EarnCache: Self-adaptive Incremental Big Data Caching on Non-Big Clusters

Junshi Guo
Fudan University

Yifeng Luo
Fudan University

Eric Lo
The Chinese University of Hong Kong

Shuigeng Zhou
Fudan University

Abstract

Memory caching plays a crucial role in satisfying people's requirements on (quasi-)real-time processing of exploding data on big-data clusters. As big data clusters are usually concurrently shared by multiple computing frameworks, applications or end users, there exists intense competition for memory cache resources, especially on small clusters which are supposed to process comparably big datasets as large clusters do, yet with tightly limited resources. Applying existing on-demand caching strategies on small shared clusters inevitably results in frequent cache thrashings when the conflicts of simultaneous cache resource demands are not mediated, leading to deterioration in overall cluster efficiency.

In this paper, we propose a novel self-adaptive incremental big data caching mechanism, called EarnCache, to improve the cache efficiency for shared big data clusters, especially for small clusters where cache thrashings are more likely to occur. EarnCache self-adaptively adjusts resource allocation strategies according to the condition of cache resource competition: evolving to incremental caching to depress competition when resources are in deficit, devolving to traditional on-demand-caching to expedite data caching-in when resources are in surplus. Our experimental evaluation shows that EarnCache's elasticity could enhance the cache efficiency for shared big data clusters with improved resource utilization.

1 Introduction

Memory caching plays a crucial role in bridging the performance gap between storage subsystems and computing frameworks, and gradually becomes the determinant of whether processing units of big data platforms could work at wire speed to satisfy vast data processing requirements. As more and more time-critical applications commence employing memory to cache datasets, big data clusters are usually concurrently shared by multiple computing frameworks, applications or end users, and there exists intense competition for memory cache resources, especially on small clusters which are supposed to process comparably big datasets as large clusters do, yet with tightly limited resources. Consequently implementing effective and adaptive management on memory cache resources becomes increasingly important for the efficiency of big data clusters, especially for small/medium enterprises who could only afford to build non-big clusters. Applying existing on-demand caching strategies on small shared clusters inevitably results in frequent cache thrashings when the conflicts of simultaneous cache resource demands are not mediated, leading to deterioration in overall cluster efficiency. The principal reason is that aggressively caching massive number of data blocks of big datasets on demand causes constant block replacement in cache, and conversely exacerbates resource competition.

In Web or traditional OLTP database applications, ranges or blocks of the same dataset usually shows vast difference in "hotness" regarding access recency and frequency. Though in big data applications, input files are usually scanned as a whole for data processing and all blocks reveal almost equal "hotness". On the other hand, traditional system-level or database-level data caching is executed on small data units (i.e. 8KB-sized pages), while big data caching is executed on much larger units(i.e. 256MB-sized blocks). So the cost of caching in/out a data unit in big data scenarios far exceeds that of traditional data caching. Accordingly, traditional caching may have millions of caching slots, which makes hotter data less likely to be cached out by colder data; while big data caching may only have thousands of slots, which makes comparatively hotter data vulnerable to be cached out by colder data.

Targeting the caching problem on non-big clusters, we propose an adaptive cache mechanism, which is named as EarnCache (from s**E**lf-**a**daptive inc**r**eme**n**tal **Cache**),

to coordinate concurrent cache resource demands to prevent exacerbation in cache efficiency when intense competitions for memory cache resources occur. As big data applications usually access their input data in Write-Once-Read-Many (WORM) fashion, we only consider read caching in this paper. Major contributions of this paper include: 1) proposing an incremental caching mechanism which could self-adaptively adjusts cache allocation strategies according to the competition condition of cache resources; 2) formulating and solving the cache resource allocation and replacement problem as an optimization problem; 3) implementing a prototype of the proposed method, and performing extensive experiments to evaluate the effectiveness of the proposed mechanism.

In the rest of this paper, we first illustrate the system design and implementation details of EarnCache in Sec. 2. We provide empirical results in Sec. 3, and present related work in Sec. 4. We finally conclude the paper in Sec. 5.

2 System Framework

We illustrate how EarnCache works in this section. Firstly we present the overview about the caching mechanism of EarnCache, and then discuss its architecture design, and finally explain the incremental cache-earning policy and its implementation.

2.1 Overview

On shared non-big clusters with relatively limited cache capacity, cache resource conflicts would be normal. When only few users are using a non-big cluster and the competition for cache resources is mild, applying on-demand caching could expedite hotter blocks taking over cache resources from colder blocks, and hotter data is less likely to be cached out by colder data. When more concurrent users consume the cluster and competition for cache resources gets wild, on-demand caching leaves concurrent cache resource demands unmediated, making hotter data more vulnerable to being cached out. Files which are frequently accessed recently sometimes could be totally cached out by files which would rarely be accessed for the second time in near future, then these hot cached-out files require to be cached in soon as their next access should occur in the upcoming future. We consequently need to revisit existing on-demand caching mechanisms and strategies, and propose more effective measures to improve the efficiency of data caching on non-big clusters.

We believe that a good caching strategy for non-big clusters should be self-adaptive to resource competition conditions, depressing competitions and preventing thrashings when resources are in desperate deficit. Obviously caching big data files on demand as a whole could not provide such self-adaptivity. Not compulsorily caching files entirely provides the elasticity of tuning the amount of cache resources allocated for different files based on their access recency and frequency.

Ideally, more recently frequently accessed files should be assigned with more cache resources, and less recently frequently accessed ones should be assigned with less cache resources. However, it's not possible to know in advance what files would be frequently accessed in the upcoming future, and we could only make predictions based on historical file access patterns, especially the most recent information. Based on files' historical access information, EarnCache implements an incremental caching strategy, where a user should earn resources to cache files from other concurrent users via accessing these files. Cache resources are incrementally allocated to files that become more frequently accessed, which gradually takes over cache resources, until all blocks of the file have been cached in. The more a file is accessed, the more cache resources it takes over. The incremental caching strategy ensures that files occupying cache resources are recently frequently accessed and will not be flushed out by files that are only accessed occasionally or randomly.

2.2 Architecture

Files originally reside in under distributed file system (e.g. Hadoop File System), and EarnCache coordinately caches them across the whole cluster. EarnCache consists of a central *master* and a set of *workers* residing on storage nodes as shown in Figure. 1. The *master* is responsible for: 1) determining how many cache resources should be allocated to a file based on recent file access information; 2) informing workers of the cache resource allocation plans via heartbeats; 3) keeping track of metadata of which storage node a cached block resides on; 4) answering clients' queries on cache metadata. And a *worker* is responsible for: 1) receiving the resource allocation plan from master; 2) calculating how many resources a file should contribute to compose the allocated resources; 3) caching in/out blocks according to the calculated resource composition plans; 4) informing the master of cached blocks via heartbeats; 5) serving clients with cached blocks.

As illustrated in Figure.1, a client accesses a block in the following procedures: 1) the client queries the master where the block is located; 2) the master tells the client which worker the requesting data resides on; 3) the client contacts the worker to access the block; 4) the worker serves the client with the block data from cache. One thing worth noting here is that: the client will not

contact any worker to access a block if the block is not in cache of any worker nodes, as the master only keeps track of cached blocks. In this situation, the client has to fetch data from the under file system.

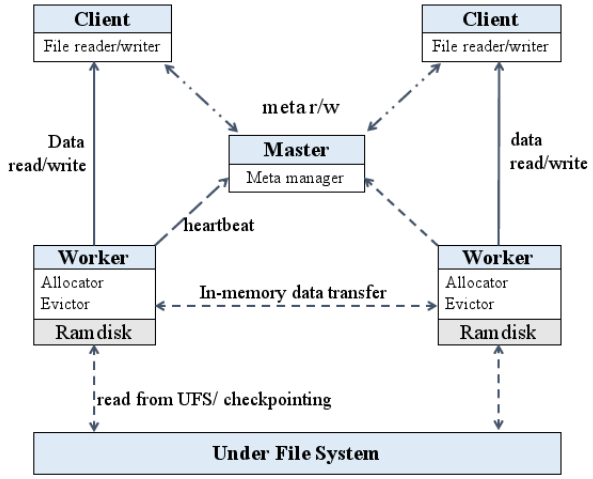


Figure 1: EarnCache's Architecture.

2.3 Incremental Caching

As we prefer recently frequently accessed files incrementally taking over resources from less recently frequently accessed files, "recently" should be defined quantitatively before we could design the incremental caching strategy, and other related elements should also be clarified. Table. 1 presents all definitions of notations involved in our incremental caching strategy.

Table 1: Notation definitions

Notation	Definition
W	predefined window size of the most recently accessed data for observing files falling within
a, b	scan time per unit data from memory(a) and hdd(b)
N	total number of files falling in the observation window
d_i	data size of the ith file
D	total data size of N files
M	cache capacity of the whole cluster
f_i	access frequency of the ith file
F	total access frequency of N files
x_i	percentage of data cached for the ith file
$h_i(x_i)$	the ith file's profit gain with x_i data cached

We define a function $h_i(x_i)$ to denote the profit gain of the ith file to instruct how cached files should contribute resources. Then we attempt to instantiate $h_i(x_i)$ and to maximize total profit gain of all files falling in the observation window, just as Equ.1 shows.

$$\sum_{i=1}^{N} f_i \cdot h_i(x_i) \tag{1}$$

According to definitions in Tab.1, we can assume that the time it takes to scan the ith file is:

$$time(x_i) = [a \cdot x_i + b \cdot (1 - x_i)] \cdot d_i \tag{2}$$

As mentioned above, we use h_i to indicate the ith file's profit gain with x_i data cached. If we take saved scan time as a file's profit gain, then we can define h_i's deviation at x_i as its gain change over δx_i, which could be further defined as the percentage of increased saving of the file's scan time with increased cache share at x_i over the total saved scan time at x_i, compared to zero cache share, just formulized as:

$$\frac{\delta h_i}{\delta x_i} = \frac{time(x_i) - time(x_i + \delta x_i)}{time(0) - time(x_i)} = \frac{\delta x_i}{x_i} \tag{3}$$

Thus we can derive that $h_i(x_i) = \ln x_i$, and now our optimization goal becomes

$$\sum_{i=1}^{N} f_i \cdot \ln x_i \tag{4}$$

subjected to

$$\sum_{i=1}^{N} x_i \cdot d_i \leq M \tag{5}$$

Note that at any given time, x_i is the only variant contained in the optimization goal, and $f_i \cdot \ln x_i$ is a convex function. After applying Lagrange multiplier method, our maximizing goal turns to:

$$L = \sum_{i=1}^{N} f_i \cdot \ln x_i - \lambda (\sum_{i=1}^{N} x_i \cdot d_i - M) \tag{6}$$

Let $\frac{\delta L}{\delta x_i}$ be 0, then we get

$$x_i \cdot d_i = \frac{f_i}{F} \cdot M \tag{7}$$

The above result shows that the amount of memory resources allocated to a file is linear to f_i at a given moment, as all files' access frequency is determined at that moment, which exactly responds to our original intention of incremental caching. One more thing worth noting is that: if the overall size of files filling in the whole observation window is smaller than the cache capacity, i.e. there are cache resources being occupied by files that are not in the observation window, EarnCache will collect resources from those obsolete files by LRU when there is a

caching request, and the requesting file could cache in its blocks once and for all, rather than gradually taking over resources from files falling within the observation window. EarnCache thereby could adaptively devolve to traditional on-demand-caching so as to expedite the process of collecting cache resources for actively accessed files when contention for cache resources is light, and evolve to incremental caching to depress competition when resources are in deficit.

2.4 Implementation Details

We implemented EarnCache by implanting our incremental caching mechanism into the modified Tachyon[4]. In EarnCache, we first evenly re-distribute a file's cached data blocks across the whole cluster, so that almost the same amount of blocks are hosted in cache on each cluster node, and all workers can manage their cache resources independently yet still in concert. As uneven data distribution will drag down completion of the whole job, evenly distributing cached data blocks guarantee that tasks running on each node could ideally finish almost simultaneously.

When the ith file needs caching, EarnCache pre-allocates f_i/F fraction of cache resources on each node to the file based on Equ.7. If resources pre-allocated to the file is more than its aggregated demands, EarnCache has other files in need of cache resources fairly share the spare cache. Each worker checks its available cache resources, and allocates as many as possible to them directly, which could make full use of cache resources. When there are not enough resources available, the worker calls *BlocksToEvict()*, which implements the eviction algorithm with incremental caching, to determine which blocks should be cached out. When evicting process is done, the worker will inform the master to update the metadata.

Alg. 1 describes the process of evicting blocks. EarnCache first checks whether the file requesting cache resources has used up its pre-allocated share in Line 1∼3. In the while loop, Line 7∼14 mainly selects files who has overcommitted the most cache resource. If no such file exists, EarnCache will reject the cache request (Line 15∼17). Otherwise, blocks of these selected files are added to the candidate block set until enough cache resources have been collected(Line 18∼24). As recency and frequency of all blocks within a file are identical, workers do not differentiate between blocks of the same file when selecting blocks to cache out. Note that by snatching cache resources from most over-consumed files, EarnCache ensures that increased cache occupation of file r causes least degradation of other files' cache occupation amount.

Algorithm 1 Eviction Algorithm: BlocksToEvict()

Input: s, requested cache resources; r, the requesting file id; A=$\{a_1, a_2...a_N\}$, a list of files' pre-allocated memory bytes; C=$\{c_1, c_2...c_N\}$, a list of current consumed memory bytes in local node; M, memory capacity of local node

Output: a list of candidate blocks to evict

1: **if** $c_r \geq a_r$ **then**
2: algorithm ends as file r has already consumed all its allocated memory
3: **end if**
4: $candidate \leftarrow \{\}$ ▷ *candidate cached out blocks*
5: $mem \leftarrow 0$ ▷ *free resources obtained from evicting candidates*
6: **while** $mem < s$ **do**
7: $j \leftarrow -1$
8: $over_j \leftarrow 0$
9: **for** a_i in A and $i \neq r$ **do**
10: **if** $c_i - a_i > over_j$ **then**
11: $j \leftarrow i$
12: $over_j \leftarrow c_i - a_i$
13: **end if**
14: **end for**
15: **if** $j = -1$ **then**
16: return as request failure
17: **end if**
18: find b_j as a block of file j and not in $candidate$
19: $candidate \leftarrow candidate + b_j$
20: $mem \leftarrow mem + sizeof(b_j)$
21: $c_j \leftarrow c_j - sizeof(b_j)$
22: **if** $mem \geq s$ **then**
23: return $candidate$
24: **end if**
25: **end while**

3 Experimental Evaluations

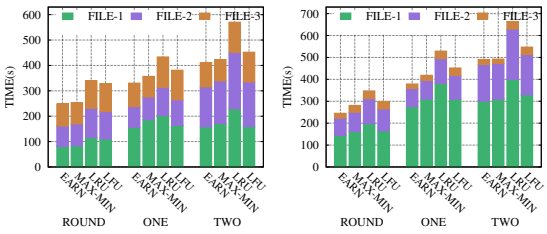
We deploy an HDFS cluster to evaluate EarnCache's performance, on which Spark and EarnCache are deployed as the upper-level application tier and the middle-level caching tier respectively. The cluster consists of five Amazon EC2 m4.2xlarge nodes, one of which serves as master and the other four serve as slaves. Each cluster node has 32GB of memory, 12GB reserved as working memory and the remaining 20GB of memory employed as cache resources, summing up to 80GB of cache in total.

We mainly evaluate EarnCache's performance by issuing jobs from Spark to scan files parallelly without any further processing, and compare the performance of EarnCache, the incremental caching, with on-demand style LRU and LFU, and MAX-MIN fair caching. We set the observation window size of EarnCache to 1000GB by

default. For each experiment, we issue file scanning jobs against three files, denoted as FILE-1, FILE-2 and FILE-3, with the following three various frequency patterns, denoted as ROUND, ONE and TWO respectively.

- ROUND Three files are accessed in pattern: FILE-1, FILE-2,FILE-3 ..., where three files are accessed with equal frequency.
- ONE Three files are accessed in pattern: FILE-1, FILE-2, FILE-1, FILE-3 ..., where one file is accessed more frequently than other two files.
- TWO Three files are accessed in pattern: FILE-1, FILE-2, FILE-1, FILE-2, FILE-3 ..., where two files are accessed more frequently than the other file.

We set the size of FILE-1, FILE-2 and FILE-3 equally to 40GB and unequally to 70GB, 40GB and 10GB respectively, and then evaluate EarnCache with different caching strategies and frequency patterns. Fig. 2(a) and Fig. 2(b) shows the averaged overall running time of jobs. Each column involves scanning equal- or unequal-sized files within one period of the ROUND, ONE or TWO frequency pattern, each including processing of 3, 4, and 5 files. We can see that EarnCache produces the best file scanning performance, which exceeds that of the LRU and LFU on-demand caching by a large margin, and leads the MAX-MIN fair caching by a smaller margin. The reason of EarnCache achieving the best performance is straight-forward, as most blocks are accessed from memory. Meanwhile we also observe that the performance of EarnCache is not as mighty as we have expected, especially compared with LRU and LFU on-demand caching. The reasons are twofold: 1) EarnCache could not hold all blocks in cache, and file scanning jobs are speeded up partially as a result; 2) cache-locality is not guaranteed, and a prohibitive number of blocks are accessed from remote cache, rather than local cache.



(a) Files with equal size (b) Files with unequal size

Figure 2: Running time of file scanning jobs.

We analyze the distribution of blocks accessed from local cache, remote cache, and the under file system respectively in detail, and the results are shown in Fig. 3. We can see that EarnCache has the largest number of blocks accessed from cache, whether locally or remotely, which means that it yields the highest memory efficiency than other caching strategies, and this self-evidently explains why EarnCache yields the best file scanning performance. However, we observe that EarnCache has the largest number of blocks accessed from remote cache among the four evaluated strategies. This means EarnCache has the largest potential of performance improvement. If cache-aware task scheduling can be integrated into the upper-level task scheduler, more blocks will be accessed from local cache and EarnCache could obtain much better overall performance then.

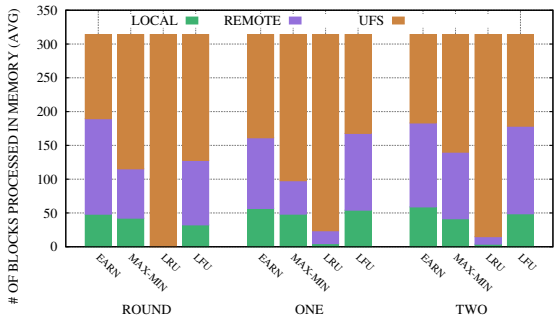
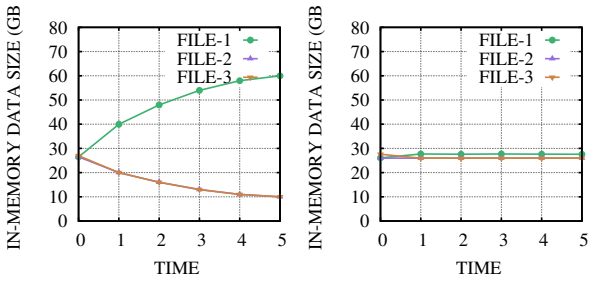


Figure 3: Distribution of blocks accessed in local cache, remote cache and under file system.

Another observation is that the performance of EarnCache is only slightly better than the MAX-MIN caching strategy, and sometimes they achieve similar performance. This is because file receives moderately divergent amounts of cache resources with these two caching strategies, as far as our experimental settings are concerned. However, the MAX-MIN caching is unable to dynamically re-allocate resources properly when there exist files not receiving any further accesses. To illustrate this, we present the process of resource re-allocation of EarnCache and the MAX-MIN caching in Fig. 4(a) and Fig. 4(b), where two out of three equal-sized files stop receiving further accesses. We can see that the file remaining accessed gradually takes over cache resources from those obsolete files with time going, while with MAX-MIN fair caching, files still holds almost equal amount cache resources. Correspondingly, the running time of each job gradually decreases with EarnCache, yet remains stable with MAX-MIN strategy.

Finally, we experimentally analyze the impact of the predefined observation window size on performance, and the results are presented in Fig. 5. When observation window is too small, the overall cache efficiency and performance degrades greatly cause competition for cache resources is not well coordinated. When the observation window size exceeds 200GB, larger enough compared



(a) EarnCache (b) MAX-MIN

Figure 4: Dynamic resource re-allocation with two files receiving no further accesses.

to file sizes, EarnCache effectively coordinates cache resources and the performance improves correspondingly.

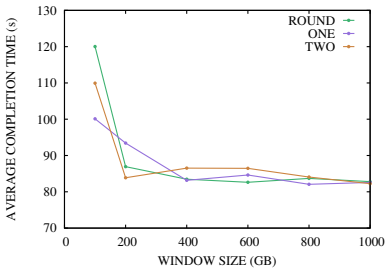


Figure 5: Impact of the observation window size.

4 Related Work

There has been extensive work on memory storage and caching, as more and more time-critical applications [16, 19] require to store or cache data in memory to gain improved data access performance, such as J. Ousterhout, et al proposed RAMCloud [2] to keep data entirely stored in memory for large-scale Web applications, and Spark [18, 9] enables in-memory MapReduce [3]-style parallel computing by leveraging memory to store and cache distributed (intermediate) datasets.

Some previous work focuses on implementing an additional layer on existing distributed file system, which enables applications to cache distributed datasets from the underlying distributed file system. J. Zhang, et al. [1] and Y. Luo, et al. [11] respectively proposed the HDCache and RCSS distributed cache system based on HDFS [6, 17], which manages cached data just as HDFS manages disk data. H. Li, et al. [4] further implemented a distributed memory file system for data caching by checkpointing data to the underlying file system. EARNCache imbeds the incremental caching into Tachyon [4] to coordinate resource competitions and avoid cache thrashings, and improves cache efficiency and resource fairness to a certain degree.

Some work focuses on optimizing data caching for specific frameworks or goals. S. Zhang, et al. [10] proposed to cache MapReduce intermediate data to speed up MapReduce applications. G. Ananthanarayanan, et al.[7] found the important All-or-Nothing property, which implies all or none input data blocks of tasks within the same wave should be cached, and then proposed PACMan to coordinate memory caching for parallel jobs. Y. Li, et al.[5], S. Tang, et al. [14] and A. Ghodsi, et al. [15] respectively proposed dynamic resource partition strategies to improve fairness, and maximize the overall performance in the meanwhile. Q. Pu, et al. [8] extended the MAX-MIN fairness [12, 13] with probabilistic blocking, and proposed FairRide to avoid cheating and improve fairness for shared cache resources.

5 Conclusion

In this paper, we have proposed the EarnCache incremental big data caching mechanism, which adaptively adjusts resource allocation strategies according to resource competition conditions: evolving to incremental caching to depress competition when resources are in deficit, devolving to traditional on-demand-caching to expedite data caching-in when resources are in surplus. On-demand big data cache usually leads to cache thrashings. With EarnCache, files are not cached on demand. Instead, applications or end users incrementally take over cache resources from others by accessing their datasets. EarnCache manages to achieve improved resource utilization and performance with such an incremental caching strategy. Experimental results show that EarnCache can elastically manage cache resources and yields the best performance against LRU, LFU and MAX-MIN cache replacement policies.

References

[1] J. Zhang, G. Wu, X. Hu, et al. A Distributed Cache for Hadoop Distributed File System in Real-Time Cloud Services. In Proceedings of GRID, 2012, pages 12-21.

[2] J. Ousterhout, P. Agrawal, D. Erickson, et al. The Case for RAMCloud. Communications of the ACM. Vol.54 No.7(2011), pages 121-130.

[3] J. Dean, S. Ghemawat, et al. MapReduce: Simplified data processing on large cluster. In Proceedings of OSDI, 2004, pages 137-150.

[4] H. Li, A. Ghodsi, M. Zaharia, et al. Tachyon: Reliable, Memory Speed Storage for Cluster Comput-

ing Frameworks. In Proceedings of SOCC, 2014, pages 6:1-6:15.

[5] Y. Li, D. Feng, Z. Shi. Enhancing Both Fairness and Performance Using Rate-aware Dynamic Storage Cache Partitioning. In Proceedings of DISCS, 2013, pages 31-36.

[6] K. Shvachko, H. Kuang, S. Radia, et al. The Hadoop Distributed File System. In Proceedings of MSST, 2010, pages 121-134.

[7] G. Ananthanarayanan, A. Ghodsi, A. Warfield, et al. PACMan: Coordinated Memory Caching for Parallel Jobs. In Proceedings of NSDI, 2012, pages 267-280.

[8] Q. Pu, H. Li, M. Zaharia, et al. FairRide: Near-Optimal, Fair Cache Sharing. In Proceedings of NSDI, 2016, pages 393-406.

[9] M. Zaharia, M. Chowdhury, T. Das, et al. Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. In Proceedings of NSDI, 2012, pages 15-28.

[10] S. Zhang, J. Han, Z. Liu, et al. Accelerating MapReduce with Distributed Memory Cache. In Proceedings of ICPADS, 2009, pages 472-478.

[11] Y. Luo, S. Luo, J. Guan, et al. A RAMCloud Storage System based on HDFS: Architecture, Implementation and Evaluation. Journal of Systems and Software. Vol.86 No.3(2013), pages 744-750.

[12] Q. Ma, P. Steenkiste, H. Zhang. Routing High-Bandwidth Traffic in Max-Min Fair Share Networks. In Proceedings of SIGCOMM, 1996, pages 206-217.

[13] Z. Cao, W. Zegura. Utility Max-Min: An Application-Oriented Bandwidth Allocation Scheme. In Proceedings of INFOCOM, 1999, pages 793-801.

[14] S. Tang, B. Lee, B. He, et al. Long-Term Resource Fairness: Towards Economic Fairness on Pay-as-you-use Computing Systems. In Proceedings of ICS, 2014, pages 251-260.

[15] A. Ghodsi, M. Zaharia, B. Hindman, et al. Dominant Resource Fairness: Fair Allocation of Multiple Resource Types. In Proceedings of NSDI, 2011, pages 323-336.

[16] Redis. http://redis.io.

[17] HDFS. http://hadoop.apache.org/hdfs.

[18] Spark. http://spark.apache.org.

[19] Memcached. http://danga.com/memcached.