this manual tuning by predicting how each cache server would operate with different resources. This thesis describes a new profiling framework, MIMIR, designed for profiling LRU cache systems. The system generates so called **hit rate curves** in real-time that describe the efficacy of each cache server as a function of cache size.

Algorithms for creating hit rate curves have been studied before, most methods focus on creating accurate hit rate curves with considerable overhead. Our method sacrifices 5 percentage points of accuracy in order to minimize the overhead.

In order to predict the hit rate for larger cache sizes than the current allocation, the meta-data for some keys that have been evicted from the cache must be available. A data structure to store this meta-data is called a *ghost list*. For some workloads, such as those seen at Facebook [8], queries for small keys dominate: the average query is for a 31 byte key and a 2 byte value. Since the keys in this case are much larger than the values, storing just the keys in a ghost list produces too much memory overhead to be applicable. To address this issue we propose a new memory efficient ghost list for storing a specific amount of evicted meta-data with Counting Filters.

1.3 Contributions

The main contributions of this work are the following:

- A new algorithm to calculate the efficacy of a cache as a function of resources used, especially main memory. This is done by generating so called hit rate curves,

defined in Chapter 3, that predict how many queries would have been responded to from the cache if the cache system would have those resources.

- Proof of the accuracy of the hit rate curve algorithm.
- Extensive implementation and experimental analysis of the hit rate curve generator both through micro-benchmarks and through implementation within the popular memcached system. The experiments show that the approach is fast compared to alternatives, and achieves high throughput and high accuracy while giving extensive flexibility to understand the cost benefits of the system at a granular level in terms of cache size.
- A new data structure for analyzing requests to cache keys that have been evicted from the cache. This data structure achieves space efficiency in exchange for modest drop in accuracy and low to sometimes significant drop in performance.

The remaining of this thesis is organized as follows. The background required for understanding this thesis is presented in Chapter 2. Chapter 3 provides definitions, introduces related work and the methods contributed in this thesis. Implementation details are discussed in Chapter 4. Experiments are evaluated in Chapter 5, and we offer concluding thoughts in Chapter 6. Finally, the Appendix contains multiple additional graphs.

Chapter 2

Background

The notion of *caching* is to store data from a slow memory in a faster memory. This is done to minimize the requests to the slow memory and thus reduce memory access latency. Caches are used in various applications: in hard disks, web servers, databases and CPUs to name a few. The performance improvements can be enormous. Table 2.1 is indicative of the speed hierarchy of computer memories. The L1 and L2 caches on the CPU are fastest, with a speed of 10x to 100x versus that of main memory. Reading 1MB from memory is 120x faster than reading 1MB from disk and is the reason why in-memory cache systems, introduced later in this chapter, are so fast.

L_1 cache reference	0.5 ns
L_2 cache reference	7 ns
Main memory reference	100 ns
Read 1MB from memory	250,000 ns
Read 1MB from a Solid State Drive	1,000,000 ns
Hard Disk Drive seek	10,000,000 ns
Read 1MB from a Hard Disk Drive	30,000,000 ns

Table 2.1: Read access latency of computer hardware [22, 1].

Big companies, such as Facebook and Twitter, alleviate their database load by using **cache systems** that store hot key value pairs in memory and serve the values via network when keys are requested. The most common cache systems are memcached [43] and Redis [7]. Figure 2.1 shows relations between a web server, database and cache. The web server first checks whether the data required is found in the cache and if not, loads the data from the database. The cache systems at Facebook and Twitter are composed of many cache servers and intermediary proxies. The load is distributed between the cache servers by partitioning the data on the keys with a method called **consistent hashing**. Consistent

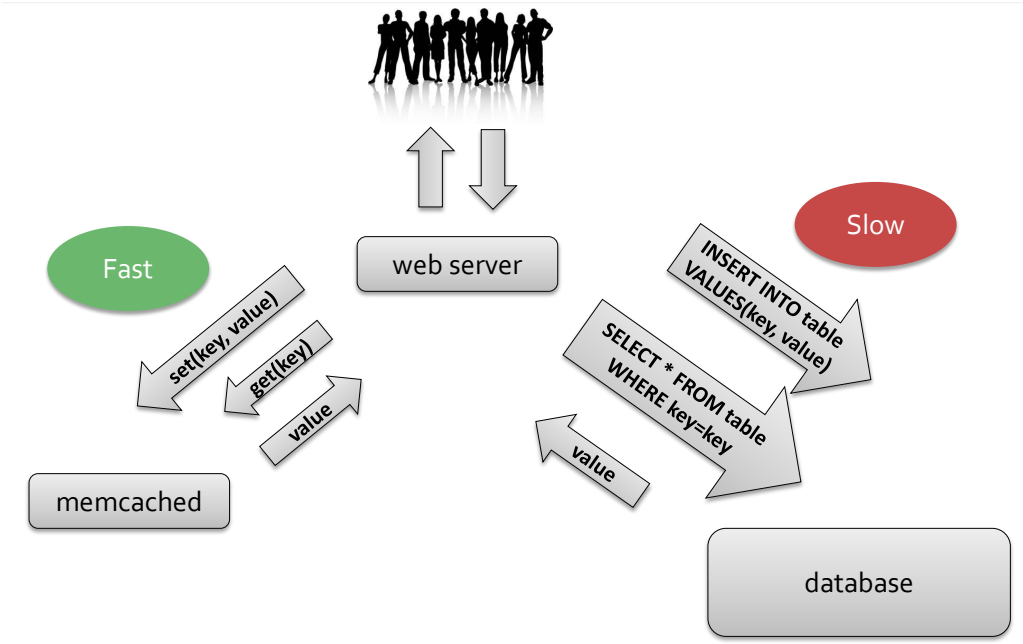


Figure 2.1: **Cache and database.** Typical request flow from a web server to a database and cache.

hashing enables operators to add and remove cache servers to the cache tier without needing to relocate keys on existing servers.

The framework presented in this thesis is aimed to augment large cache systems and predict accurately how the systems would behave under a different setting. One of the key differences in the performance of those systems is the mechanism by which they replace old elements when the cache memory has been filled [31], the topic of the much studied field of cache replacement policies.

2.1 Cache Replacement Policies

Replacement policies (cache algorithms) are used to choose which element to remove from the cache when space for a new element is needed. The element that the replacement policy chooses is then removed from the cache; this is called *evicting* the element from the cache. When we get a request to retrieve an element we first check whether the element is stored in the cache. If the element is in the cache a *cache hit* occurs; otherwise a *cache miss* occurs and the element must be fetched from a slow memory. Cache algorithms that do not depend on knowing the future are called *online* algorithms, while those that require on knowledge of future accesses are called *offline* algorithms.

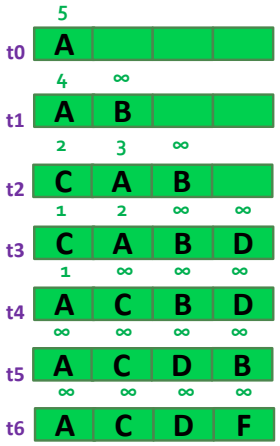


Figure 2.2: Illustrative diagram showing how the optimum cache replacement algorithm, **OPT**, handles the request stream A,B,C,D,C,A,F. The numbers above show the time until the next request and the elements are ordered by that number.

We now give an overview of cache algorithms, starting with an optimal one and working towards more practical ones.

2.1.1 OPT: Belady's algorithm

L. A. Belady described an optimal cache algorithm (OPT) in 1966 [13]. When the cache is full and a new element must be inserted, OPT replaces the element that will not get a cache request for the longest period of time in the future, see Figure 2.2 for an example of how OPT works.

In practice, cache sequences arrive in an online fashion and future requests cannot be known or inferred. OPT thus cannot be used in practice, but still provides an important baseline against which to compare other cache replacement algorithms.

2.1.2 LRU: Least Recently Used

A particularly popular cache replacement policy is the Least Recently Used (LRU) algorithm, which replaces the element that was least recently used onan eviction; see Figure 2.3 for an example of how LRU works. The extensive literature on this algorithm dates back to at least 1965 [39].

> **Definition 1.** The **LRU stack distance** of an element e in an LRU stack is the number of different elements between the head of the LRU stack and the element e. If e is not in the LRU stack, the stack distance is defined to be infinite.

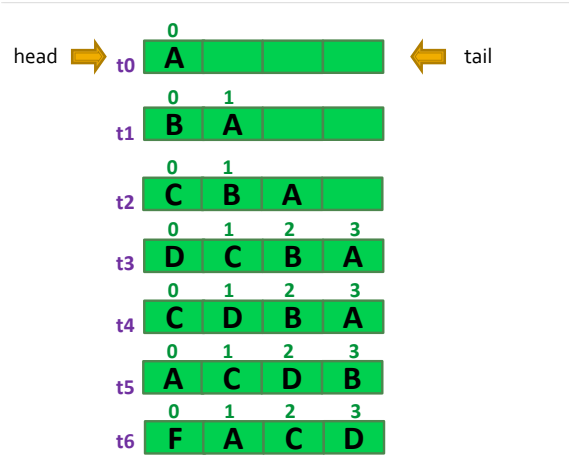


Figure 2.3: Illustration of how the **LRU** cache replacement algorithm handles the request stream A,B,C,D,C,A,F. The numbers above show the stack distance.

LRU handles many workloads well because in practice, recently used data tends to be reused in the near future. The algorithm is based on a similar idea to OPT, namely using the requests to elements to determine which elements to keep in the cache. Nevertheless, LRU is an online algorithm as opposed to the offline nature of OPT.

LRU is usually implemented with a doubly linked list. This is a drawback because moving elements to the most recently used position in the linked list at every request is expensive and does not lend itself easily to parallelism. Modifying a doubly linked list when many threads are accessing it at the same time typically requires locks and which further degrades the performance.

Another drawback of LRU is that many workloads use some elements more frequently than others and LRU does not make use of frequency information at all. LRU is also vulnerable to a scan of data, i.e., a sequence of requests to elements that are not requested again, a scan may replace all the elements in the cache regardless of whether the elements will be used again or not.

There are several algorithms related to LRU. Databases typically have access patterns where LRU performs poorly and the algorithms LRU-K [47] and 2Q [35] improve on LRU for such patterns. LRU-K keeps track of the last k references of hot items in a priority queue and evicts the item with the oldest k-th access. When $k = 1$ this algorithm is LRU but when $k > 1$ this algorithm is not vulnerable to scans. 2Q uses two queues to provide similar results as LRU-K when $k = 2$ but with constant time overhead versus logarithmic time complexity of a priority queue. Another relative is S4LRU [31] which is made of four LRU stacks and items get promoted when they are hit again.

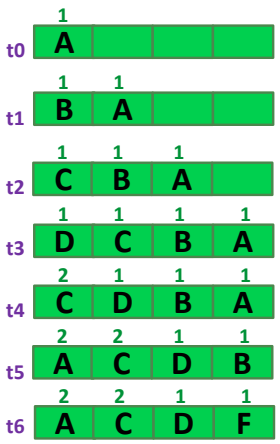


Figure 2.4: Illustrative diagram showing how the **LFU** cache replacement algorithm handles the request stream A,B,C,D,C,A,F.

2.1.3 Randomized LRU

This replacement policy is the default replacement policy in the Redis key-value store [7]. It fetches m random ($m = 3$ by default) elements and evicts the oldest one. On a cache hit the timestamp of the element is updated.

This method saves the memory and the maintenance of a linked list but trades off computation time by calling the random number generator several times.

By configuring Redis to choose more sample elements, specifically to increase m, this policy converges to the LRU policy which chooses the oldest element of all elements to evict. Figure A.3 in the Appendix shows this phenomenon on a variety of workloads by comparing regular LRU against Randomized LRU with $m = 3$ and $m = 10$, called LRU3 and LRU10 respectively here (not to be confused with LRU-K). This figure shows that using only 10 random samples produces hit rate performance very close to that of LRU.

2.1.4 LFU: Least Frequently Used

Another one of the earliest caching algorithms is LFU, Least Frequently Used, which dates back to at least 1971 [39]. LFU evicts the least frequently used item when the cache is full; see Figure 2.4 for an example of how LFU works.

LFU is not vulnerable to scans of requests and captures the frequency of workloads.

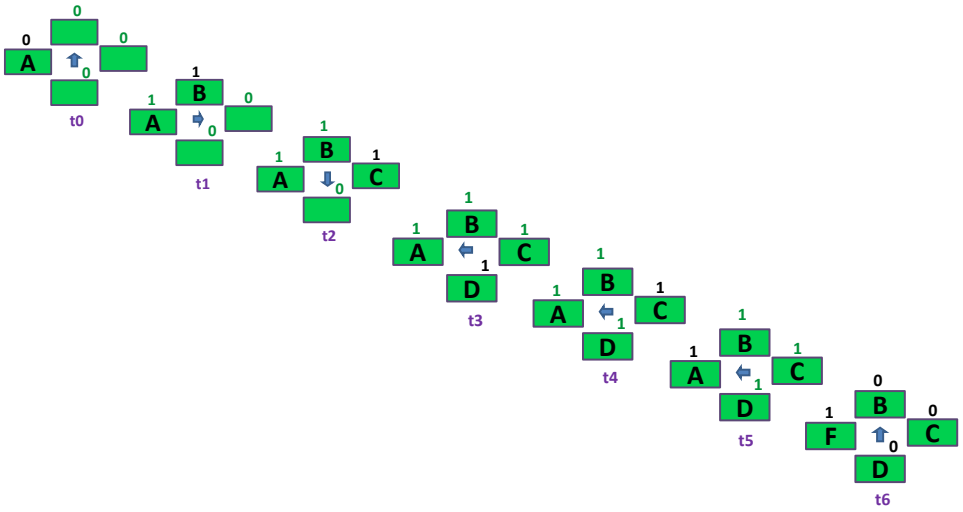


Figure 2.5: Illustrative diagram showing how the **CLOCK** cache replacement algorithm handles the request stream A,B,C,D,C,A,F. The arrows indicate the CLOCK hand.

However, implementing LFU requires keeping track of the request frequency of each element in the cache. Usually this is done with some number of bits for each element, where the number of bits limits how accurately the frequency is monitored. Regardless of the number of bits, finding the element with the lowest frequency is usually implemented with a priority queue resulting in logarithmic complexity for all operations. Another approach is to use two nested doubly linked lists, as described in [50], which transforms the time complexity of all operations to $O(1)$.

2.1.5 CLOCK

Introduced in 1968 by F. J. Corbato [20], the CLOCK algorithm arranges cache elements in a circle and captures the recency of a workload, similar to LRU but with much less effort.

Every element has an associated bit called the recently used bit, which is set every time an element is accessed. The clock data structure has one hand. When an element needs to be evicted from the cache, we check whether the recently used bit is set on the element e to which the hand points. If the recently used bit is not set on e, we replace e with the new element. However if the recently bit is set on e, we unset the bit on e and advance the hand to the next element. We repeat this until we find an element that does not have the recently used bit set. In the worst case the hand must traverse an entire circle and remove the element to which it pointed originally. This is precisely what happens at time $t6$ in Figure 2.5, where A is evicted to give space for F.

CLOCK uses the recency of elements, similar to LRU, but without requiring locks in parallel systems. The retrieval time for each element is lower because there is no unlinking and linking required. The removal time depends, however, on how far the hand has to traverse. CLOCK also handles more requests per time unit because it does not move elements to a new position in a list at every request. Figure A.2 shows head-to-head throughput comparison between the algorithms.

The hit rate of CLOCK is close to that of LRU even though CLOCK uses only one bit to capture the recency, see Figure A.1 for a hit rate comparison between the methods.

2.1.6 ARC: Adaptive Replacement Cache

The Adaptive Replacement Cache (ARC) algorithm introduced in 2003 [40] provides good performance on workloads where the access pattern is based on recency and frequency. To achieve this performance ARC combines LRU and LFU and is furthermore resistant to scans. It also adapts in real-time to the recency or frequency access pattern of the workload.

ARC uses two lists L_1 and L_2. L_1 stores elements that have been seen only once recently but L_2 stores elements that have been seen at least twice, recently. It is useful to think of L_1 as the LRU list and L_2 as the LFU list. ARC then adaptively changes the number of elements stored in the cache from L_1 and L_2. This is done to meet the access pattern of the workload. The elements in L_1 and L_2 that are not in the cache are said to be in the **ghost list**. Ghost lists are discussed further in Chapter 3.

Since L_2 contains elements that have been seen at least twice recently it does not have logarithmic complexity on each request like LFU. Both L_1 and L_2 suffer from the same problem as LRU, as every action requires a reordering of the elements in the list. To address this issue another similar algorithm called Clock with Adaptive Replacement (CAR) [10] was proposed in 2004. It uses the clever solution from the CLOCK algorithm of using circular lists to reduce the computational complexity. Both ARC and CAR are patented by IBM [42, 11].

2.1.7 LIRS: Low Inter-reference Recency Set

Since its introduction in 2002, the Low Inter-reference Recency Set algorithm (LIRS) [34] has seen some popularity, including being used in the popular MySQL open source database [32]. LIRS is similar to LRU, but does not use recency as a measure to evict

elements. Instead, it uses the more insightful **reuse distance** for eviction decisions, more precisely LIRS evicts the element with the largest reuse distance.

> **Definition 2.** The **reuse distance** of a request r_1 to an element e is the number of different requests between r_1 and the last request r_2 to the same element e. If r_1 is the first request to e then the reuse distance is defined to be infinite.

Let us now look at the request stream: a, b, b, c, a. The first time a is requested it has infinite reuse distance but the second time a is requested the reuse distance is 2 because there are two elements, b and c, requested in between. In the same manner, the reuse distance of b is infinite the first time it is requested and 0 the second time it is requested. The reuse distance of c is infinite.

> **Lemma 1.** An element is contained in an LRU cache of size N if the reuse distance of the element is at most N. This is true because the reuse distance is equal to the stack distance in an infinite LRU stack.

Internally, LIRS uses a stack S and a list Q. The stack S can grow unboundedly in size which could eat up a lot of memory.

2.1.8 Clock-PRO

For the same reason that CLOCK was proposed to speed up LRU, and CAR was proposed to speed up ARC, an algorithm called CLOCK-Pro was introduced in 2005 [33] to optimize LIRS. At the foundation, CLOCK-Pro is based on LIRS but uses circular lists. The CLOCK-Pro algorithm has been used in the NetBSD operating system [32] and in the Linux kernel [33].

2.1.9 Hit Rate and Throughput Comparison

Graphs showing hit rate and throughput comparison of the LRU, LFU, OPT, ARC, LIRS, RANDOM and LRU3 cache replacement algorithms can be seen in the Appendix, hit rate in Figure A.4 and throughput in Figure A.5.

2.2 Memcached

A wide variety of caching systems exist that rely on those algorithms. One particularly popular implementation is the memcached (www.memcached.org), which uses the LRU

policy. Improvements to memcached use the CLOCK policy [26] because it is faster and works better with multiple threads, while providing a similar hit rate to LRU. Because of their popularity we will focus on these two cache replacement policies (LRU and CLOCK) in the remainder of the thesis.

`Memcached` is an open source [44] key-value store written in approximately 10.000 lines of C code, developed initially by Brad Fitzpatrick for the website `LiveJournal.com` at Danga Interactive. Early versions of memcached used the default malloc from glibc for storing items but because of internal fragmentation the servers stalled the CPU after a week of up-time [28]. The memcached team then implemented their own memory allocator to address this problem.

The memory allocator puts items into different slab classes, each containing its own LRU linked list. Each slab class owns several 1MB pages split into equally sized chunks, with the chunk size depending on the slab class. The default settings of memcached uses 42 slab classes. The slab class sizes increase exponentially with factor 1.25 (can be changed with the -f parameter). The first is responsible for 96B items (henceforth B refers to bytes), the second 120B items, and the last 1MB items. Each item is put in the slab class with the smallest possible chunk size. Depending on the distribution of the value sizes, this factor must be configured manually to balance items evenly across the slab classes. When a slab class is full, a new 1MB page is requested. If all pages are in use, the server evicts the least recently used item from the slab class. Expiration of elements via a Time-To-Live (TTL) flag is supported and if an item has been hit very recently, it is not moved to the LRU head.

If the workload is dynamic, some slab classes might become stale, which is referred to as "slab calcification". This issue has been solved in the latest versions of the open source memcached by removing pages from other slab classes. Twitter has an open source modification of memcached, called twemcache, with a different solution with configurable strategies to reassign pages between slabs. At Facebook a page is moved to a slab class if the next item to be evicted was used at least 20% more recently than the average of the LRU tail in other slab classes [45]. The page that is moved is the one containing the overall least recently used element.

The memcached server uses 4 threads by default; increasing the number of threads does not improve the performance, due to internal locking [30]. One global lock guards the LRU cache and another lock guards the hash table. This has been improved by Fan *et al*. in the MemC3 [26] system where the LRU cache replacement was replaced with the CLOCK cache replacement and the hash table was changed to concurrent cuckoo hashing,

developed by the same team. This removes the thread scalability bottleneck and improves the throughput of memcached by 3x.

Facebook has been using memcached since August 2005, when Mark Zuckerberg installed it on Facebook's web servers. In 2013 they had around 1000 memcached servers handling billions of requests per second to serve over 28 terabytes of data to alleviate this load from the back-end MySQL databases [49]. Since then, Facebook has customized and improved the memcached code and contributed some of the improvements to the open source version of memcached [45].

Chapter 3

Methods

3.1 Introduction

In a setup with multiple cache servers we would like to monitor the performance of each server and predict what would happen if resources for the servers would be changed. Resources can be changed by adding or removing a cache server. But also, the memory of a server can be increased or decreased and this affects the performance of the cache tier. Our goal in this thesis is to profile the performance of each cache server and produce efficacy graphs showing how the hit rate would change if resources were changed. In order to do that we must know how the cache server would perform if memory was increased or decreased. To assess the effects of changes we generate, in real-time, so called **hit rate curves** that describe the efficacy of each cache server as a function of cache size. More precisely:

> **Definition 3.** Let $H(n)$ be the hit rate for cache size n. We call H the hit rate function. A **hit rate curve** (HRC) is a plot of the hit rate function as a function of cache size. For a cache is running at size N, it is possible to generate the HRC for all cache sizes n, where $0 < n \leq kN$; in the thesis we focus on $k = 2$.

See Figure 3.1 for an example of a hit rate curve showing the hit rate for smaller and larger cache sizes than the current allocation.

To solve this problem we propose the MIMIR profiling framework. This framework collects data from each cache server and produces hit rate curves. Figure 3.2 shows how the cache server contacts the interface of MIMIR. The framework is notified when an element encounters one of four possible events: HIT; MISS; SET; and EVICT. The functions for those events are described in detail in Table 3.1. All functions take an

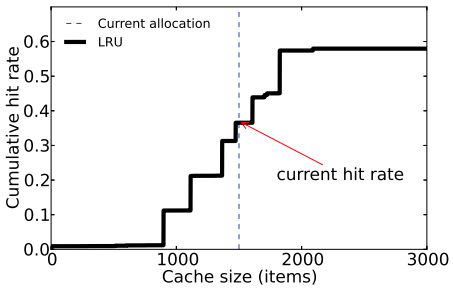


Figure 3.1: **Hit rate curve example.** Diagram showing normalized hit rate achieved for different cache sizes than currently allocated.

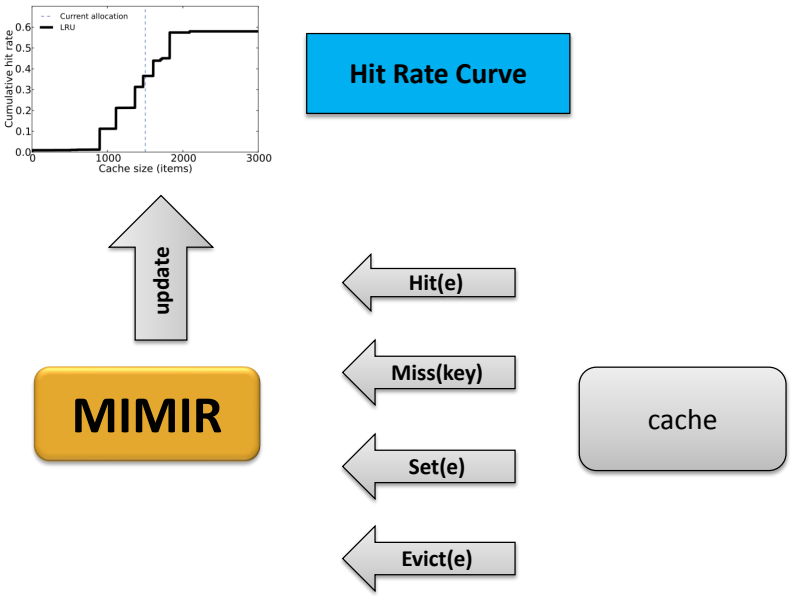


Figure 3.2: The MIMIR profiling framework is notified of HIT, MISS, SET and EVICT events in the cache and produces a HRC when requested.

element as an argument except the MISS function which takes a key. We store a timestamp on each element and need to access it on HIT; MISS and SET. On a miss, however, no element is available and we only have the key.

How to handle those events correctly depends on the cache replacement policy; in this thesis we describe an implementation of this interface that works with high accuracy when running either the LRU or the CLOCK cache replacement policy.

Handling the four events happens synchronously inside MIMIR and results in an update to an internal data structure in the framework. When the HRC is requested, it is generated asynchronously from the internal data structure and served to the cache operator who can then display it for each cache server in a web interface.

HIT(e)	Accessing the requested element e causes a cache hit
MISS(key)	Accessing the key key causes a cache miss
SET(e)	An element e is set in the cache
EVICT(e)	A currently cached element e is being evicted from the cache

Table 3.1: Description of **MIMIR's interface**.

3.2 Creating an HRC for the LRU Policy

To generate a hit rate curve for an LRU cache we use Lemma 1 from Section 2.1.7 on page 12. The lemma states that an element is contained in an LRU cache of size N if the reuse distance is at most N. The reuse distance is equivalent to the stack distance and this gives us an inclusion property for the LRU cache replacement policy:

> **Lemma 2.** Contents of an LRU cache of size N are contained in an LRU cache of size M if $N \leq M$.

To see why this is true, consider how an LRU stack orders elements by access time; an LRU stack of size N is the prefix of all LRU stacks of size M where $M \geq N$. This inclusion property holds for other stack algorithms such as LFU and OPT [38] but not for a First In First Out (FIFO) algorithm [14].

Using Lemma 2 we now highlight an important concept. By tracking the stack distance of every element we can create a hit rate curve, because the number of hits in a cache of size n is the number of items hit with stack distance less or equal to n.

This means that creating a hit rate curve for $n \leq N$ simply boils down to tracking stack distances for elements in the cache. Creating hit rate curves for $n > N$ requires tracking elements that have been evicted, but the principle is the same.

This is a previously studied problem dating back to at least 1970 when Mattson described an intuitive approach, referred to in this thesis as **Mattson's algorithm** [38]. This algorithm assumes that the LRU cache is represented as a linked list. On a cache hit to element e, we traverse the linked list from the head and count how many elements are located in front of e. This is inefficient since the worst case time complexity is linear in the cache size.

Another approach is to organize the LRU linked list in a balanced binary tree ordered by the access time [56, 57]. This lowers the worst case time complexity to be $\mathrm{O}(\log N)$. The stack distance is retrieved from the tree by counting the sizes of sub-trees with earlier access times than the requested element.

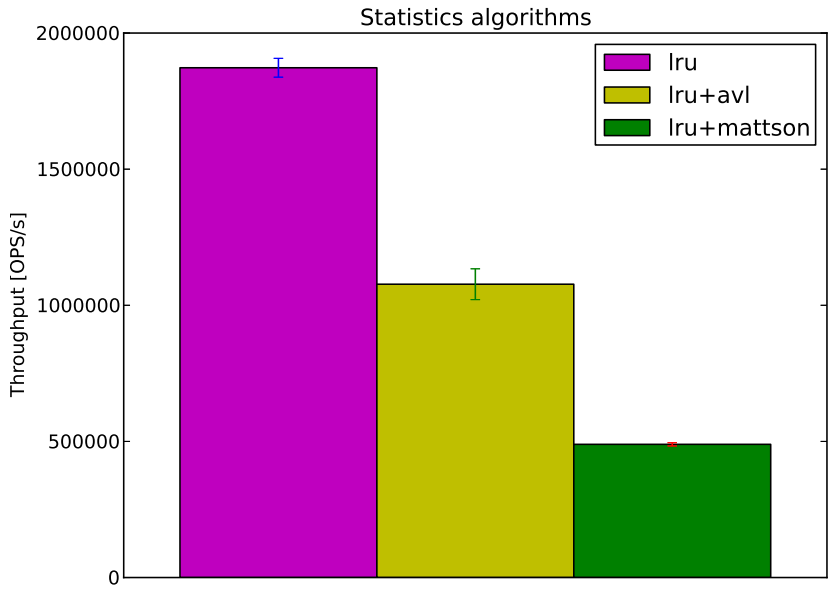


Figure 3.3: **Overhead comparison** of regular LRU, LRU represented as an AVL tree [57, 56] and LRU with Mattson's algorithm [38]. The AVL tree proposes 73.8% overhead on regular LRU and Mattson's algorithm proposes 282.7% overhead. The LRU cache has capacity for 5000 elements in this experiment and the bars show the standard deviation from 10 runs.

Both of those approaches are non-trivial to parallelize. Also, figure 3.3, shows that the overhead of both approaches is non-negligible. The figure shows the throughput of a C++ simulator (described in Chapter 4) for the P10 workload (presented in Chapter 5) for LRU with no distance tracking, and with distance tracking using both an AVL tree and Mattson's algorithm. As the Figure shows, the overhead of both algorithms is very significant and much too high for the methods to be usable in practice.

We propose to trade off some accuracy in order to maximize performance, by splitting the LRU stack dynamically into a fixed number of buckets. When an element is hit in the cache we find the bucket it belongs to and estimate its LRU stack distance range by summing up the number of items in buckets with lower stack distances. Note that the number of buckets is independent of the cache size; thus the average number of elements per bucket increases with increasing cache sizes.

In order to facilitate performance, the size of each bucket can vary. In Section 3.3, we propose two efficient algorithms for dynamically maintaining the buckets. In Section 3.4, we then propose an efficient algorithm for approximating stack distances for items that have been evicted from the cache. Finally, in Section 3.5, we compare our methods to the related work.

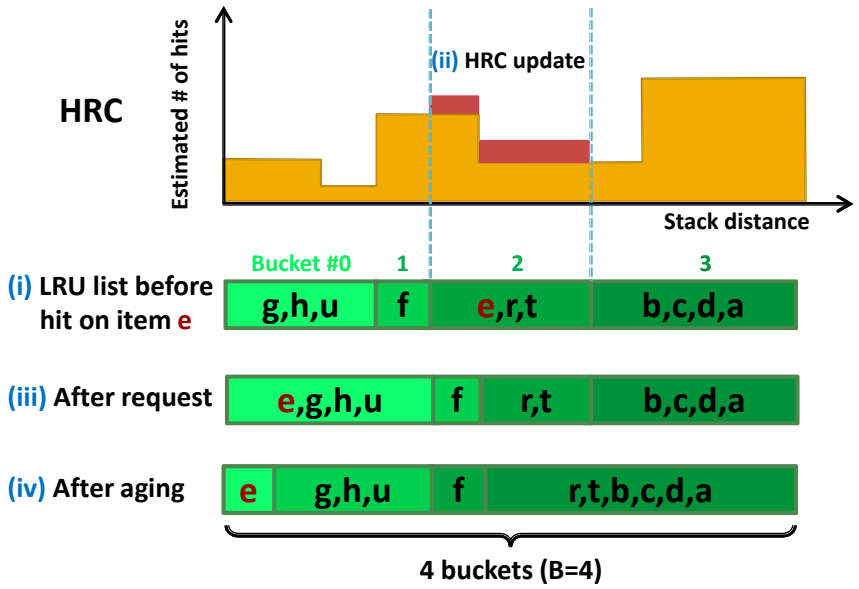


Figure 3.4: Illustration of ROUNDER. Updates to the hit rate curve and the bucket lists of the LRU stack when element e is hit in the cache.

3.3 Estimating Cache Utility for $n \leq N$

We now introduce simple yet efficient methods to minimize the overhead of retrieving stack distances for elements in the cache. The methods group items together in buckets and produce stack distance estimates. The accuracy is tunable with the number of buckets, but using fewer buckets yields higher performance. The methods are called ROUNDER and STACKER, the former of which is designed for higher performance and the latter is designed for higher accuracy.

3.3.1 The Intuition behind ROUNDER and STACKER

The basic idea is to split the LRU stack into buckets. When an item is hit, we find the region represented by the bucket and update the corresponding part of the HRC with unit volume.

ROUNDER accumulates elements in the first bucket. When this front bucket is full, all buckets are shifted down the list, bottom two buckets are merged and the first bucket is freed. This aging method distributes the items across all buckets by limiting the number of elements in the first bucket. The process is illustrated for the ROUNDER algorithm in Figure 3.4. When element e is hit, it is located in the third bucket (buckets are numbered from 0). The element is then removed from the third bucket and inserted into the first (head) bucket. Now the first bucket is full and aging is performed. The aging merges the last two buckets, so that afterwards it contains items r, t and b, c, d, a from the second-

to-last and the last bucket respectively. Now the first bucket is shifted down and a new empty bucket appears in front. Finally we insert e into the new bucket. We keep a 4 byte timestamp per item to know which bucket the item belongs to. To make the aging as fast as possible, instead of aging every element, we shift the frame of reference, update the timestamp for the first bucket and increasing a cyclical index into a circular array of bucket counters, all in constant time.

The last bucket can get filled up with an adversarial workload. We designed the STACKER algorithm to prevent such cases. STACKER accumulates elements in the first bucket, like ROUNDER, but when the first bucket is full we shift some items down one bucket, i.e. we only shift elements that correspond to the hot part of the LRU stack. The intuition here is that when an element e is hit in a regular LRU stack, all items with lower stack distances than e get shifted one position down the stack but elements below e's original position are not moved. Now if the bottom of the stack is never being hit, those elements should not be moved to a lower bucket, and the aging routine prevents it from happening. ROUNDER is incapable of doing this since all items are shifted down every time the aging routine is called.

3.3.2 Pseudo-Code

To update the HRC in constant time we use an intermediate array, called `DELTA`. We update the `DELTA` array with the `updateDELTA` routine, see Algorithm 1. It takes a startpoint and an endpoint and updates two locations in the DELTA array. The scale and offset arguments are used when creating a HRC for larger cache sizes than the current allocation using a ghost list, described and defined in Section 3.4. The scale parameter is used to scale down the estimated hit value because the ghost list is probabilistic and the offset is used to update the ghost list part of the HRC, after the end of the main cache.

Algorithm 1 The updateDELTA routine.

UPDATEDELTA($start, end, scale, offset$)

1 $start = start + offset$
2 $end = end + offset$
3 $val = 1.0/(end - start)$
4 $val = val \cdot scale$
5 $DELTA[start] = DELTA[start] + val$
6 // every value $i \geq start$ in the HRC should be incremented by val
7 $DELTA[end] = DELTA[end] - val$
8 // every value $i \geq end$ in the HRC should be decremented by val

The makeHRC routine, shown in Algorithm 2, creates the HRC directly from the DELTA array without using a PDF array. Notice that the resulting HRC is not normalized. HRCs are often normalized by the number of requests to the cache so that the values range from 0 to 1.

Algorithm 2 The makeHRC routine. Updates the HRC from the intermediate DELTA array.

MAKEHRC()
1 $HRC = [0, 0, \ldots, 0]$
2 **for** $i = 1$ **to** $DELTA.length - 1$
3 $\quad HRC[i] = HRC[i-1] + DELTA[i]$

The ROUNDER algorithm is initialized according to Algorithm 3, by saving the cache sizes and the number of buckets, lines 1-2. We then initialize bucket counters to 0 in line 3 and set the head and tail bucket indices to their initial values in lines 4-5.

Algorithm 3 The Initialization routine for ROUNDER.

INITIALIZATION($cachesize, numbuckets$)
1 $N = cachesize$
2 $B = numbuckets$
3 $buckets = [0, 0, \ldots, 0]$ // B buckets
4 $head = B\text{-}1$
5 $tail = 0$

The HIT routine for the ROUNDER algorithm, see Algorithm 4, takes an element as an argument. It resets the activity of the value to the current tail if it has fallen behind, in lines 1-2. We next retrieve the current stack distance for the element and use it to update the DELTA array in line 5. Finally we get the correct bucket index for the element and remove it from the current bucket by decrementing the correct bucket counter, lines 7-8. Next we set the activity of the item to the head value and update the counter for the head bucket, lines 9-10. Notice the circular indexing into the buckets array, this trick saves us space and time by reusing the array after every aging phase.

The SET routine for the ROUNDER algorithm, see Algorithm 5, performs aging if required, in line 2. It also sets the activity of the item in line 3 and updates the bucket counter for the head bucket.

The EVICT routine for the ROUNDER algorithm, see Algorithm 6, updates the correct bucket counter where the element is located.

The age routine in ROUNDER, see Algorithm 7, shifts the frame of reference, merges the last two buckets and frees up one bucket.

Algorithm 4 The HIT routine for ROUNDER.

HIT(e)

```
1  if e.activity < tail
2        e.activity = tail
3  if buckets[head] ≥ N/B
4        AGE()
5  (start, end) = getStackDistance(e)
6  UPDATEDELTA(start, end, 1, 0)
7  i = e.activity mod B
8  buckets[i] = buckets[i] − 1
9  e.activity = head
10 buckets[head mod B] = buckets[head mod B] + 1
```

Algorithm 5 The SET routine for ROUNDER.

SET(e)

```
1  if buckets[head mod B] ≥ N/B
2        AGE()
3  e.activity = head
4  buckets[head] = buckets[head] + 1
```

Algorithm 6 The EVICT routine for ROUNDER.

EVICT(e)

```
1  if e.activity < tail
2        e.activity = tail
3  i = e.activity mod B
4  buckets[i] = buckets[i] − 1
```

Algorithm 7 The internal age routine in ROUNDER.

AGE()

```
1  // merge the two bottom buckets and empty the top bucket
2  buckets[(tail + 1) mod B] = buckets[(tail + 1) mod B] + buckets[tail mod B]
3  head = head + 1
4  buckets[head mod B] = 0
5  tail = tail + 1
```

The getStackDistance routine in ROUNDER, see Algorithm 8, calculates the estimated stack distance from the bucket counters.

The routines for STACKER are highly similar to the routines for ROUNDER except for the *age* function, which loops through all the cache and ages only the items that have an activity lower than a running average of items recently hit in the cache. They are not shown in this thesis.

Algorithm 8 The internal getStackDistance routine in ROUNDER.

GETSTACKDISTANCE(e)

```
1  start = 0
2  end = 0
3  for i = head to tail
4       end = end + buckets[i mod B]
5       if e.activity == i
6            break
7       start = start + buckets[i mod B]
8  return (start, end)
```

3.3.3 Proof of Bounded Accuracy

This section provides a proof of bounded accuracy for bucket algorithms. The proof uses the Mean Average Error (MAE) to provide bounds on the bucket sizes. The MAE is calculated by the following formula, Where M is the size of the HRC:

$$\text{MAE}(\text{HRCa}, \text{HRCb}) = \frac{1}{M} \sum_{x=1}^{M} |\text{HRCa}(x) - \text{HRCb}(x)| \,. \tag{3.1}$$

The following theorem shows that the accuracy of the HRC is limited by the size of the largest bucket:

> **Theorem 3.** For an LRU cache of size M during a trace of R requests, ROUNDER and STACKER with B buckets have a mean average prediction error (MAE) bounded by the largest bucket size during the trace, divided by $M/2$. Consequently, if no bucket grows larger than $\alpha M/B$ for $\alpha \geq 1$ during the trace, then the MAE for ROUNDER and STACKER is at most $\frac{2\alpha}{B}$.

Proof. We consider R cache requests to have true reuse distance $r_1, r_2, \ldots, r_R$. It suffices to consider only requests that result in LRU hits, so $r_i \leq N$ for all i. Define $\delta_t(x) = 1$ if

$x = r_t$ and $\delta_t(x) = 0$ otherwise. Then the optimal hit rate curve HRC* satisfies:

$$\text{HRC}^*(x) = \frac{1}{R}\sum_{t=1}^{R}\sum_{z=0}^{x}\delta_t(z)$$

In STACKER, there are B buckets with variable boundaries over time. For request t with true reuse distance r_t, we estimate the reuse distance over an interval $[a_t, b_t]$ that includes r_t. Furthermore, we assign uniform probability to all possible distances within that interval. Define $c_t(x) = \frac{1}{b_t - a_t}$ when $x \in [a_t, b_t)$ and $c_t(x) = 0$ otherwise. Then the hit rate curve for our algorithm satisfies:

$$\text{HRC}(x) = \frac{1}{R}\sum_{t=1}^{R}\sum_{z=0}^{x}c_t(z)$$

We obtain the following upper bound on the mean average error for the two HRCs.

$$\begin{aligned}
&\text{MAE}(\text{HRC}, \text{HRC}^*) = \frac{1}{M}\sum_{x=0}^{M-1}|\text{HRC}(x) - \text{HRC}^*(x)| \\
= \;& \frac{1}{MR}\sum_{x=0}^{M-1}\left|\sum_{t=0}^{R}\sum_{z=0}^{x}\delta_t(z) - c_t(z)\right| \leq \frac{1}{MR}\sum_{t=1}^{R}\sum_{x=a_t}^{b_t}\sum_{z=0}^{x}|\delta_t(z) - c_t(z)| \\
\leq \;& \frac{1}{MR}\sum_{t=1}^{R}\sum_{x=a_t}^{b_t}\sum_{z=0}^{x}(|\delta_t(z)| + |c_t(z)|) \leq \frac{1}{MR}\sum_{t=1}^{R}\sum_{x=a_t}^{b_t}(1+1) \\
= \;& \frac{1}{MR}\sum_{t=1}^{R}2(b_t - a_t) \leq \frac{2}{M}\sup_{t=1,\ldots,R}(b_t - a_t).
\end{aligned}$$

□

The result enables operators to dynamically track the MAE of the HRC estimate even without computing the optimal hit rate curve. The algorithm could be extended to adaptively add or remove buckets depending on changes in the MAE so that resolution is maintained.

Note that the supremum in the last expression measures the size of the largest bucket during the workload. In some cases, as we have seen in our experiments, the least-significant bucket which tracks the largest reuse distances can consume a significant portion of the cache. Instead, the average bucket size for hits $\frac{2}{R}\sum_{t=1}^{R}(b_t - a_t)$ can be tracked and used as a stronger upper bound.

3.4 Estimating Cache Utility for $n > N$

How can we predict whether the cache needs to grow in size? Typically, data-less items called *ghosts* [25] are used as placeholders to record accesses to items whose data *would* have been included in the cache if more memory had been available [48]. The ghosts are contained in a **ghost list**:

> **Definition 4.** A ghost list is a data structure for storing items that have been evicted from a cache.

Placeholders consume a small amount of memory relative to the data normally stored by items, so their memory overhead can be viewed as a "tax" on elements actually stored in the LRU list. Thus when an item is evicted from the primary LRU list, it is added to a ghost LRU stack. The last ghost is also popped off and discarded. This method is at the heart of recent breakthroughs in cache replacement algorithms, including the ARC, CAR, LIRS and Clock-PRO policies [41, 12, 34, 33]. But if the values are very small relative to key size, e.g., as seen at Facebook [8], the tax can be significant. In this section we describe a solution to this issue. The solution is to use approximate filters to estimate the presence of items in the cache. We propose to use Counting Filters, which are a variant of Bloom Filters. In the following, we first describe these filters before moving on to present the algorithm, called COUNTINGGHOST.

While hits in the ghost list are still cache misses because no data could be returned to the user, statistics of the item itself can be gathered. Recall that H is the hit rate function and $H(n)$ is the hit rate for cache size n. In summary, to estimate $H(n)$ for cache memories larger than the current allocation, that is $N \leq n \leq k \cdot N$, we employ a ghost list of length $(k-1) \cdot N$.

3.4.1 Bloom Filters and Counting Filters

A Bloom Filter [17] is a compressed hash set which trades off space for less certainty in query answers. When a Bloom Filter is queried for a specific key it returns either "no" with full certainty or "yes" with high certainty. A false "yes" is defined as a false positive; the certainty can be increased by using more memory for the filter.

Internally the Bloom Filter uses an array $A[0, ..., m-1]$ of size m and l hash functions:

$$h_1, h_2, \ldots, h_l.$$

To insert a key into the filter, the key is hashed with the l hash functions to produce l hash values:

$$h_1(\text{key}), h_2(\text{key}), \ldots, h_l(\text{key})$$

and then the bits in the corresponding locations are set to 1, i.e.:

$$\begin{aligned} A[h_1(\text{key}) \bmod m] &= 1 \\ A[h_2(\text{key}) \bmod m] &= 1 \\ &\vdots \\ A[h_l(\text{key}) \bmod m] &= 1 \end{aligned}$$

To check whether a key is present in the filter, the same hashing is done as with an insert but instead of setting the bits to 1 we check if they are all set to 1. If they are all set to 1, we return yes but otherwise no. It is easy to see that even though all the keys are set to 1 the key was not necessarily inserted into the filter. Perhaps some other keys were mapped to the same locations and set the bits to 1. That event is called a false positive and the probability of a false positive is tuned with the size of the filter and the number of hash functions. The lowest false positive rate is achieved with the number of hash functions equal to:

$$l = \frac{m}{n} \ln 2$$

where n is the expected number of keys in the filter.

There is no good way to remove a key from a Bloom Filter without possibly damaging the presence of other keys. To solve this issue, Counting Filters were introduced in 1998 by Fan *et al*. [27]. Instead of using an array of bits, it is replaced with an array of counters. On insertion, the l counters (at the hashed locations) are incremented and on removal the same l counters are decremented. To check for a key in the filter, we simply check if the l counters are non-zero.

3.4.2 Intuition behind COUNTINGGHOST

COUNTINGGHOST is based on ROUNDER but must handle evictions on its own since it is also a ghost list. We use three filters to represent the buckets. When the first filter is full, we empty the last filter and make it the new first filter, the old first filter becomes the

second filter and the old second filter becomes the last filter. The first two filters therefore have capacity for the entire ghost list but the last filter is used as an evictable buffer to handle the evictions.

When an element is missed in the main cache, we check if its key is found in any of the three filters. If found, we update the corresponding region in the intermediate `DELTA` array which is the base for the HRC. We then remove the element's key from the filter since we expect it to be inserted in the main cache after a miss. Notice that if we were using Bloom Filters we could not perform this removal.

There is a subtle addition here to balance the false positive rate of the Counting Filter. When we update the DELTA array, we scale the value with $1.0 - \text{FPP\_RATE}$ because we want the total sum of the DELTA array to equal the number of hits and we would overestimate the number of hits without scaling.

3.4.3 COUNTINGGHOST Algorithm Details

COUNTINGGHOST is a sufficient ghost list that uses three Counting Filters instead of three buckets. Each bucket has capacity for half the cache size. The last bucket is a buffer to flush out old keys. With a cache of size N, the ghost list keeps track of the footprint for at least $(k-1) \cdot N$ extra elements ($k = 2$ is default). It uses three counting filters, each with a capacity of $(k-1) \cdot N/2$ elements. The last filter of $(k-1) \cdot N/2$ elements ensures that we are able to flush the last filter and make it the first filter while still keeping track of $(k-1) \cdot N$ elements in the ghost list. We do this because we need to evict some keys from the ghost list but we do not know the keys themselves. When there is a miss in the main cache, the function MISS in the ghost list interface is called. Upon an eviction, the function EVICT is called.

We use the dablooms [16] Counting Filter library from bit.ly. They use it to efficiently check whether an URL is malicious or not. This library is written in C and offers Python bindings and we use both. We set the false positive rate to 1% in all our experiments.

Now let us walk through the illustration of COUNTINGGHOST in Figure 3.5. This illustration assumes that the cache has size for 4 items and runs the LRU policy. The COUNTINGGHOST algorithm contains 3 Counting Filters, each with capacity for 2 items. Here we assume that each get request is followed by a set request after a cache miss.

Part (a) of the illustration is the initial setup. Part (b) shows what happens after a get request for d, it is moved from the LRU tail to the LRU head, HIT(d) is called, and nothing happens in the ghost list. Part (c) shows what happens after a get request for m

(a) Initial setup.

(b) After a get request for d.

(c) After a get and a set request for m.

(d) After a get and a set request for h.

Figure 3.5: Illustration showing elements inserted into the ghost list and how the filters **rotate**. Each filter has a maximum capacity of 2 and the cache has a maximum capacity of 4. The cache replacement policy in the main cache is **LRU**.

which is neither in the cache nor in the ghost list, MISS$(m.key)$ is called. This forces the cache to evict the least recently used item c, EVICT(c) is called, and insert it into the ghost list. The ghost list puts c into the first filter. Part (d) shows what happens after a get request for h. It is not located in the cache, MISS$(h.key)$ is called, but it is found in the second filter. It is removed from the second filter and inserted at the LRU head and the LRU tail, item b, is evicted, EVICT(b) is called. Now the first filter is full so we rotate the filters and then insert b into the new and empty first filter.

3.4.4 Pseudo-code

The COUNTINGGHOST algorithm is initialized, see Algorithm 9, by allocating three Counting Filters each with a capacity of half the cache size, lines 7-9.

The MISS routine in COUNTINGGHOST, see Algorithm 10, takes a key as an argument. The routine looks up the key in the three filters and updates the HRC accordingly.

The EVICT routine for the COUNTINGGHOST, see Algorithm 11, rotates the filter if necessary and inserts the key into the first filter.

The rotateFilters routine in the COUNTINGGHOST, see Algorithm 12, flushes the last filter and makes it the new empty filter. This method serves the same purpose as the age routine in ROUNDER, see Algorithm 7.

Algorithm 9 The Initialization routine for COUNTINGGHOST.

INITIALIZATION($capacity$)

```
1  capacityPerFilter = capacity/2.0
2  counters = [0, 0, 0]
3  firstFilter = 0
4  secondFilter = 1
5  thirdFilter = 2
6  filters = array of three Counting Filters
7  filters[firstFilter].allocateCapacity(capacityPerFilter)
8  filters[secondFilter].allocateCapacity(capacityPerFilter)
9  filters[thirdFilter].allocateCapacity(capacityPerFilter)
```

Algorithm 10 The MISS routine for COUNTINGGHOST.

MISS(key)

```
 1  scale = (1.0 − FPP_RATE)
 2  if filters[firstFilter]. contains(key)
 3      UPDATEDELTA(0, counters[firstFilter], scale, cachesize)
 4  elseif filters[secondFilter]. contains(key)
 5      start = counters[firstFilter]
 6      end = start + counters[secondFilter]
 7      UPDATEDELTA(start, end, scale, cachesize)
 8      filters[secondFilter]. remove(key)
 9      filters[firstFilter]. insert(key)
10      counters[thirdFilter] = counters[secondFilter] − 1
11      counters[firstFilter] = counters[firstFilter] + 1
12  elseif filters[thirdFilter]. contains(key)
13      // If the first two filters are not full, the third filter is responsible
14      start = counters[firstFilter] + counters[secondFilter]
15      end = start + counters[thirdFilter]
16      UPDATEDELTA(start, end, scale, cachesize)
17      filters[thirdFilter]. remove(key)
18      filters[firstFilter]. insert(key)
19      counters[thirdFilter] = counters[thirdFilter] − 1
20      counters[firstFilter] = counters[firstFilter] + 1
```

Algorithm 11 The EVICT routine for COUNTINGGHOST.

EVICT(key)

```
1  // If the first filter is full, rotate the filters
2  if counters[firstFilter] ≥ capacityPerFilter
3      ROTATEFILTERS()
4  // Insert the element into the first filter
5  counters[firstFilter] = counters[firstFilter] + 1
6  filters[firstFilter]. insert(key)
```

Algorithm 12 The internal rotateFilters in COUNTINGGHOST.

ROTATEFILTERS()
1 $filters[lastFilter].flush()$
2 $counters[lastFilter] = 0$
3 // The other counters are maintained
4 $firstFilter = lastFilter$
5 $secondFilter = (firstFilter + 1) \mod 3$
6 $lastFilter = (firstFilter + 2) \mod 3$

3.5 Comparison to Related Work

Much work has been put into creating the HRC for the entire working set. We are looking at creating the HRC for just the cache size along with the size of the ghost list. We also want to do this online so we cannot do a prepass through all the data like much of the related work does. A prepass is to go through the workload and store alongside each request to an element e the last reference to e. We now give a brief overview of the highly related algorithms to our approach.

3.5.1 Previous Methods

In 1970, Mattson *et al.* [38] studied stack algorithms in cache management and defined the concept of stack distance. They described the first measurement algorithm for reuse distance using a stack represented as a list. The time complexity of the algorithm is linear in the cache size and traverses the stack to find the element.

Several papers [57, 46, 56] have been written on measuring reuse distances with AVL trees. Those methods have the logarithmic time complexity in common due to the AVL tree which is ordered by access times.

Bennett and Kruskal introduced [15] a method called blocked hashing to preprocess the workload in a single pass and then create the reuse distance histogram by splitting the workload into segments. Using this method for our purposes is impossible due to the prepass. Olken [46] improved Bennett and Kruskal's method by using an AVL tree for the entire workload, which is logarithmic in the length of the workload and not applicable in our setting.

Ding and Zhong described a compression method in 2003 [24]. They store *reuse distance intervals* as tree nodes and store multiple items per node. The height of the tree is logarithmic in the cache size and the compression guarantees $\log \log$ time complexity.

The complexity of this method is much higher than our method and making it parallel would not be trivial.

Kim *et al*. [36], and later systems in cache architecture such as RapidMRC [53] and PATH [9], partition the LRU list into groups to reduce cost of maintaining distances, which is conceptually similar to our approach except the group sizes are fixed as powers of two. Our variable sized buckets approach affords substantially higher accuracy in trade for modest overhead.

3.5.2 Performance Comparison

Making trees parallel has been the subject of intricate work, suggesting parallelizing an AVL tree or the methods from [46, 24]. ROUNDER is highly parallel while being simple, but has a weakness with the last bin getting too big. In our experiments, however, presented in Chapter 5, this was not an issue.

STACKER is similar to ROUNDER but has a better aging method and is thus more accurate, but the overhead of running STACKER over the cache replacement policy is higher than running ROUNDER. The time complexity of the aging function is $\mathrm{O}(N)$, but is called in worst case every N/B requests. Assuming that the total number of requests in the workload is Q, then the number of aging operations is

$$Q/(N/B) = \frac{Q \cdot B}{N}$$

and the total time spent in the aging function is then

$$\mathrm{O}\left(\frac{Q \cdot B}{N} \cdot N\right) = \mathrm{O}(Q \cdot B)$$

which is $\mathrm{O}(B)$ amortized per request over the Q requests.

It is worth taking a moment to notice that the $O(B)$ time complexity of ROUNDER is independent of the cache size. Table 3.2 shows a comparison of the performance of ROUNDER and STACKER to the previous work, focusing on those methods that do not require preprocessing. To compare the overhead head to head, we implemented the following methods in C++: LRU, LRU with ROUNDER, LRU represented as an AVL tree [56, 57] and LRU with Mattson's algorithm [38]. We did not implement STACKER in C++ since it is slower than ROUNDER and we wanted to focus on the high performance of ROUNDER in this comparison. Figure 3.6 shows a throughput comparison of these methods. As the figure shows, using ROUNDER with LRU ROUNDER has the lowest

Method	Time complexity	Accuracy
Mattson's algorithm[38]	$\mathrm{O}(N)$	100%
AVL-Tree [56, 57]	$\mathrm{O}(\log(N))$	100%
Dynamic Tree Compression(e) [24]	$\mathrm{O}\left(\log_2(\log_{1+e'}(N))\right)$	$e \times 100\%$
SC2 [18]	$\mathrm{O}(1)$	Low
ROUNDER	$\mathrm{O}(B)$	$\leq 100 \times 2LB/N$ %
STACKER	Amortized $\mathrm{O}(B)$	$\leq 100 \times 2LB/N$ %

Table 3.2: Overview of methods for creating an LRU histogram. N is the cache size, time complexity is per request, for the tree compression $e' = \frac{1}{1+e}$ where e is the desired accuracy of the reuse distance, LB is the size of the largest bucket for ROUNDER and STACKER. With ROUNDER only the size of last bucket can grow above N/B.

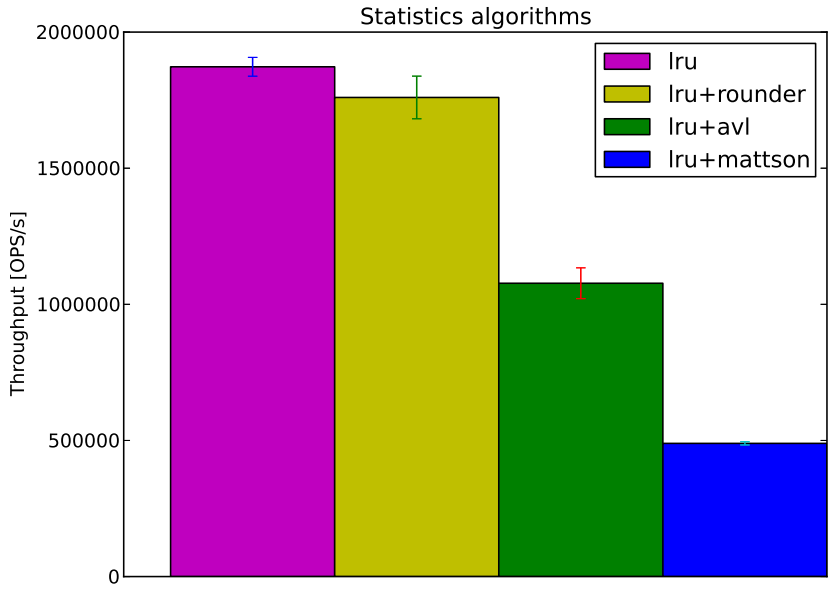


Figure 3.6: **Overhead comparison** of regular LRU, LRU with ROUNDER, LRU represented as an AVL tree [57, 56] and LRU with Mattson's algorithm [38]. ROUNDERwas set to use 8 buckets and places 6.3% overhead on regular LRU, the AVL tree causes 73.8% overhead and Mattson's algorithm yields 282.7% overhead. The LRU cache has capacity for 5000 elements in this experiment and the bars show the standard deviation from 10 runs.

overhead while, using Mattson's algorithm reduces the throughput much more than an AVL tree. We evaluate the accuracy and overhead of ROUNDER further in Chapter 5.

Chapter 4

Implementation

4.1 MIMIR Profiling Framework

The MIMIR profiling framework hooks into the replacement policy with a simple interface consisting of four commands: HIT, MISS, SET and EVICT. MIMIR provides a ghost list to contain meta-data on evicted keys if the cache service does not provide that functionality already. After an eviction from the main cache, the item is added to the ghost list MIMIR consists of two algorithms. ROUNDER is responsible for generating the HRC for cache sizes smaller than the current allocation. COUNTINGGHOST is responsible for cache sizes larger than the current allocation.

The manner by which MIMIR hooks into the replacement policy and contacts ROUNDER and COUNTINGGHOST is described in Figure 4.1.

Notice that the calls to the ghost list on MISS and EVICT, if the item is found in the ghost list after a miss in the cache, the HRC is updated. All commands take an element as an argument except the MISS command which takes a key. The reason is that on a cache miss, no element is available.

The Python implementation of MIMIR consists of three components. The first two are ROUNDER and STACKER described in Chapter 3. The third component is COUNTING-GHOST also described in Chapter 3.

Our C implementation of MIMIR is focused on high performance in highly parallel systems and therefore we omit STACKER which has higher time complexity than ROUNDER.

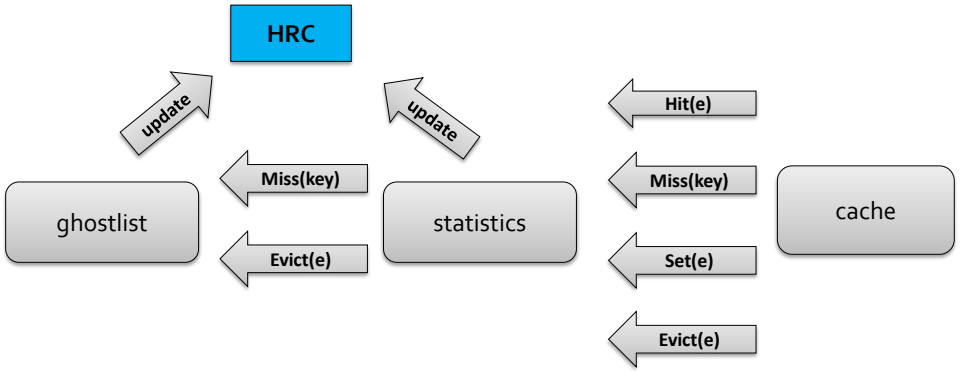


Figure 4.1: **MIMIR's interface:** Communication between the cache and the profiling framework.

$$\mathrm{LD}(n) = \begin{cases} 0 & \text{if } n = NULL \\ \mathrm{LD}(\mathrm{ANC}(n)) + \mathrm{size}(\mathrm{LC}(n)) + 1 & \text{if } n \neq NULL \end{cases}$$

Figure 4.2: Recursive formula from [57] to calculate the number of younger elements than a given node n. $\mathrm{LC}(n)$ is the left child of n and $\mathrm{ANC}(n)$ is either $NULL$ or the nearest ancestor m of n such that m's left child is neither n nor n's ancestor. The intuition behind the formula is to sum up the the sizes of the left sub-trees up the path from n to the root of the tree.

4.2 Related Work Experiment: C++ Simulator

To compare the overhead of related work we implemented a few methods. We chose C++ to use an AVL tree implementation [52] based on the Introduction to Algorithms by MIT on Open Courseware [23] written by an Icelandic competitive programmer. The workload used is $P10$ described in Section 5.1 and the cache size is 5000 elements.

The baseline with respect to efficiency is LRU without HRC collection. To calculate the stack distance with the AVL tree we used the recursive formula, see Equation 4.2 from [57]. Each AVL node contains a timestamp used for comparing items, the LRU head is located at the leftmost leaf and the LRU tail is located at the rightmost leaf in the tree. The baseline with respect to efficiency is LRU without collecting the HRC.

The implementation of Mattson's algorithm is a 33 LOC (Lines of Code) add-on to LRU by walking the linked list. The AVL tree implementation extended with formula 4.2 is in total 445 LOC. The C++ ROUNDER implementation totals to 243 LOC but the multi-threaded C implementation of ROUNDER and COUNTINGGHOST together, discussed in Section 4.3, is 503 LOC.

	Rounder	Stacker	Regular LRU ghost list	Countingghost
Activity counter	4B	4B	0B	5B
Pointers	0B	0B	8B	0B

Table 4.1: Number of bytes required **per item** in each data structure.

4.3 Implementation in Memcached

Since memcached is widely used as a key-value store to speed up web sites and it uses the LRU replacement policy, it was a good fit to evaluate the overhead of the MIMIR profiling framework which is designed for LRU. The memcached server uses 4 threads by default and in order to handle multiple threads we made MIMIR highly parallel with CAS operations and GCC atomic builtins. Each thread updates a local copy of the HRC to prevent locks and the HRCs are joined together when requested. To serve the HRC we added the *stats hrc* command to our fork of memcached and to visualize it we use the Flask [29] web framework to poll the HRC and plot it client side in the browser with D3.js [21].

4.3.1 Memory Overhead

Table 4.1 shows the memory overhead of our methods. `Memcached` uses a 56 byte header for each item; we add a 4B timestamp for STACKER and ROUNDER.

The HRC itself is compressed to contain only 100 floating point numbers per slab class per thread, totalling 16.8KB independent of the cache size. When we get a hit in the statistics, we map the corresponding region to the correct range in the 100 element HRC in the thread local array (actually we use the intermediate PLUS array and generate the HRC when requested).

The counting filter uses approximately 5 bytes per element when the false positive rate is 1%. With the Facebook workload with 31 byte keys and 2 byte values in mind this makes it an affordable memory tax. Using a regular linked list in the ghost list would require 8 bytes for pointers and 31 bytes for the key, a total of 39 bytes which is not reasonable since the values are so small.

We run one instance of ROUNDER for every slab class since each slab class has its own LRU but one instance of COUNTINGGHOST since when a miss occurs the size of the item is unknown and we do not know which slab class it belongs to.

4.3.2 Joining HRCs from Different Slab Classes

Since memcached uses by default 42 slab classes to store differently sized items there are several ways to join the HRCs, represented as $\mathrm{HRC}_i, 1 \leq i \leq 42$, from each slab class into a single HRC. Each slab class has its own LRU linked list so we hook one instance of ROUNDER to each slab class. If we had one instance of COUNTINGGHOST per slab class we would need 42 lookups on a cache miss since the value size is not known when a cache miss occurs. Thus we only run one instance of COUNTINGGHOST and assume that all items have equal sizes.

We assume that the least recently used item in each slab class has similarly "low recency". Our formula aims to join the HRCs together into a single HRC that would have been made if there was only one global LRU running in memcached. To join the 42 HRCs together we use the following formula:

$$\mathrm{globalHRC}(n) = \sum_{i=1}^{42} \mathrm{HRC}_i \left(\frac{n}{C} \cdot 100 \right)$$

Figure 4.3: Formula for joining HRCs from different slab classes in memcached. C is the cache size in bytes.

Notice that since each HRC_i is a compressed 100 bucket histogram, and we have to map the index to the correct bucket. The intuition behind the formula is that we take the same fraction of bytes from each slab class and sum up the hits for each histogram at the correct index.

4.4 Potential Optimizations

The 23-41% throughput degradation of MIMIR within memcached can be improved with several steps. We integrated MIMIR into memcached 1.4.15 but in memcached 1.4.18 the default hash function has been changed to MurmurHash which is the hash function used by the ghost list. Reusing the hash value and reusing the key length on a *cache miss* to skip a call to *strlen* would lower the performance costs. Also introduced in memcached 1.4.18 is a new background thread called **lru_crawler**, using this thread to alleviate some of the work from MIMIR off the critical path could also significantly reduce the overhead.

4.5 Availability

Most of the code used in this this thesis is available under a BSD License on GitHub at `https://www.github.com/trauzti/mimir`. The Python simulator supports several replacement policies and the basic functionality, of *get* and *set* from the memcached API (without support for flags and expiry times).

The Python simulator is not ready for a production environment at the moment but is ready for experimenting with different replacement policies and the MIMIR profiling framework. It uses Twisted [37] for asynchronous network I/O. The MIMIR profiling framework is available inside the Python simulator and also hooked into memcached-1.4.15. Like memcached augmented with the MIMIR profiling framework, the Python simulator also supports the **stats hrc** command. To visualize the HRCs from either the Python simulator or memcached the repository contains a Flask web interface that pools HRCs via *stats hrc*.

Chapter 5

Experiments

In this chapter we evaluate the proposed algorithms. We first evaluate the accuracy using a Python simulator and then evaluate overhead of the framework within memcached.

5.1 Workloads

A workload is a history of cache requests saved for future use and offline analysis. Here we present two types of workloads, **extreme** and **smooth**. The hit rate for the **extreme** workloads is harder to predict than the hit rate for the **smooth** workloads. The reason is that the slope of the hit rate curve for **extreme** workloads is increases and decreases irregularly while the slope for **smooth** workloads increases or decreases regularly.

5.1.1 Extreme Workloads

We use workloads and benchmarks that are commonly used by the cache replacement algorithm community [34, 33, 41]. The workloads **2pools**, **glimpse**, **cpp**, **cs**, **ps** and **sprite** were collected respectively from a synthetic multi-user database, the `glimpse` text information retrieval utility, the GNU C compiler pre-processor, the `cs` program examination tool, join queries over four relations in the `postgres` relational database, and requests to file server in the Sprite network file system [34, 33]. The workloads **multi1**, **multi2** and **multi3** are obtained by executing multiple workloads together [34].

The **P1**-**P10** workloads are captured from IBM SAN controllers at customer premises [41] and were collected by disk operations on different workstations over several months.

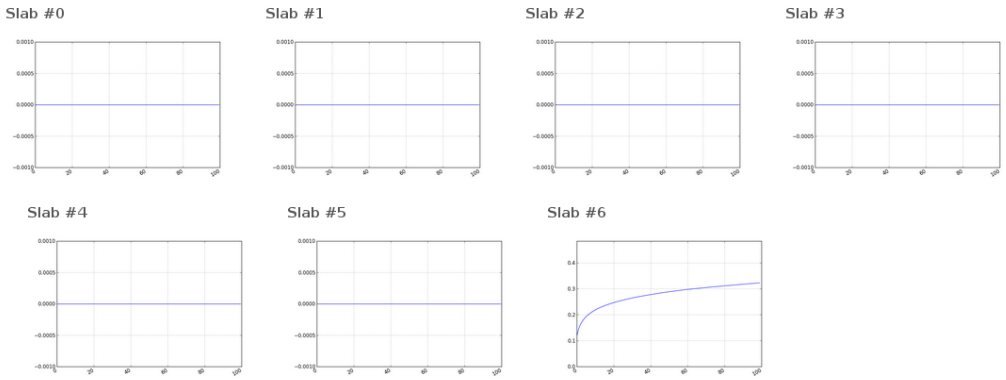


Figure 5.1: HRCs for the first 6 slab class after running the **YCSB b2** workload.

WebSearch1 consists of disk read accesses by a large search engine in response to web search requests over an hour, and **Financial1** and **Financial2** are extracted from a database server at a large financial institution [41].

While these workloads are from a variety of sources, they present workloads whose hit rate curves are hard to approximate. The difficulty stems from abundance of sequential and looping references in the buffer cache that are characteristic of file-system accesses [36]. We refer to those workloads as **extreme** because of the sharp increases and decreases in the slope of the LRU hit rate curve while running those workloads. They are well suited to test the edge cases of our algorithms

5.1.2 Smooth Workloads

Workloads seen in cloud caches tend to be **smooth** as they do not have irregularly increasing and decreasing slope like the **extreme** workloads.

An example is the **YCSB b2** [19] which occupies only one slab class in memcached with default settings, namely slab class #6 and the **smooth** HRC can be seen on Figure 5.1.

The **OZ** workloads are from a varnish cache [4] serving video chunks. The cache is set up to use the LRU replacement policy. To see how different cache replacement algorithms handle this workload see Figure A.6. As can be seen from the figure this workload has no spikes or cliffs as seen in the extreme workloads.

Again the workloads are **smooth** because the slope of the LRU hit rate curve does not change abruptly as the cache size increases.

5.2 Accuracy

5.2.1 Experimental Setup

We measured the accuracy of ROUNDER, STACKER and COUNTINGGHOST in a Python simulator. For the accuracy experiments on ROUNDER and STACKER on the first nine workloads, we use identical cache set-up as the authors of the LIRS algorithm [34].

5.2.2 ROUNDER

This section evaluates the accuracy of ROUNDER which was introduced in Chapter 3. To get a feel for how the accuracy changes with different number of buckets we vary the bucket sizes on a variety of workloads and run the algorithm on top of LRU and CLOCK.

Tables 5.1 and 5.2 summarize the results for LRU and CLOCK respectively and hand picked lines from those tables are presented in Figure 5.2.

Running on *LRU*, the overall MAE is 1.93% on average for all the workloads when using only 8 buckets but goes down to 0.95% with 128 buckets. The worst performance is on the **cs** and **WebSearch1** workloads with 5.41% and 4.02% respectively using 8 buckets but goes down to 0.93% and 4.02% with 128 buckets for the same workloads. In fact the accuracy of **WebSearch1** does not change with more buckets.

Running on *CLOCK*, the overall MAE is 1.08% on average for all the workloads when using only 8 buckets but goes down to 0.80% with 128 buckets. The worst performance occurs on the **postgres** and **glimpse** workloads with 7.93% and 6.46% respectively using 8 buckets but goes down to 5.98% and 4.94% with 128 buckets.

Ultimately this experiment shows that ROUNDER is very accurate in estimating the real HRC of LRU achieving a worst case MAE of 5.41% with very few buckets. With CLOCK, on the other hand the worst case MAE is 7.93% with as little as 8 buckets. Using 128 buckets the worst cases are 4.02% and 5.98% respectively. This shows that ROUNDER works better on LRU in the worst case but better on CLOCK on average. Recalling from Section 2.1.5 that CLOCK has very similar performance to LRU we conclude that ROUNDER works well on both LRU and CLOCK, still being designed for LRU.

Workload	**Requests**	**Cache size**	$B = 8$	$B = 16$	$B = 32$	$B = 64$	$B = 128$
2pools	100K	450	0.52	0.30	0.20	0.18	0.18
cpp	9K	900	1.92	1.17	0.72	0.47	0.33
cs	7K	1K	5.41	2.21	1.68	1.32	0.93
glimpse	6K	3K	4.34	2.94	1.83	1.48	1.38
multi1	16K	2K	3.56	3.83	3.48	3.16	3.00
multi2	26K	3K	2.11	1.82	1.52	1.34	1.14
multi3	30K	4K	1.14	0.86	0.73	0.54	0.45
postgres	10K	3K	3.47	1.67	1.16	0.85	0.61
sprite	134K	1K	2.09	1.82	1.65	1.57	1.53
Financial1	1M	50K	2.02	0.85	0.37	0.09	0.05
Financial2	3M	50K	1.82	0.98	0.77	0.74	0.78
WebSearch1	1M	50K	4.02	4.02	4.02	4.02	4.02
P1	3M	50K	1.64	1.30	1.19	1.14	1.12
P2	666K	50K	0.93	0.84	0.80	0.80	0.77
P3	239K	50K	0.76	0.42	0.28	0.24	0.21
P4	967K	50K	1.01	0.78	0.58	0.53	0.45
P5	1M	50K	1.08	0.81	0.68	0.57	0.51
P6	520K	50K	1.31	1.18	0.98	0.86	0.80
P7	751K	50K	0.93	0.69	0.58	0.50	0.44
P8	2M	50K	2.24	2.21	2.20	2.17	2.15
P9	682K	50K	0.97	0.80	0.68	0.63	0.60
P10	1M	50K	1.16	0.85	0.74	0.62	0.58
P12	547K	50K	0.94	0.67	0.60	0.58	0.56
P13	1M	50K	0.82	0.66	0.56	0.50	0.46
Average (%)			1.93	1.40	1.17	1.08	0.96

Table 5.1: **Accuracy** of ROUNDER running on LRU: Each result is given as a percentage (results generally have around 0-5% error).

5.2.3 STACKER

This section evaluates the accuracy of STACKER, which was also introduced in Chapter 3. To get a feel for how the accuracy changes with different number of buckets we vary the bucket sizes on a variety of workloads and run the algorithm on top of LRU and CLOCK.

Tables 5.3 and 5.4 summarize the results for LRU and CLOCK respectively and hand picked lines from those tables are presented in Figure 5.3.

Running on *LRU*, the overall MAE is 1.73% on average for all the workloads when using only 8 buckets but goes down to 0.20% with 128 buckets. The worst performance is on the **cs** and **WebSearch1** workloads with 5.30% and 4.02% respectively using 8

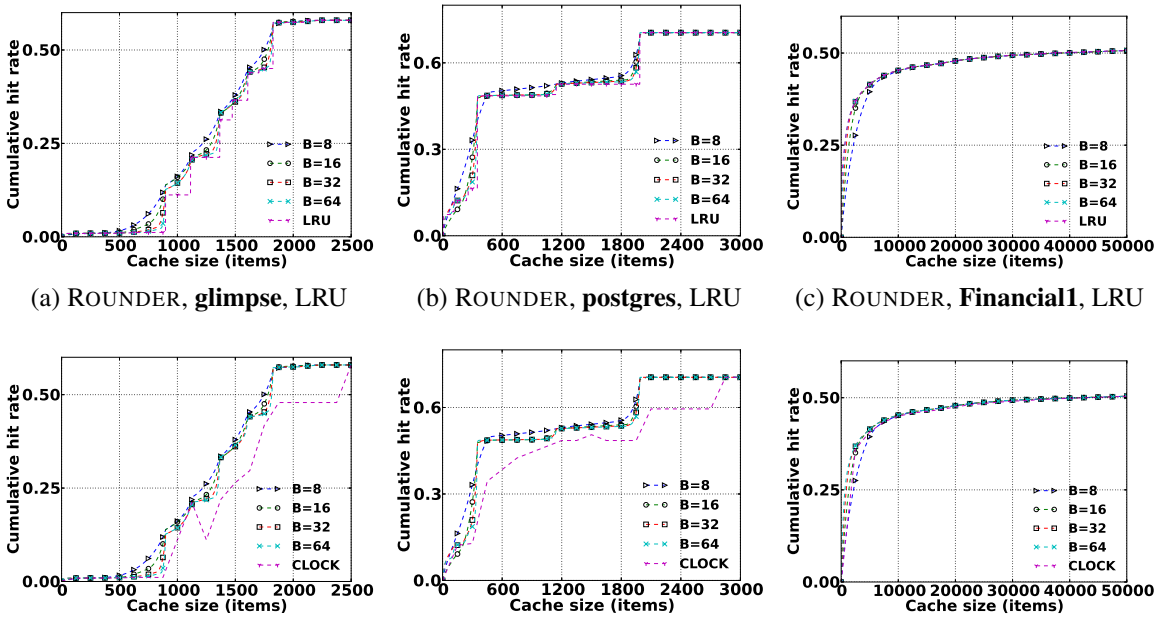
Workload	**Requests**	**Cache size**	$B = 8$	$B = 16$	$B = 32$	$B = 64$	$B = 128$
2pools	100K	450	1.49	1.66	1.74	1.77	1.78
cpp	9K	900	1.81	1.40	1.10	0.94	0.83
cs	7K	1K	3.14	1.15	0.91	0.84	0.64
gli	6K	3K	6.46	5.74	5.19	5.01	4.94
multi1	16K	2K	2.10	2.88	2.61	2.38	2.28
multi2	26K	3K	2.31	2.43	2.29	2.19	2.07
multi3	30K	4K	1.77	1.91	1.90	1.76	1.70
ps	10K	3K	7.93	6.86	6.28	6.08	5.98
sprite	134K	1K	1.52	1.27	1.14	1.08	1.05
Financial1	1M	50K	0.02	0.01	0.01	0.01	0.01
Financial2	3M	50K	0.02	0.01	0.01	0.01	0.01
WebSearch1	1M	50K	0.07	0.07	0.07	0.07	0.07
WebSearch2	5M	50K	0.00	0.00	0.00	0.00	0.00
WebSearch3	4M	50K	0.00	0.00	0.00	0.00	0.00
P1	3M	50K	0.02	0.01	0.01	0.01	0.01
P2	666K	50K	0.02	0.02	0.02	0.02	0.02
P3	239K	50K	0.09	0.04	0.03	0.02	0.02
P4	967K	50K	0.04	0.03	0.02	0.02	0.02
P5	1M	50K	0.05	0.03	0.02	0.02	0.02
P6	520K	50K	0.05	0.03	0.02	0.01	0.01
P7	751K	50K	0.05	0.03	0.02	0.02	0.02
P8	2M	50K	0.03	0.03	0.03	0.03	0.03
P9	682K	50K	0.03	0.02	0.02	0.02	0.02
P10	1M	50K	0.05	0.03	0.03	0.02	0.02
P12	547K	50K	0.04	0.03	0.03	0.02	0.02
P13	1M	50K	0.04	0.03	0.02	0.02	0.02
P14	4M	50K	0.02	0.02	0.02	0.02	0.01
Average (%)			1.08 %	0.95 %	0.87 %	0.83 %	0.80 %

Table 5.2: **Accuracy** of ROUNDER running on CLOCK: Each result is given as a percentage (results generally have around 0-8% error).

buckets but using the same workloads this decreases down to 0.20% and 4.34% with 128 buckets.

Running on *CLOCK*, the overall MAE is 1.04% on average for all the workloads when using only 8 buckets but goes down to 0.75% with 128 buckets. The worst performance occurs on the **postgres** and **glimpse** workloads with 7.42% and 5.55% respectively using 8 buckets and goes down to 5.65% and 4.60% with 128 buckets.

As with ROUNDER, the bucket parameter trades off overhead for accurate HRCs, and the improvement in accuracy is evident as we increase the number of buckets B in the algorithms. Like with ROUNDER, this experiment shows that STACKER is very accurate



(a) ROUNDER, **glimpse**, LRU (b) ROUNDER, **postgres**, LRU (c) ROUNDER, **Financial1**, LRU

(d) ROUNDER, **glimpse**, CLOCK (e) ROUNDER, **postgres**, CLOCK (f) ROUNDER, **Financial1**, CLOCK

Figure 5.2: **Accuracy graphs** Hit rate curves of ROUNDER on LRU (top row) and CLOCK (bottom row) with varying bucket sizes (B) on three workloads. The true LRU and CLOCK hit rate curves are also shown.

in estimating the real HRC of LRU, achieving even better accuracy than ROUNDER. The worst case MAE of 5.30% is better than the worst case MAE of 5.41 when using only 8 buckets with ROUNDER. With CLOCK and 8 buckets the worst case MAE is 7.42% compared to 7.93% with ROUNDER.

Using STACKER and 128 buckets, the worst cases are 0.82% and 4.6% respectively compared to 4.02% and 5.98% respectively with ROUNDER and 128 buckets. STACKER has much higher accuracy than ROUNDER on the workload **WebSearch1** and the accuracy increases with more buckets as opposed to the fixed accuracy with ROUNDER.

5.2.4 COUNTINGGHOST

Although the use of ghost list is intuitive there are settings where maintaining the ghost list structure imposes significant overhead on the memory cache. For instance, according to [8], the vast majority of values in the Facebook memory cache occupy only a few bytes making them significantly smaller than the keys themselves. In Section 3.4.3 we introduced the algorithm COUNTINGGHOST to attack this problem and in this section we evaluate the accuracy of this algorithm. In Section 3.4.3 we introduced a mechanism that

Workload	**Requests**	**Cache size**	$B = 8$	$B = 16$	$B = 32$	$B = 64$	$B = 128$
2pools	100K	450	0.59	0.31	0.11	0.07	0.05
cpp	9K	900	1.90	1.07	0.54	0.28	0.16
cs	7K	1K	5.30	1.56	0.88	0.42	0.20
glimpse	6K	3K	2.56	1.62	1.03	0.42	0.21
multi1	16K	2K	3.43	3.56	2.19	1.29	0.82
multi2	26K	3K	2.16	1.47	0.92	0.67	0.42
multi3	30K	4K	1.23	0.72	0.56	0.38	0.37
postgres	10K	3K	3.77	1.78	1.00	0.50	0.23
sprite	134K	1K	1.47	0.46	0.19	0.14	0.08
Financial1	1M	50K	1.97	0.85	0.34	0.07	0.03
Financial2	3M	50K	1.85	0.85	0.44	0.25	0.20
WebSearch1	1M	50K	4.02	0.73	0.72	0.75	0.34
P1	3M	50K	1.11	0.51	0.33	0.28	0.17
P2	666K	50K	0.70	0.31	0.25	0.25	0.24
P3	239K	50K	0.76	0.34	0.21	0.15	0.10
P4	967K	50K	1.05	0.59	0.28	0.13	0.07
P5	1M	50K	1.00	0.51	0.26	0.15	0.11
P6	520K	50K	1.09	0.61	0.32	0.21	0.15
P7	751K	50K	0.82	0.39	0.20	0.12	0.10
P8	2M	50K	0.92	0.41	0.34	0.22	0.21
P9	682K	50K	0.94	0.42	0.17	0.08	0.10
P10	1M	50K	1.13	0.69	0.45	0.34	0.24
P12	547K	50K	1.01	0.60	0.30	0.21	0.09
P13	1M	50K	0.79	0.34	0.17	0.12	0.07
Average (%)			1.73	0.86	0.51	0.32	0.20

Table 5.3: **Accuracy** of STACKER running on LRU: Each result is given as a percentage (results generally have around 0-5% error).

improves on the regular ghost list by being more space and time efficient, in exchange for accuracy, in cases where keys are significantly longer than the values.

As opposed to ROUNDER and STACKER, which have a tunable number of buckets, this algorithm contains 3 hypothetical buckets represented as Counting Filters to maintain the ghost list. To get a feel for the accuracy of this algorithm predicting what would happen if the cache size would be doubled, we run the algorithm on the **extreme** workloads on top of LRU.

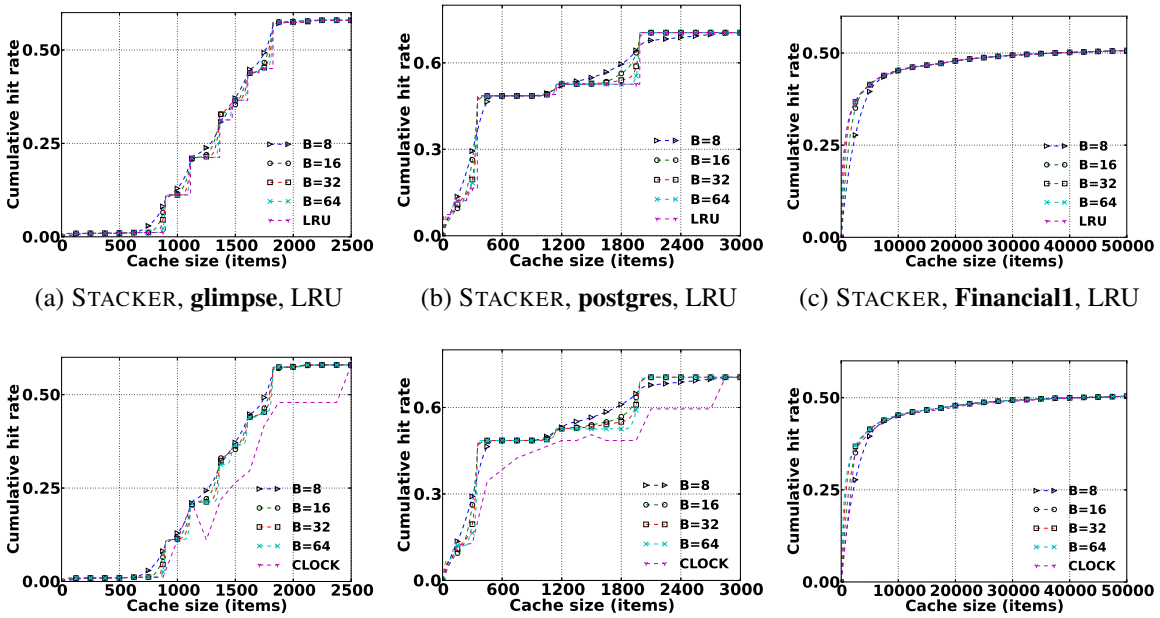
In this experiment we measured the accuracy of this method by running the ghost list with LRU on some of the **extreme** workloads. For reference a regular ghost list for LRU, implemented as a linked list using Mattson's algorithm for evaluating stack distances, would have predicted the hits in the ghost list with 100% accuracy.

Workload	**Requests**	**Cache size**	$B = 8$	$B = 16$	$B = 32$	$B = 64$	$B = 128$
2pools	100K	450	1.45	1.61	1.68	1.70	1.73
cpp	9K	900	1.70	1.33	1.07	0.98	0.88
cs	7K	1K	3.04	0.80	0.45	0.26	0.10
gli	6K	3K	5.55	5.02	4.85	4.68	4.60
multi1	16K	2K	2.79	2.75	2.63	2.23	2.19
multi2	26K	3K	2.32	2.33	2.11	2.08	2.12
multi3	30K	4K	2.29	2.19	2.14	2.18	2.10
ps	10K	3K	7.42	7.13	6.45	5.89	5.65
sprite	134K	1K	0.95	0.42	0.42	0.47	0.50
Financial1	1M	50K	0.02	0.01	0.01	0.01	0.01
Financial2	3M	50K	0.01	0.01	0.01	0.01	0.01
WebSearch1	1M	50K	0.07	0.05	0.05	0.05	0.05
WebSearch2	5M	50K	0.00	0.00	0.00	0.00	0.00
WebSearch3	4M	50K	0.00	0.00	0.00	0.00	0.00
P1	3M	50K	0.01	0.01	0.01	0.01	0.01
P2	666K	50K	0.02	0.02	0.02	0.02	0.02
P3	239K	50K	0.09	0.04	0.03	0.02	0.02
P4	967K	50K	0.04	0.03	0.02	0.02	0.02
P5	1M	50K	0.05	0.03	0.02	0.02	0.02
P6	520K	50K	0.05	0.03	0.02	0.01	0.01
P7	751K	50K	0.05	0.03	0.03	0.03	0.03
P8	2M	50K	0.01	0.01	0.01	0.01	0.01
P9	682K	50K	0.03	0.02	0.02	0.02	0.02
P10	1M	50K	0.05	0.04	0.03	0.02	0.02
P12	547K	50K	0.04	0.03	0.03	0.03	0.03
P13	1M	50K	0.04	0.03	0.03	0.02	0.02
P14	4M	50K	0.02	0.02	0.02	0.02	0.02
Average (%)			1.04 %	0.89 %	0.82 %	0.77 %	0.75 %

Table 5.4: **Accuracy** of STACKER running on CLOCK. Each result is given as a percentage (results generally have around 0-8% error).

We ran the experiment with different cache sizes containing N elements and with a ghost list capacity for another extra N elements. To measure the accuracy of the predicted hit rate, we ran another simulation with a cache of size $2N$ and compared the two hit rate values.

The estimated hit rate for several different values of N along with the real hit rate for a cache of size N are shown in Table 5.5 and Table 5.6. The table also contains the accuracy of each prediction and the average of all the 64 accuracy 64 entries in the table is 95.8%. The results are presented visually in Figure 5.4. If we look at individual data points in the table we can see that there are a few notable outliers. For example in **multi1** at cache size 1500 the ghost list falsely predicts hit rate to surge 67% where hit rate actually stays



(a) STACKER, **glimpse**, LRU (b) STACKER, **postgres**, LRU (c) STACKER, **Financial1**, LRU

(d) STACKER, **glimpse**, CLOCK (e) STACKER, **postgres**, CLOCK (f) STACKER, **Financial1**, CLOCK

Figure 5.3: **Accuracy graphs** Hit rate curves of STACKER on LRU (top row) and CLOCK (bottom row) with varying bucket sizes (B) on three workloads. The true LRU and CLOCK hit rate curves are also shown.

at 49% The sharp incline in the hit rate suggests that the underlying workload has scans which the ghost list is not sensitive enough to pick up and instead averages the incline over a wider area. This experiment shows how the algorithm predicts the hit rate for a cache size of size $2N$ when running a cache of size N. Here $N = 1500$. Each of the three counting filters contains between 0 and 500 elements. They contribute to the hit rate curve at different intervals depending on how many elements are in each filter. Thus the algorithm is able to predict all hit rates for cache sizes between N and $2N$, not only for $2N$ like shown in this experiment.

This experiment shows that COUNTINGGHOST is fairly accurate in predicting the hit rate of LRU if the cache size would be doubled. On 5 out of 64 different settings the accuracy drops below 90% but stays above 90% for all other settings. Those outliers happen when there is a looping pattern in the underlying workload, creating a sudden steep increase in the hit rate as the cache size increases. Using only three filters is not enough to capture those events.

Overall the average accuracy is 95.8% and we conclude that the method provides high accuracy on a variety of workloads, suggesting that Counting Filters are effective in minimizing space and time overhead of ghost lists.

Workload	**Cache size**	**Hit rate**	**Predicted hit rate**	**Accuracy** [%]
2pools	500	51.06200	51.86246	98.5
2pools	1000	54.41500	55.32395	98.4
2pools	1500	56.87700	57.96308	98.1
2pools	2000	59.32600	60.48172	98.1
2pools	2500	61.64600	62.82262	98.1
2pools	3000	64.00100	65.13756	98.3
2pools	3500	66.27000	67.33176	98.4
2pools	4000	68.52100	69.39331	98.7
cpp	500	84.77948	85.34166	99.3
cpp	1000	86.40433	86.48657	99.9
cpp	1500	86.48171	86.47950	100.0
cpp	2000	86.48171	86.48093	100.0
cpp	2500	86.48171	86.48171	100.0
cpp	3000	86.48171	86.48171	100.0
cpp	3500	86.48171	86.48171	100.0
cpp	4000	86.48171	86.48171	100.0
cs	500	1.82864	2.69002	68.0
cs	1000	1.82864	2.92361	62.5
cs	1500	79.22135	78.47663	99.1
cs	2000	79.22135	78.47663	99.1
cs	2500	79.22135	78.44743	99.0
cs	3000	79.22135	79.22135	100.0
cs	3500	79.22135	79.22135	100.0
cs	4000	79.22135	79.22135	100.0
gli	500	0.94747	1.95096	48.6
gli	1000	11.20346	18.02892	62.1
gli	1500	36.55253	38.65043	94.6
gli	2000	57.39694	56.17803	97.9
gli	2500	57.94548	57.13414	98.6
gli	3000	57.94548	57.74801	99.7
gli	3500	57.94548	57.83278	99.8
gli	4000	57.94548	57.93999	100.0

Table 5.5: **Accuracy** of CountingGhost running on LRU. Each entry in the table shows the actual hit rate of LRU on cache size n and the predicted hit rate of LRU running at size $n/2$ with ghost list of capacity $n/2$. The average accuracy of all the 64 entries in the table is 95.8%.

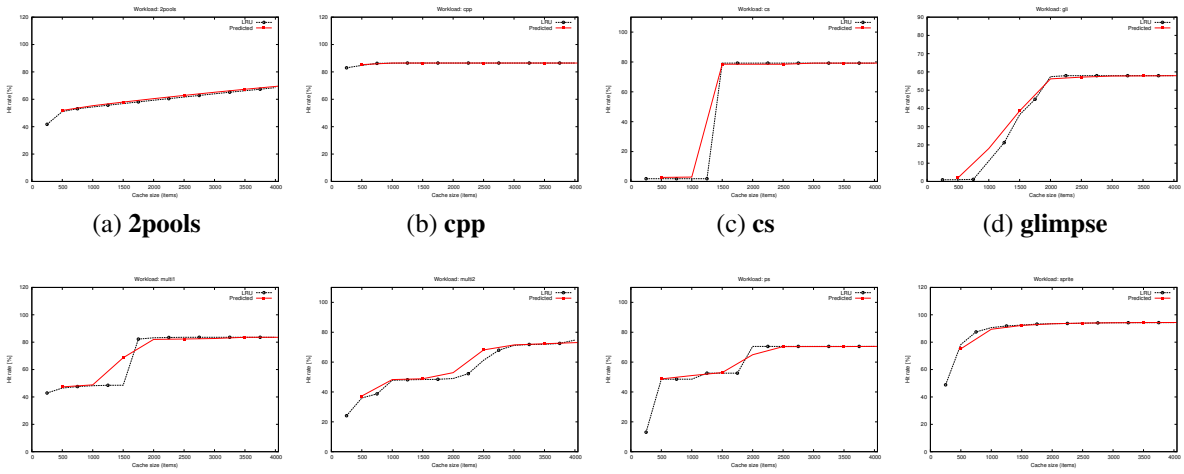
5.2.5 Different Cache Replacement Algorithms

Now we know the profiling framework works well on LRU and that the framework without a ghostlist works relatively well on CLOCK. But how does it perform on other cache replacement policies?

Workload	Cache size	Hit rate	Predicted hit rate	Accuracy [%]
multi1	500	46.50650	47.35654	98.2
multi1	1000	48.22802	48.83510	98.8
multi1	1500	48.55593	68.65450	70.7
multi1	2000	83.21352	82.02087	98.6
multi1	2500	83.56665	82.31082	98.5
multi1	3000	83.56665	82.69214	99.0
multi1	3500	83.56665	83.56596	100.0
multi1	4000	83.56665	83.56312	100.0
multi2	500	35.97735	37.29596	96.5
multi2	1000	47.80130	48.28133	99.0
multi2	1500	48.31059	48.84664	98.9
multi2	2000	48.99852	52.92984	92.6
multi2	2500	61.24815	68.13827	89.9
multi2	3000	71.17935	71.49249	99.6
multi2	3500	71.88248	72.28809	99.4
multi2	4000	74.72920	73.03455	97.7
ps	500	48.54518	48.74933	99.6
ps	1000	48.54518	50.98038	95.2
ps	1500	52.58423	52.97023	99.3
ps	2000	70.48239	64.91884	92.1
ps	2500	70.48239	70.36026	99.8
ps	3000	70.48239	70.38869	99.9
ps	3500	70.49196	70.38869	99.9
ps	4000	70.49196	70.51082	100.0
sprite	500	78.30234	75.18021	96.0
sprite	1000	90.63853	89.44534	98.7
sprite	1500	92.48410	92.22287	99.7
sprite	2000	93.47667	93.44312	100.0
sprite	2500	93.85579	93.92417	99.9
sprite	3000	94.16102	94.19080	100.0
sprite	3500	94.26028	94.32896	99.9
sprite	4000	94.32147	94.35735	100.0

Table 5.6: Table 5.5 continued. All estimates (except 5) have over 90% accuracy and the average accuracy is 95.8%.

This experiment tests the accuracy of MIMIR on the extreme **postgres** workload described in Section 5.1 running on several cache replacement algorithms. In particular we ran ARC, CLOCK, LRU, LFU, LRU3 and RANDOM within the Python simulator with the MIMIR profiling framework producing HRCs at the same time. We ran each simulation with a 1500 element cache and set $k = 2$ to produce a HRC for all cache sizes up to 3000 elements. Internally ROUNDER was set to use 64 buckets and COUNTINGGHOST was set to use 3 filters. We then ran the cache replacement



(a) **2pools** (b) **cpp** (c) **cs** (d) **glimpse**

(e) **multi1** (f) **multi2** (g) **postgres** (h) **sprite**

Figure 5.4: The **accuracy** of the Counting Filter ghost list predicting the hit rate for a cache of size n using only $n/2$ elements. This is a visual representation of the hit rate data from Table 5.5 and Table 5.6. The black dotted line is the real LRU hit rate for a cache of each size. The red filled line is the predicted hit rate from a cache of half the size. Under a perfect prediction the two lines would coincide.

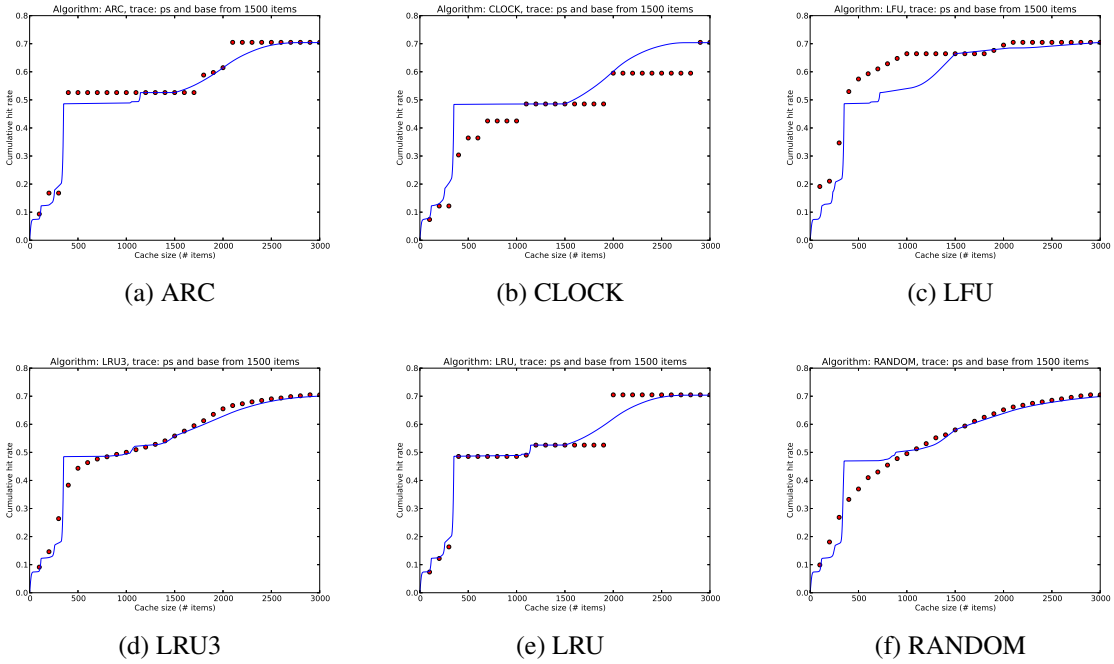
algorithm on cache sizes which are multiples of 100 elements ranging from 100 to 3000 elements.

Now results from the experiment can be seen in Figure 5.5 and MAE values for the corresponding Figure are in Table 5.7. The real hit rate in the figure is marked as red dots and the predicted HRC is a blue line. Ideally the red dots would be located on the predicted blue line.

LRU has the lowest MAE in this experiment which should be intuitive since the profiling framework was designed for LRU. If we look at the blue and red curves for LRU we see that we curves are aligned for cache sizes smaller than 1500 items but not so well

Cache replacement algorithm	Maximum discrepancy	MAE
ARC	6.7%	2.1%
CLOCK	18.0%	5.5%
LFU	13.3%	4.9%
LRU3	10.2%	1.7%
LRU	8.5%	1.5%
RANDOM	13.7%	2.4%

Table 5.7: Overview of the MAE for MIMIR running on the extreme **postgres** workload at cache size 1400 predicting the HRC from all cache sizes between 0 and 3000. The maximum discrepancy is the Kolmogorov-Smirvnov [55] distance between the HRCs which measures the largest vertical distance of the two curves.



(a) ARC (b) CLOCK (c) LFU

(d) LRU3 (e) LRU (f) RANDOM

Figure 5.5: HRC from MIMIR hooked into ARC, CLOCK, LFU, LRU3, LRU and RANDOM with a cache size of 1500 items on the **postgres** workload. The red dots show the real hit rate and the blue line is the predicted HRC.

aligned for cache sizes larger than 3000 items. This is because ROUNDER was set to use 64 buckets but COUNTINGGHOST only uses 3 filters. When the cache size increases to 2000 items, a high increase in hit rate occurs (the red dots) and 3 filters do not capture this steep increase but smooth it out. It is indeed the same effect as described in Section 5.2.4. This issue also appeared in our experiments with the SC2 algorithm [18] since it uses only 2 recency values, either the least recently used bit is set to 0 or 1. If we would increase the number of filters for COUNTINGGHOST we would be able to capture steep increases better, just like with ROUNDER and STACKER.

Regarding the other cache replacement algorithms, MIMIR does a fairly good job to predict them all with respect to MAE but the maximum discrepancy is high (except for ARC).

5.3 Overhead

5.3.1 Experimental Setup

We ran all our experiments on memcached-1.4.15 extended with the MIMIR profiling framework. We chose to use ROUNDER instead of STACKER for higher performance and because ROUNDER is simpler to parallelize. We deployed `libmemcached` 1.0.16 on 4 nodes and used the built-in workload generator. Each node requests 2 million random 16 byte unique keys and 32 byte values via 10 threads and 60 connections. The proportion of GET requests to SET requests is 9:1, and we bundle 100 GETs together in a single MULTI-GET request. Our experimental set-up follows Fan *et al.* [26].

We ran each experiment 10 times and present the average throughput of the 10 runs with error bars showing the standard deviation.

5.3.2 ROUNDER

This section evaluates the overhead of ROUNDER running in memcached.

We measured the impact on performance in memcached with and without ROUNDER, running at several bucket sizes. Figure 5.6 shows the total throughput from the clients to the central memcached server, each point measuring throughput in a 2 minute benchmark averaged over 10 runs.

The throughput of our augmented memcached is 2.2% lower than that of the original memcached implementation with $B = 4$ buckets, running on a 8GB cache size. The highest overhead is 14.6% with a 4GB cache and 4 buckets for ROUNDER.

We observe a paradoxical drop in throughput for all three services as cache size increases. This stems from memory management inefficiencies and coarse-grained lock contention within memcached [54, 26] as the hit rate rises from $\sim 40\%$ at 1GB to effectively 100% at 4GB and up.

A larger number of buckets, $B = 128$, to produce more granular statistics does not significantly impair throughput in the experiment. When using 4 buckets and a $8GB$ or $16GB$ cache ROUNDER is extremely lightweight, only taking a $< 3\%$ throughput tax.

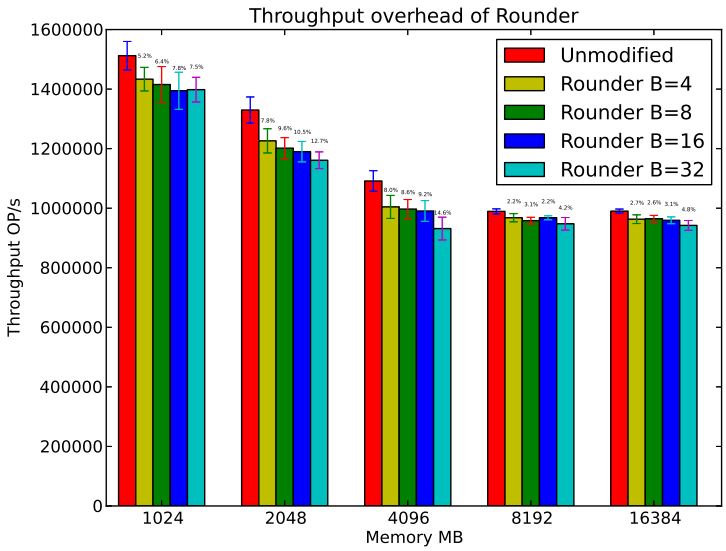


Figure 5.6: **Overhead** of ROUNDER with different bucket sizes.

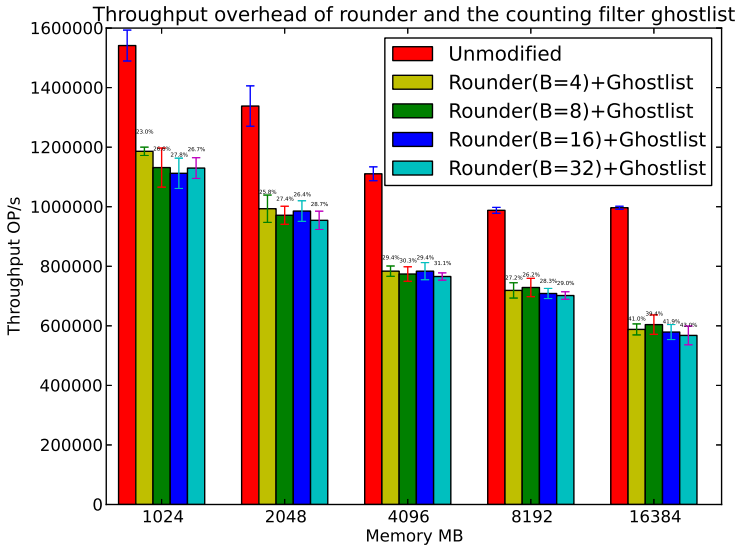


Figure 5.7: **Overhead** of the full MIMIR profiling framework within memcached

5.3.3 MIMIR Profiling Framework

This section evaluates the overhead of the full MIMIR profiling framework running in memcached.

We measured the impact on performance in memcached with and without MIMIR running at several bucket sizes for ROUNDER while keeping COUNTINGGHOST fixed with 3 filters. Figure 5.7 shows the total throughput from the clients to the central memcached server, each point measuring throughput in a 2 minute benchmark averaged

over 10 runs. The throughput of our augmented memcached is 23% lower than the original memcached implementation with $B = 4$ buckets, running on a 1GB cache size. The highest overhead is 43.0% with a 16GB cache and 32 buckets for ROUNDER.

Providing a HRC for all cache sizes up to double the cache size requires in the worst case a 41% throughput degradation within memcached. We have plans to optimize this significantly as described in Section 4.4. Running at $1GB$ it requires an overhead of 23%.

5.4 Summary

We evaluated the accuracy and overhead of our three algorithms, ROUNDER, STACKER and COUNTINGGHOST, to understand how well ROUNDER, STACKER and COUNTINGGHOST would perform in a real world setting and thus how MIMIR would perform in this setting.

The bucket parameter trades off accuracy in ROUNDER and STACKER for performance. More buckets result in higher accuracy but worse performance.

ROUNDER is precise in estimating the real HRC of LRU, achieving over 94% accuracy on all workloads in low-profile mode, but achieving over 92% accuracy on all workloads in low-profile mode when running on CLOCK.

STACKER is more accurate than ROUNDER. STACKER achieves over 94% accuracy on all workloads in low-profile mode when running on LRU, but achieves over 92% accuracy on all workloads in low-profile mode when running on CLOCK. Like with ROUNDER, our experiments shows that STACKER is very accurate in estimating the real HRC of LRU achieving over 99% accuracy on all our workloads with 128 buckets when running on LRU. However STACKER has a higher time complexity and in practice ROUNDER is a more suitable algorithm, still guaranteeing over 95% accuracy when running with 128 buckets. To minimize overhead one would choose ROUNDER with 8 buckets or less, which results in at least 94% accuracy in the worst case.

Assuming the cache server contains its own meta-data collection on evicted keys with a ghost list, e.g., an extended LRU stack without values when running LRU, either ROUNDER or STACKER suffices to produce hit rate curves for smaller and larger cache sizes. However if no meta-data is collected in the cache server and values are small compared to keys, using a regular ghost list is memory inefficient and COUNTINGGHOST was designed to tackle this problem. Our micro-benchmark for COUNTINGGHOST show

that we predict the hit rate for twice the current allocation with over 90% accuracy on most workloads (59 out of 64 different workload and cache size combinations).

Since memcached uses the LRU policy it was a good ground to evaluate the MIMIR profiling framework. We connected the framework to memcached and evaluated the performance before and after. Our test bed was made up of a single server and multiple clients using several connections. The result is that the framework takes only a small toll, 3-8%, on the server when generating hit rate curves with ROUNDER for smaller cache sizes but a little higher, 23-41%, when evaluating hit rate curves for smaller and larger cache sizes with ROUNDER and COUNTINGGHOST.

The framework was designed for LRU but we tried it on other cache replacement policies, and as could be expected this resulted in lower accuracy. To achieve higher accuracy on other cache replacement policies like ARC, RANDOM, LRU3, LFU, CLOCK, ARC our method would have be customized specifically for every algorithm.

Chapter 6

Conclusions

In this thesis we asked two questions particularly relevant to many cache operators managing large distributed caches:

> *"how much total memory should be allocated to the cache tier?"*

and

> *"what is the minimum cache size for a given hit rate?"*.

In order not to overload databases and to maximize performance, operators often err on the side of caution by scaling up rather than scaling out. Scaling up means adding servers or increasing memory on existing servers while scaling out means removing servers or decreasing memory on existing servers. To figure out cache performance under a different allocation, operators can conduct offline simulations on the current setup and add resources progressively until performance goals are reached. However, this is not acceptable due to a number of reasons. First, it may not give up to date results. Second, it disrespects dynamicity of workloads. Third, it is manually labor intensive. And fourth, offline simulations require request logs of cache requests which use a lot of disk space when the request rate in the cache tier is high.

To enable cache operators to dynamically profile cache resources in distributed caches, we propose a new cache profiling framework called MIMIR that generates efficacy graphs from each cache server in the cache tier. This happens in real-time so there is no offline simulation of the cache tier necessary to understand how it would perform under a different setting. The efficacy graphs are called hit rate curves that describe the hit rate of allocated cache servers as a function of cache size. Our framework currently supports both the LRU and CLOCK cache replacement policies.

To generate the hit rate curves we track stack distance estimates for each cached element. Generating hit rate curves for the LRU cache replacement policy from stack distances is a widely studied problem but previous methods have significant overhead and lend themselves poorly to concurrency. Most prominent are Mattson's algorithm that requires linear traversal of elements in the cache on every access and commands 283% throughput overhead on a regular cache implementation. Using balanced trees such as AVL trees improves the throughput but still commands a 74% percent overhead in our micro-benchmarks.

To find an efficient method for dynamic profiling we trade off some accuracy in order to minimize the overhead, on the cache server and produce the hit rate curves in highly concurrent systems. The overhead is 6.3% in the same setup as Mattson's algorithm and the AVL tree.

To estimate stack distances we introduced three algorithms: ROUNDER, STACKER and COUNTINGGHOST. ROUNDER and STACKER estimate stack distances for all elements in the cache with over 95% accuracy on all workloads we used in our evaluation. In the case where you want to estimate efficiency for cache sizes larger than the current allocation. Implies that meta-data for evicted keys must be tracked. A list of data-less keys is called a ghost list. If the cache server contains its own meta-data collection on evicted keys with a ghost list, e.g., an extended LRU stack without values when running LRU, either ROUNDER or STACKER suffices to produce hit rate curves for smaller and larger cache sizes.

Maintaining a ghost list requires storing some amount of evicted keys in memory and can be viewed as a tax on the currently cached elements. Some workloads, however, like seen at Facebook have smaller values than keys and in this setting the memory tax overhead is too high for a ghost list to be an option. To address this problem we proposed the third algorithm, COUNTINGGHOST, to compress the data structure for the keys and provide a memory efficient ghost list to support a workload with small values. In our evaluations on COUNTINGGHOST for predicting the hit rate if the cache size would be doubled show that the algorithm predicts the hit rate with 95% accuracy on average.

The accuracy is thus high for our methods. On the other hand, in order to evaluate the overhead of our methods we integrated them into the popular memcached cache server. When running our parallel implementation of ROUNDER within memcached we propose a maximum of 8.0% overhead when running it in low-profile mode. Running the COUNTINGGHOST algorithm within memcached proposes higher overhead, at most 41.0% in our evaluations.

There are many avenues for future work. First we aim to either optimize the COUNTING-GHOST algorithm or move it to a background thread, whichever makes the overhead more acceptable. Also, memcached is only one of many caching services and the methods described in MIMIR can be extended to profile other services. LRU and its variants, such as CLOCK, are among the most studied and widely deployed cache replacement algorithms. Profiling performance of other policies is an understudied area and the topic of future work. Cache profiling also opens a new window to look at cost-benefit analysis of cloud services and could be extended to provide performance analysis of CPUs, hard drives and other tunable components in today's highly dynamic cloud environments. Cost benefit analysis of resources could expand the usability and minimize pricing in multi-tenant [18, 51] services like Heroku [6], Amazon ElastiCache [2] or Google's App Engine [5]. Virtualization management is already being made easier by CloudPhysics [3] and integration with such a framework is a viable option.

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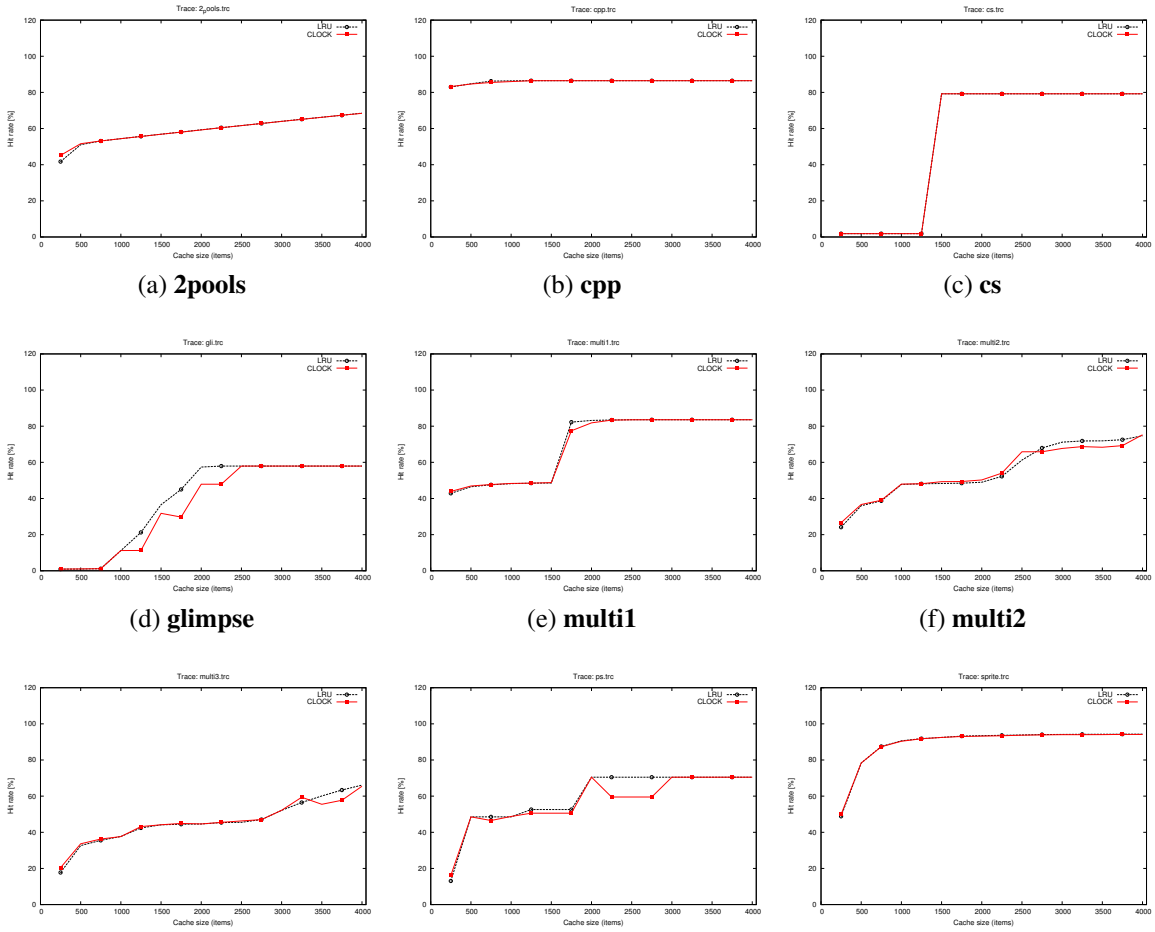
Appendix A

Appendix

This chapter contains performance and throughput graphs for several experiments to save space from the main chapters of the thesis.

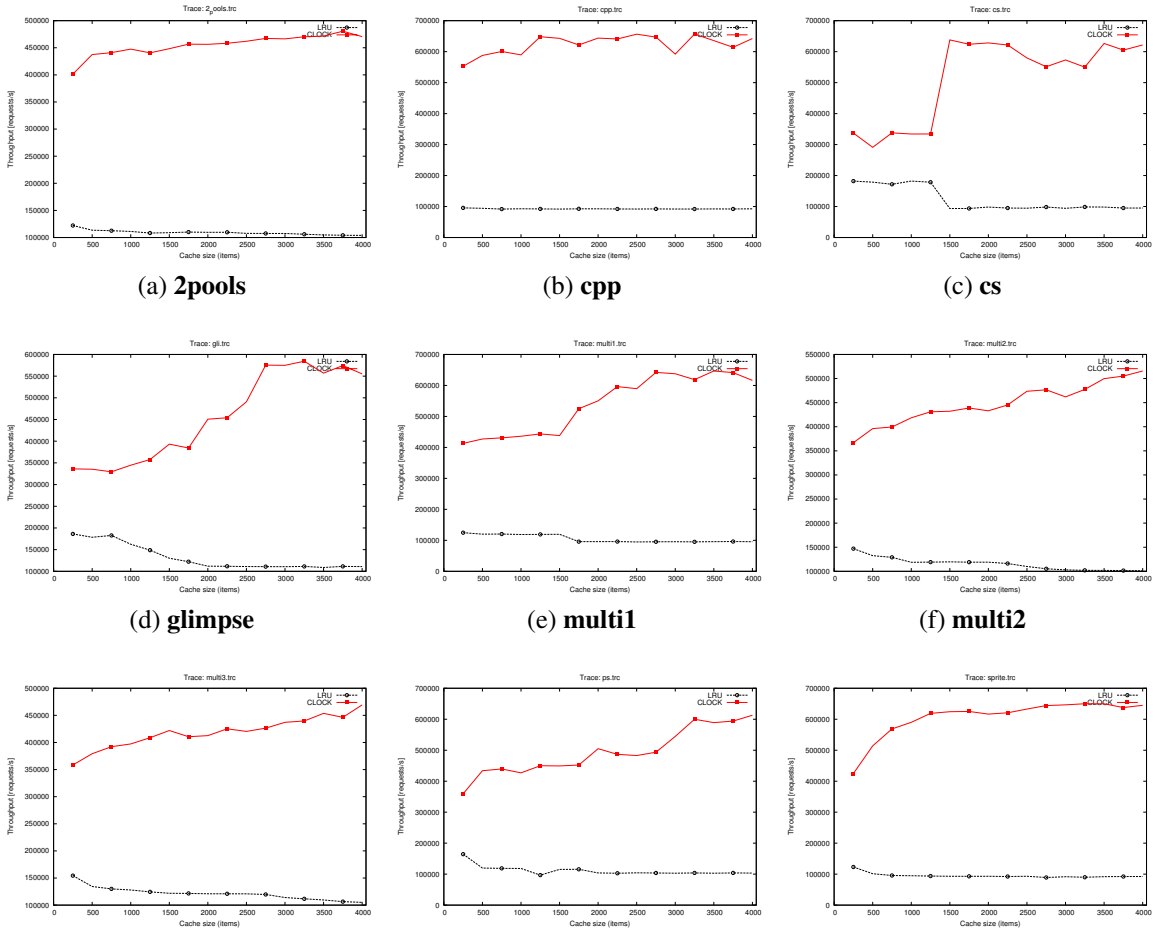


(a) **2pools** (b) **cpp** (c) **cs**

(d) **glimpse** (e) **multi1** (f) **multi2**

(g) **multi3** (h) **postgres** (i) **sprite**

Figure A.1: The hit rate of LRU vs CLOCK in the Python simulator. Note that the hit rate of CLOCK decreases as the cache size increases from 2000 elements to 2200 elements. This phenomeon is called Belady's anomaly [14]

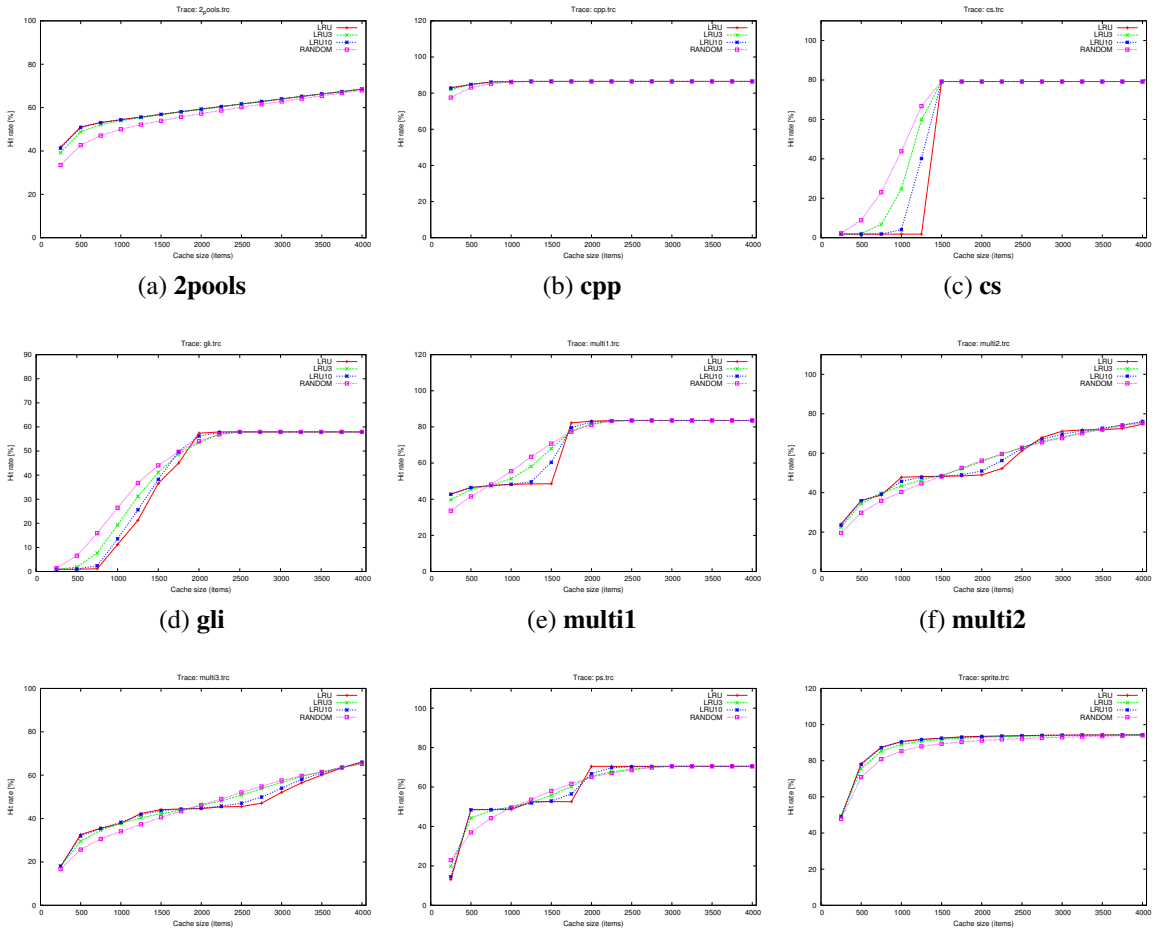


(a) **2pools** (b) **cpp** (c) **cs**

(d) **glimpse** (e) **multi1** (f) **multi2**

(g) **multi3** (h) **postgres** (i) **sprite**

Figure A.2: The throughput of LRU vs CLOCK in the Python simulator.

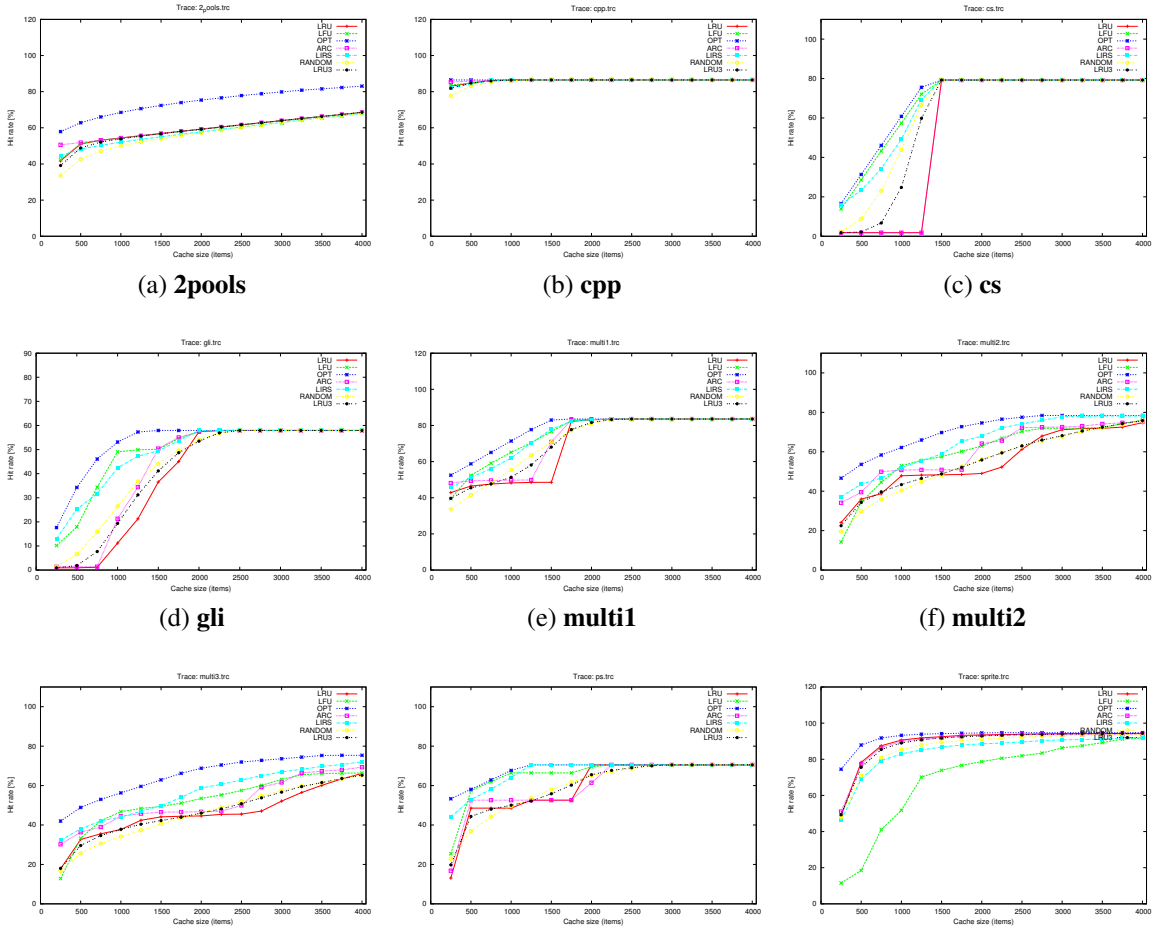


(a) **2pools** (b) **cpp** (c) **cs**

(d) **gli** (e) **multi1** (f) **multi2**

(g) **multi3** (h) **ps** (i) **sprite**

Figure A.3: **Hit rate** comparison on the default **Redis** cache replacement policy, *volatile-lru*. This policy mixes LRU with (Time To Live) TTL expiry, but in this simulation we ignore the TTL. We simulated with 3 and 10 random samples here denoted LRU3 and LRU10, respectively. The hit rate is compared to that of RANDOM and LRU.

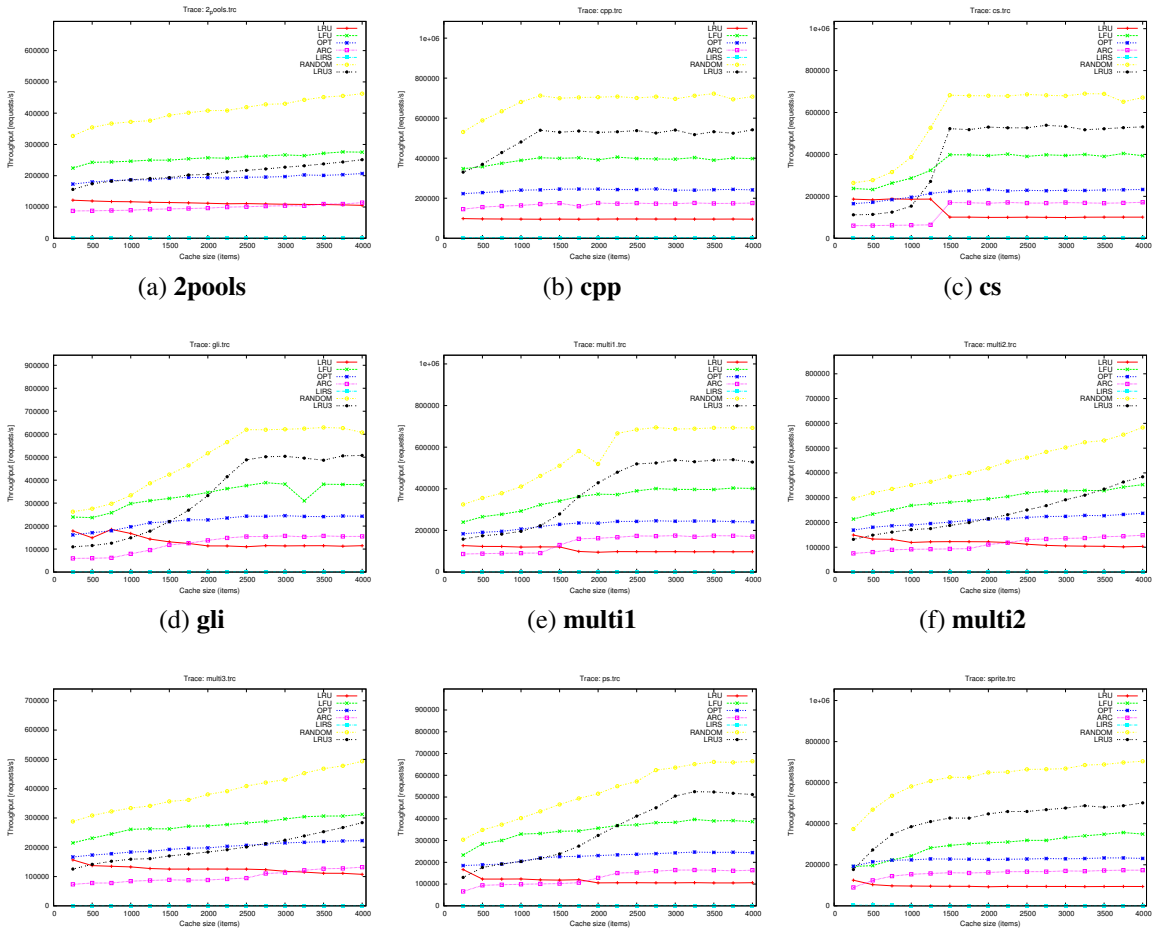


(a) **2pools** (b) **cpp** (c) **cs**

(d) **gli** (e) **multi1** (f) **multi2**

(g) **multi3** (h) **ps** (i) **sprite**

Figure A.4: Comparison of the **hit rate** of LRU, LFU, OPT, ARC, LIRS, RANDOM and LRU3 for the extreme workloads in the Python simulator.

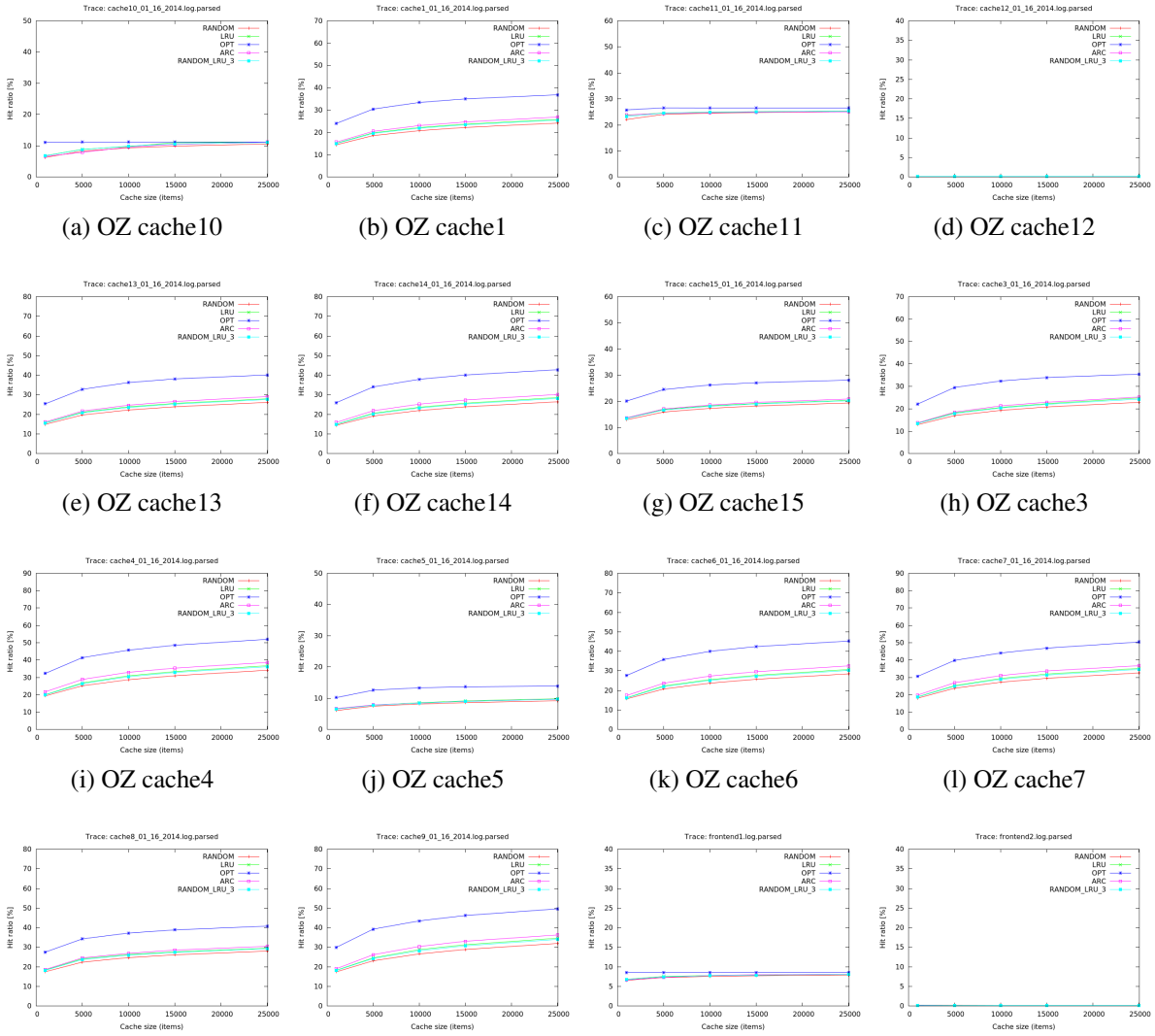


(a) **2pools** (b) **cpp** (c) **cs**

(d) **gli** (e) **multi1** (f) **multi2**

(g) **multi3** (h) **ps** (i) **sprite**

Figure A.5: Comparison of the **throughput** of LRU, LFU, OPT, ARC, LIRS, RANDOM and LRU3 for the extreme workloads in the Python simulator.



(a) OZ cache10 (b) OZ cache1 (c) OZ cache11 (d) OZ cache12

(e) OZ cache13 (f) OZ cache14 (g) OZ cache15 (h) OZ cache3

(i) OZ cache4 (j) OZ cache5 (k) OZ cache6 (l) OZ cache7

(m) OZ cache8 (n) OZ cache9 (o) OZ frontend1 (p) OZ frontend2

Figure A.6: The **hit rate** of RANDOM, LRU, OPT, ARC and LRU3 for workloads from a varnish LRU cache for video chunks at the Icelandic startup company **OZ**.

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