SOPA: Selecting the Optimal Caching Policy Adaptively

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With the development of storage technology and applications, new caching policies are continuously being introduced. It becomes increasingly important for storage systems to be able to select the matched caching policy dynamically under varying workloads. This article proposes SOPA, a cache framework to adaptively select the matched policy and perform policy switches in storage systems. SOPA encapsulates the functions of a caching policy into a module, and enables online policy switching by policy reconstruction. SOPA then selects the policy matched with the workload dynamically by collecting and analyzing access traces. To reduce the decision-making cost, SOPA proposes an asynchronous decision making process. The simulation experiments show that no single caching policy performed well under all of the different workloads. With SOPA, a storage system could select the appropriate policy for different workloads. The real-system evaluation results show that SOPA reduced the average response time by up to 20.3% and 11.9% compared with LRU and ARC, respectively.

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1. INTRODUCTION

Caches can greatly improve the overall performance of storage systems. They are widely used in file systems [Nelson et al. 1998], database systems [Li et al.

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2005; Chou and Dewitt 1985], RAID controllers [Menon 1994], disks [Menon and Hartung 1988], Web servers [Cao and Irani 1997], and so on. With the development of storage architecture and applications, new caching policies are continuously being designed to suit the different needs of applications, such as MQ [Zhou and Philbin 2001], ARC [Megiddo and Modha 2003], SANBoost [Ari et al. 2004], DULO [Jiang et al. 2005], and WOW [Gill and Modha 2005]. Some of them are adaptive, such as MQ and ARC, while others try to make optimizations for specific workloads, for example, DULO targets achievement of a high hit ratio under workloads with many sequential accesses.

In fact, as a result of the evolving and changing access patterns, no single policy is able to adapt to all workloads [Ari et al. 2004]. This makes it increasingly important for cache systems to be capable of selecting the matched caching policy dynamically. In most of existing systems, caching policies are tightly coupled with the cache systems, making it hard to perform policy switches.

In this article, we propose SOPA, a framework that evaluates all available candidate policies according to the change of workloads, selects the matched one, and performs a policy switch online. SOPA uses the following two techniques.

—*The modularization of caching policies and policy switch*. Cache systems call the functions of the various caching policy modules through a unified interface, and they do not depend on the implementation details of these policies. By policy reconstruction, SOPA enables online switching between any two caching policies.
—*The online policy selection*. SOPA can select the matched caching policy dynamically for a varying workload. It collects the access trace and selects the matched policy through trace analyzing.

SOPA was evaluated via two experiments on a simulation system and on a real system. The simulation results show that a single caching policy could not perform well under all of the different workloads, while SOPA could select the matched policy for each workload and achieve a satisfactory hit rate. The real system evaluation shows that SOPA reduced the average response time by up to 20.3% and 11.9% compared with LRU and ARC, respectively.

This article is organized as follows. Section 2 briefly reviews the related work. In Section 3, the architecture of SOPA is introduced. In Sections 4 and 5, we present the evaluation results on the simulation and real systems. Finally some conclusions and comments on future work are given in Section 6.

2. RELATED WORK

With the development of storage systems, various caching policies have been introduced. LRU and LFU are the earliest caching policies. Later policies take into account both recency and frequency factors, such as LRU-k [O'Neal et al. 1993], 2Q [Johnson and Shasha 1994], FBR [Robinson and Devarakonda 1990], LRFU [Lee et al. 2001], LIRS [Jiang and Zhang 2002], MQ [Zhou and Philbin 2001], ARC [Megiddo and Modha 2003] and CAR [Bansal and Modha 2004]. These policies mainly try to raise the hit rate and require no additional information from the cache system. Some policies also take into account other effects, or try to use some additional information from the cache system. SANBoost [Ari et al. 2004], WOW [Gill and Modha 2005] and Karma [Yadgar and Factor 2007] are such examples.

It should be pointed out that, since access patterns have always been evolving and changing, no single policy is able to adapt to all workloads [Ari et al. 2002]; in addition, existing policies may also continuosly be replaced by new ones. Therefore, it is necessary to employ a method to match the proper caching policy to a specific workload.

Some caching policies have parameters tunable for performance. By tuning these parameters, the policies could deal with a wide variety of workloads. For some of them, the tuning of parameters is done manually by the administrator. For example, the *Correlated Reference Period* in LRU-k, K_{in} and K_{out} in 2Q, L_{hir} in LIRS, λ in LRFU, and F_{new} and F_{old} in FBR, are parameters that are tuned by rule of thumb. The designers of these policies give some suggestions about the tuning of these parameters, but it requires the administrators to be very experienced and it is also difficult to change these parameters online.

Adaptive caching policies can tune the parameters online without interference by the administrators. MQ and ARC are two typical adaptive caching policies. The *lifetime* parameter of MQ is adaptive. MQ uses several queues to identify the priority of a cache block and uses lifetime to determine how long a cache block can stay in a queue. MQ recommends using the peak temporal distance as the value of lifetime; this distance can be dynamically estimated for the current workload. ARC uses two queues, T_1 and T_2, to balance recency and frequency. The sizes of T_1 and T_2 are adaptive. T_1 contains blocks that have been accessed only once recently, while T_2 contains blocks that have been accessed at least twice recently. Two history lists, B_1 and B_2, are kept for T_1 and T_2, respectively. When ARC finds that an access hits B_1, it will increase the size of T_1 and decrease the size of T_2. When an access hits B_2, ARC will increase the size of T_2 and decrease the size of T_1. In this way, ARC can automatically tune the size of T_1 and T_2 according to the characteristics of the workload. Adaptive policies can adapt to a wide range of workloads without the interference of users, but such adaptation is still limited to the parameters of the policy. In most cases, the adaptive policies cannot behave as well as the ones most matched with the workload.

ACME (Adaptive Caching using Multiple Experts) [Ari et al. 2002] combines several policies to reduce the risk of a wrong cache replacement. It simulates several policies and assigns a weight to each. Each policy votes on the blocks it wants to keep, assigning higher values to blocks that it believes are more worth keeping. The block with the lowest sum of weighted votes is selected as the replacement victim. In ACME, the weights of the policies could be adjusted by a machine learning method. The weakness of ACME is that it introduces a large latency and computation overhead. Furthermore, ACME has to maintain several policies simultaneously, which takes up more memory space.

Salmon et al. [2003] introduce a policy decision-making method for disk systems. Although it is suggested that the method can also be used for cache systems, there is no implementation and verification. Different from disk

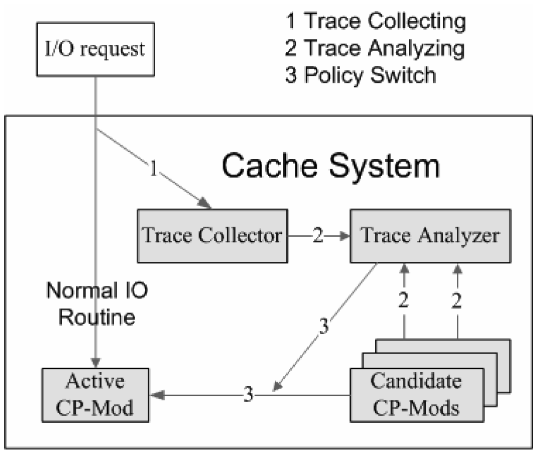


Fig. 1. Architecture of SOPA. CP-Mod stands for caching policy module. 1. The Trace Collector collects I/O traces; 2. the Trace Analyzer decides the optimal policy; 3. the cache system performs a policy switch.

systems, cache systems have stricter requirements of latency and efficiency. It is difficult for this method to satisfy these requirements.

Instead of introducing a new policy, SOPA makes better use of existing ones. Compared with intrapolicy adaptation, interpolicy adaptation can adapt to a wider range of workloads, but it usually has a larger overhead. SOPA selects the matched policy from a large candidate set, so it is an interpolicy adaptation. Different from ACME, SOPA selects the matched policy, but not the optimal victim block, so the overhead is reduced. In most cases, the overhead of SOPA is negligible.

3. THE ARCHITECTURE OF SOPA

The architecture of SOPA is depicted in Figure 1. SOPA consists of three components: Caching policy Modules (CP-Mods), Trace Collector, and Trace Analyzer. Every CP-Mod encapsulates the functions of a caching policy and exports these functions to other modules, which are called caching policy users (CP-Users), through a fixed interface. By policy reconstruction, the CP-User can dynamically switch between any two CP-Mods. The cache system itself is a CP-User and its caching policy is determined by the currently-used CP-Mod, which is called an “active CP-Mod.” The cache system can select a candidate CP-Mod and switch the active CP-Mod. It can also deploy a new policy by adding a new CP-Mod. The Trace Collector records I/O traces when policy decision-making is needed. It first stores the I/O traces in a memory trace pool, and when the pool is full, it moves them to a file on the disk and empties the memory pool. The Trace Analyzer is also a CP-User. It selects the matched policy for the cache system when enough traces are collected. The Trace Analyzer replays the access trace collected by the Trace Collector with all the candidate policies. Then it selects the optimal one and informs the cache system of the result.

This framework has several advantages. First, the cache system can perform policy switching online; thus it can adapt to the varying workloads. Second, new polices can be deployed dynamically; thus the future caching policy can also be utilized. Third, when no policy decision is performed, SOPA introduces only a small CPU overhead and memory cost.

3.1 Modularization of Caching policies

The key idea of the modularization of caching policies is as follows. The CP-Mod implements a group of interface functions, and registers these functions to the CP-User; then the CP-User calls the functions of the CP-Mod through this interface. The modularization of caching policies separates the CP-User from the implementation details of the CP-Mod; thus supporting online policy switching.

After studying the well-received caching policies, we designed the interface and metadata organization for the modularization of caching policies. In this article, metadata refers to the data used to describe the cache system and the caching policy. The design complies with three rationales.

(1) *Efficiency*. SOPA should not add much overhead to the execution of the caching policies.
(2) *Function encapsulation*. The CP-Mod should only deal with the logic of the caching policy, without the need of considering the other functions of the CP-User. This allows the policy designers to focus on their policies and simplifies their work.
(3) *Metadata separation*. The CP-User should not maintain the policy-specific metadata, which should be managed by the CP-Mod. This rationale enables the deployment of new CP-Mods and reduces the memory requirement.

3.1.1 *Interface and Metadata Organization.*

To design an interface and metadata that are suitable for a wide range of policies, we have studied the design and implementation of various policies, including LRU, LFU, LRU-k, 2Q, FBR, LRFU, LIRS, MQ, ARC, CAR, DULO, and SANBoost. The design is depicted in Figure 2. An interface is composed of three groups of functions, and the CP-Mod registers the implementation of the interface to the CP-User. There are two types of metadata, universal metadata and policy metadata. The universal metadata is allocated and maintained by the CP-User and has a pointer to the policy metadata, which is managed by the CP-Mod. The CP-User does not need to know about the policy metadata, which satisfies the rationale of metadata separation.

The interface of the CP-Mod is composed of three groups of functions; (1) initialization and release functions, including the *initialize* function to allocate and initialize the policy metadata and the *release* function to release the policy metadata; (2) cache access processing functions, including the *blk_hit* function to process a cache block hit event, the *blk_new* function to process a cache block insertion event, and the *blk_find_victim* function to process the cache block replacement event—he cache system will call these functions when the corresponding cache event occurs; (3) cache access preprocessing functions,

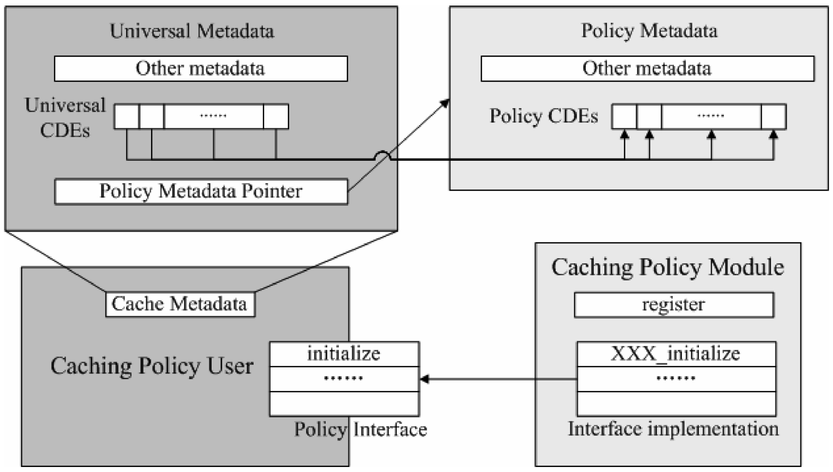


Fig. 2. Design of the interface and the metadata organization. The cache directory entry (CDE) carries the information describing a cache block.

including the *pre_blk_access*, *pre_blk_hit*, *pre_blk_new*, and *pre_blk_find_victim* functions to preprocess the corresponding cache events.

Generally speaking, on-demand caching policies (i.e., every missed block is migrated into the cache) only require the implementation of the first two groups. The other caching policies such as SANBoost or prefetching policy may require the implementation of all three.

The design of the interface has several advantages; (1) SOPA can easily make use of existing caching policies. They can be brought into SOPA with a little adjustment; (2) The CP-Mod does not need to deal with the details of the cache system, which satisfies the rationale of function separation.

The metadata organization is required to satisfy the rationale of metadata separation and it should also guarantee the efficiency of policy execution. SOPA takes both requirements into account. A normal cache implementation uses a specific data structure to describe the information of a cache block, which we call the Cache Directory Entry (CDE) structure [Robinson and Devarakonda 1990]. Some other data structures are used to look up the CDEs or to implement the caching policy, such as hashtable [Robinson and Devarakonda 1990], LRU list [O'Neal et al. 1993; Ari et al. 2002; Johnson and Shasha 1994; Zhou and Philbin 2001; Megiddo and Modha 2003], history records [Zhou and Philbin 2001; Megiddo and Modha 2003], and so on. As shown in Figure 2, SOPA divides CDEs into Universal CDEs and Policy CDEs, and also divides the other metadata into two parts. SOPA recombines them into universal metadata and policy metadata. The universal metadata is maintained by the CP-User, and policy metadata is allocated and managed by the CP-Mod. The CP-Users need not to know the organization of the policy metadata, which satisfies the rationale of metadata separation. To improve the efficiency of metadata lookup, SOPA adds a pointer in each Universal CDE, which points to its corresponding Policy CDE. Additionally, SOPA keeps the most frequently and widely used policy metadata in the Universal CDE to improve the accessing efficiency.

SOPA provides a balance between the rationale of efficiency and the rationale of metadata separation.

3.1.2 *Caching Policy Switch.* The basic process of policy switching is as follows. The CP-User *releases* the current caching policy, then registers and *initializes* the new caching policy. The main problem is that after a period of time of running, some blocks have been migrated into the cache, but after the policy switching, the new policy does not have the record. A simple solution is to empty the cache before performing the switching. However, this has two main drawbacks. First, all the dirty blocks have to be written to the disks, which brings a large latency. Second, the cache has to be rewarmed, which reduces the hit rate and brings an extra cost of block remigration.

SOPA initializes the policy metadata according to the existing cache blocks to reflect the current status of cache. It does not require any disk accesses or cache block movements. Furthermore, SOPA can provide warm-up for the new caching policy and avoids the costs of block remigration. As a result of the rationale of metadata separation, the CP-User does not understand the organization of the policy metadata, and thus cannot build up the policy metadata directly. To solve this problem, the CP-User keeps an LRU History List (LHL) for the existing cache blocks. When a new block is migrated into the cache or when a block is hit, this block is moved to the tail of the LHL (just the adjustment of a pointer, requiring no data movement); when a block replacement occurs, the victim block is removed from the LHL, and the new block is moved to the tail of the LHL. In this way, the CP-User keeps an access history for the existing cache blocks in an LRU order. When a policy switching is performed, the CP-User calls the *blk_new* function of the new CP-Mod for each LHL record in order. In this way, the CP-Mod can reconstruct its own policy metadata indirectly through the *blk_new* interface function. The policy reconstruction does not require the CP-User to understand the policy metadata and can be used in switching between any two CP-Mods. The cost of this method is that an LRU list entry has to be added to each Universal CDE to maintain the LHL.

3.2 Policy Decision-Making

Policy decision-making is used to select the matched policy. The process consists of three steps. First, the Trace Collector records the I/O traces. Second, when enough traces are collected, the Trace Analyzer replays these I/O traces with all the candidate caching policies and selects the best matched CP-Mod. Finally, a policy switch is performed if the Trace Analyzer finds that the Active CP-Mod is not the optimal one. The I/O traces are deleted after each decision process.

Figure 3 depicts the decision process. T_c is the time for trace collecting, T_a is the time for trace analyzing and T_r is the time for normal running without additional operations. In most cases, $T_a << T_c << T_r$, so this overhead will not have a heavy impact on the cache system. Typically, replaying 1M accesses for one policy takes only tens of seconds on a modern CPU.

To make a good and quick decision, SOPA introduces multi-round decisions. When the hit ratio of the cache system drops greatly, which means that the

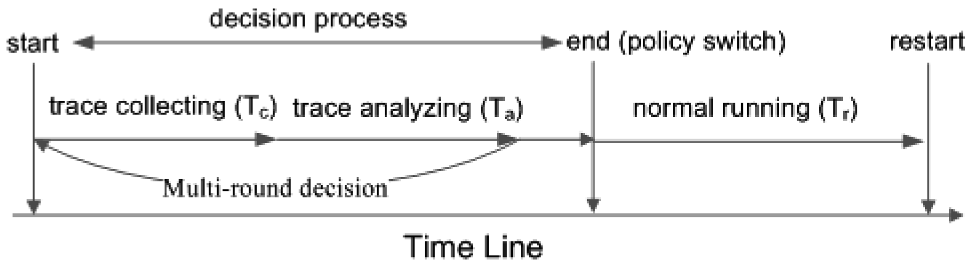


Fig. 3. The decision-making process.

workload has changed greatly and the last decision result may not be matched any more, a new decision process will restart.

One major problem of the decision process is how to determine the value of T_c. If T_c is set too small, the traces collected may not have enough information about the workload and the decision process will not achieve good results. If T_c is too long, the trace collecting process will introduce more overhead. To deal with this problem, SOPA introduces multi-round decisions to ensure the quality of the decision with limited T_c. When a fixed number of traces is collected, the Trace Analyzer replays these traces and makes a decision, and then the Trace Collector continues to collect traces for the Trace Analyzer for another round of decision. The decision process does not stop until two consecutive rounds of decisions reach the same result. Empirically, we found that in each round, collecting one million block requests is enough, and normally two to four rounds of decisions can succeed in reaching the final decision.

The Trace Analyzer requires a criterion to determine which policy is optimal among the current set of candidate policies. The hit rate is the most widely used criterion (used in LRU-k, 2Q, FBR, LRFU, LIRS, MQ, ARC, CAR, etc). Other criteria, such as the hit density (in SANBoost) are also used in practice. In SOPA, the total cost of all operations in policy adaption is used as the criterion to evaluate the candidate caching policies.

$$C_{all} = C_{hit} \times N_{hit} + C_{migration} \times N_{migration} + C_{direct} \times N_{direct} \tag{1}$$

C is the average cost of the operation specified as the subscript, and N is the number of operations executed. The subscript "hit" stands for a cache hit. The subscript "migration" stands for a migration of data from the slow device to the fast device. The subscript "direct" stands for an access to the slow device. One typical scenario of a direct operation is as follows. When a cache miss appears, the slow device is accessed directly. The Trace Analyzer selects the policy with the minimum C_{all}.

For on-demand caches, since every missed block is migrated into the cache, N_{direct} is zero, so we have:

$$\begin{aligned} C_{all} &= C_{hit} \times N_{hit} + C_{migration} \times (N_{all} - N_{hit}) \\ &= N_{all} \times \left[C_{hit} \times h + C_{migration} \times (1-h)\right] \quad h = N_{hit}/N_{all}. \end{aligned} \tag{2}$$

Since $C_{hit} << C_{migration}$ and N_{all} is a fixed number, the larger the h (hit rate) is, the smaller the C_{all} is. So for on-demand caches, C_{all} is equivalent to the hit rate. For caching policies not only based on hit rate like SANBoost, N_{direct} is not zero, and C_{all} can evaluate these policies more precisely. C_{all} is compatible with the most widely used hit rate criterion. It can also describe various caching policies. So SOPA can be applied to a wide range of cache systems.

The values of C depend on the cache system. In the current version of SOPA, they are set manually. In Chen et al. [2005], the latencies of different storage systems are measured and they can be used as the values of C. Some tools such as lmbench [Mcvoy and Staelin 1996] can measure the bandwidth and latency of the disks and memories, which can also help the setting of C. Improving the C_{all} expression (for example to distinguish read/write or sequential/random operations) and automatically collecting the required parameters are not in the scope of this article.

The number of candidate policies will increase with the deployment of the new caching policies, and this will add work to the trace analyzing process, so less frequently used policies should be dropped. In SOPA, the usage rate $\frac{\text{time as Active CP-Mod}}{\text{elapsed time since deployed}}$ is used to evaluate each policy. When the number of candidate policies goes beyond a threshold, SOPA drops the policy with the lowest usage rate.

4. SIMULATION EVALUATION

We implemented a simulator for the evaluation. We simulated four kinds of representative workloads and observed whether SOPA could correctly select the optimal policy.

4.1 Traces and Caching policies

The traces we used include two SPC-1 Financial traces (F1, F2), three SPC-1 Websearch traces (W1-W3) [SPC-1 traces], one Cello99 trace (C1) [Ruemmler and Wilkes 1993; HP traces], and one TPC-C trace (T1) [TPC-C trace].

SPC-1 Financial traces contain two I/O traces (F1, F2) from OLTP applications running at two large financial institutions. F1 contains 5.3 million references and accesses 17.2 GB of data in 12.1 hours. F2 contains 3.7 million references and accesses 8.4 GB of data in 11.4 hours.

SPC-1 Websearch traces contain three I/O traces (W1-W3) from a popular search engine. W1 contains 1.1 million references and accesses 15.2 GB of data in 0.88 hours. W2 contains 3 million references and accesses 43.0 GB of data in 2.5 hours. W3 contains 4.3 million references and accesses 62.6 GB of data in 83.0 hours (99.98% of them are in the first 6.3 hours).

The Cello99 trace is a low-level disk I/O trace collected on an HP UNIX server with 2 GB of memory [Chen et al. 2003]. We use a one-week trace (C1) between 12/01/1999 and 12/07/1999. C1 contains 43 million references and accesses 350.8 GB of data in a week.

TPC-C contains a disk trace (T1) of the TPC-C database benchmark with 20 warehouses. The client ran 20 iterations for Postgres 7.1.2. It was collected with DTB v1.1. T1 contains 10 million references and accesses 438.4 GB of data in 14.5 hours.

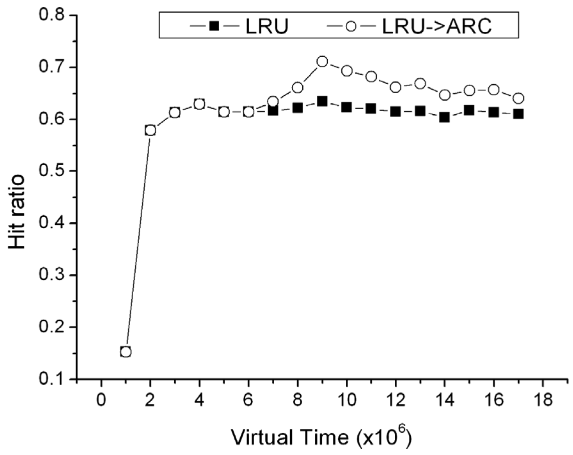


Fig. 4. Fluctuation of the hit ratio on W3, switching from LRU to ARC at time 5. Cache size was 4G.

LRU, 2Q, MQ, ARC, and LIRS were used in our evaluation, since they are all hit ratio-based general-purpose policies and require no additional information from the cache system. LRU-k and LRFU are not used because of their large overhead [Megiddo and Modha 2003]. Nine caching policies were selected as candidates, including the same policy with different parameters (cache contains c blocks): LRU, ARC, MQ (with 8 queues and 4c history records), $2Q_1$ (K_{in} is 0.2c, K_{out} is 0.5c), $2Q_2$ (K_{in} is 0.3c, K_{out} is 0.5c), $LIRS_1$ (L_{hir} is 0.01c), $LIRS_2$ (L_{hir} is 0.1c), $LIRS_3$ (L_{hir} is 0.2c), and $LIRS_4$ (L_{hir} is 0.3c). These policies were all implemented according to the information from the publication. The parameters of these policies used in the experiments were all suggested or used by the authors of the policies in the published articles. Without loss of generality, the initial policy of SOPA was ARC in the evaluation.

These evaluations ran on a machine with four Xeon 700MHz CPUs and block size is 4 KB in all tests. Virtual time, which is the number of blocks requested, was used in this section to depict the variation of the hit ratio in the process.

4.2 The Process of Policy Switching

First, we observed the fluctuation of the hit ratio in the process of policy switching. The LRU policy was first used for trace W3, and it was switched to the new policy, ARC, at virtual time 5 ($x10^6$). Here, the virtual time is denoted by the number of I/O operations. The fluctuation of the hit ratio is shown in Figure 4.

Figure 4 depicts the fluctuation of hit ratio with time. After the policy switching was performed at time 5, the hit ratio was retained between times 5 and 6. From time 7, the hit ratio of the new policy overcame that of the original LRU policy. This reveals that the old policy can be switched to a new one smoothly, without an obvious performance penalty.

Table I. Hit Ratio of Different Policies on Different Traces. Underlined Numbers Designate the Highest Hit Ratio Achieved by a Single Policy

Trace	LRU	ARC	MQ	2Q		LIRS				SOPA	
				0.2	0.3	0.01	0.1	0.2	0.3		Selected Policy
SPC-1 Financial											
F1,4M	66.4	66.4	$\underline{67.3}$	65	66.1	57.6	65.6	66.2	66.4	67.2	MQ
F1,8M	68.3	68.3	68.9	68.5	$\underline{69.1}$	62.4	68	68.2	68.2	68.7	2Q(0.3)
F1,16M	70.1	70.2	70.3	71	$\underline{71.4}$	67.1	70	70.1	70.1	71	2Q(0.3)
F1,32M	71.8	72	72	72.7	$\underline{72.9}$	70.6	71.9	71.9	71.9	72.7	2Q(0.3)
F1,64M	73.2	73.3	73.2	73.8	$\underline{74}$	72.6	73.2	73.3	73.3	73.3	LIRS(0.3)
F2,4M	53.5	54.2	$\underline{56.5}$	56.1	56.1	49.6	53.4	54	54.1	56.1	MQ
F2,8M	61.9	62.3	64.3	$\underline{64.6}$	64.5	59.1	61.9	62.1	62.2	64.1	2Q(0.3)
F2,16M	71.2	70.8	72.3	73	$\underline{73.2}$	68.5	70.3	70.7	70.9	72.7	2Q(0.3)
F2,32M	78.2	77.7	78.6	$\underline{80.1}$	$\underline{80.1}$	76	77.5	78.1	78.3	79.5	2Q(0.2)
F2,64M	83.2	83.1	83.3	$\underline{84.6}$	84.5	81.5	83.3	83.5	83.5	84.2	2Q(0.2)
SPC-1 Websearch											
W1,1G	0.3	0.7	5.4	1.3	1.3	$\underline{13.2}$	12.2	11.1	10	10.5	LIRS(0.01)
W1,2G	11.2	20.6	17.9	19.9	18.7	$\underline{30.8}$	28.8	26.5	24.1	27.5	LIRS(0.01)
W1,4G	48.9	50.7	49.9	44.2	44.2	$\underline{53.5}$	51.7	50.6	50.1	51.6	LIRS(0.01)
W2,1G	0.4	2	12.2	4.2	4.2	$\underline{14.8}$	13.7	12.5	11.1	13.7	LIRS(0.01)
W2,2G	12.5	30.2	27.3	29	25	$\underline{35.1}$	32.9	30.5	27.7	33.8	LIRS(0.01)
W2,4G	57.5	61.6	61.2	57.9	56.9	$\underline{65.4}$	62.9	61.4	60.9	64.6	LIRS(0.01)
W3,1G	0.4	2.9	$\underline{15.7}$	5.8	5.8	15.2	14	12.7	11.2	14.5	LIRS(0.01)
W3,2G	11.9	31.5	31.5	30.8	26.2	$\underline{36.2}$	33.9	31.3	28.3	35.4	LIRS(0.01)
W3,4G	58.7	62.8	64.6	60.3	58.8	$\underline{67.5}$	65	63.3	62.7	67	LIRS(0.01)
Cello99											
C1,4M	34.8	36.5	36.9	$\underline{38.3}$	38.2	25.5	36.3	36.3	36.2	38.2	2Q(0.2,0.3)
C1,8M	37.3	38.7	38.7	$\underline{40.2}$	$\underline{40.2}$	37.4	38.5	38.6	38.5	40.1	2Q(0.2,0.3)
C1,16M	40.4	41.3	41.3	$\underline{42.7}$	$\underline{42.7}$	40.4	40.9	40.9	41	42.5	2Q(0.3), LIRS(0.1), ARC
C1,32M	44.4	44.9	44.8	45.4	$\underline{45.6}$	42.9	43.4	43.6	43.8	45.4	2Q(0.3), LIRS(0.2), ARC
C1,64M	48.8	49	49	49.4	$\underline{49.8}$	45.9	46.6	47.1	47.4	49.2	ARC, 2Q(0.3)
C1,128M	53	53	53.1	53.7	$\underline{54.1}$	49.2	50.4	51.1	51.7	53.3	MQ, 2Q(0.2)
C1,256M	56.2	56.2	56.2	57.2	$\underline{57.6}$	52.4	54.2	55.3	55.7	56.2	MQ, LIRS(0.3)
C1,512M	59	59.2	59	60.4	$\underline{60.7}$	55.9	58.3	59	59.2	59.1	LRU, LIRS(0.2)
C1,1G	61.6	61.8	61.6	63.5	$\underline{63.7}$	59.3	61.8	62.1	62.2	61.7	LRU, ARC
TPC-C											
T1,128M	5.2	12.5	5.8	7.4	7.4	$\underline{19.6}$	18.3	16.8	15.4	19.5	ARC, LIRS(0.01)
T1,256M	5.4	19.5	19.6	5.4	5.4	$\underline{34.3}$	31.7	28.8	25.8	33.9	ARC, LIRS(0.01)
T1,512M	9.3	13.4	35.6	43.6	31.5	$\underline{63.6}$	58.4	52.8	47.4	63.3	LIRS(0.01)
T1,1G	94	93.9	91.7	91.8	$\underline{96}$	$\underline{96}$	95.1	94.2	93.4	94.2	LIRS(0.2)
T1,2G	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	$\underline{99.6}$	LRU

4.3 Simulation Results

In this section, we perform the simulation with all the traces in the on-demand cache environment. The results of SOPA and other policies are compared in Table I. Since for on-demand caches, C_{all} is equivalent to the hit rate, hit rates are used in this table. The highest hit rate achieved by a single policy was underlined.

In the listed 19 cases of SPC-1 Financial and SPC-1 Websearch, where only one decision was needed, SOPA selected the optimal policy in 16 cases and selected the second optimal policy in 2 cases. In the Cello99 and TPC-C cases,

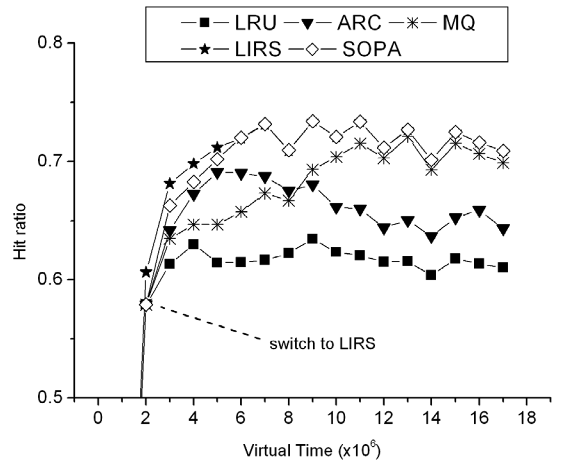


Fig. 5. The variation of hit ratio with time on (W3, 4G).

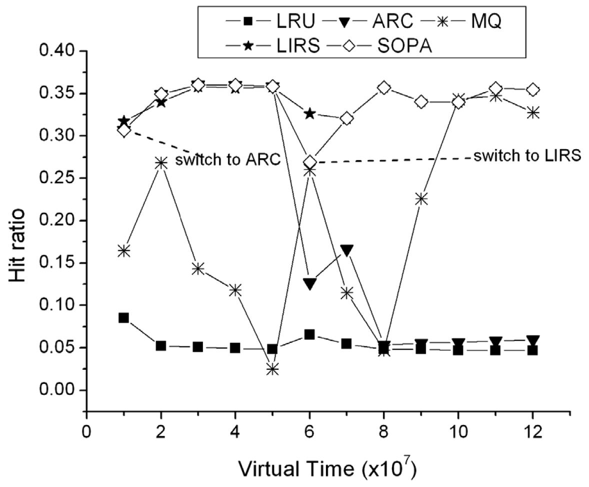


Fig. 6. The variation of hit ratio with time on (T1, 256M).

where two or more decisions were needed, the hit rates of SOPA were also the optimal ones.

This test shows that SOPA could correctly select the policy among the candidates. Conversely, no single policy could behave satisfactorily on all the traces. In our experiments, LIRS performs best on Websearch and TPC-C traces, 2Q performs best on Cello and Financial traces, but they cannot perform equally well on all the traces; and parameter tuning is also required.

Figure 5 takes a detailed view of one trace, W3. After the decision at time 2, SOPA selected LIRS and performed the policy switch. Then its hit ratio went beyond those of LRU, ARC, and MQ.

Figure 6 depicts the variation of hit ratio on T1. Since T1 is a trace with varying characteristics, more decisions were needed. SOPA selected ARC in the

Table II. Average Response Time (ms) of Different Policies on W3

	LRU	ARC	MQ	SOPA
w3, IG	9.5	9.4	8.5	8.3
w3, 2G	8.3	6.9	6.6	6.6
w3, 3G	6.1	5.4	5.4	5.0

first decision, but after time 5, the hit ratio dropped and SOPA started a new decision. This time, SOPA selected LIRS and went beyond the other policies.

5. REAL SYSTEM EVALUATION

We implemented a write-through cache system for an iSCSI target [UNH project 2006]. SOPA was applied to this system and compared with two adaptive policies, ARC and MQ. The target machine was equipped with a Xeon 2.8 GHz CPU, 4 GB memory, and six Maxtor MaxLine Plus II 250 GB SATA disks. The initiator machine was equipped with a Xeon 2.4 GHz CPU and 1 GB memory. The target machines installed Linux 2.4.31 and the initiator machine installed Windows 2003 and Microsoft iSCSI Initiator. Two machines were connected through Gigabyte Ethernet. The cache block size was 4 KB in all experiments. SPC-1 Websearch and TPC-C traces were used in this evaluation. SPC-1 Financial and Cello99 traces were not used since they require too many disks (more than 20). Traces were played on the initiator machine through direct I/Os.

5.1 Results on Websearch Workload

In this experiment, trace W3 was played on the initiator machine. The cache size was set to 1 G, 2 G, and 3 G respectively. Since the total length of W3 is 63 hours and 99.98% of the requests are in the first 6.3 hours, the last 0.02% requests are dropped to save time. The average response times were shown in Table II.

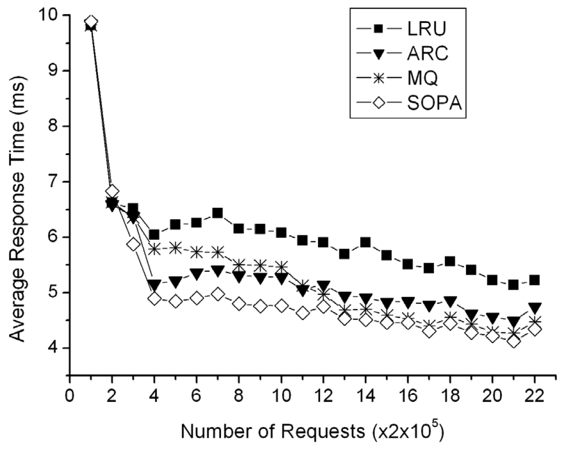
The evaluation results showed that on W3, SOPA could reduce the average response time by up to 20.3% compared with LRU, up to 11.8% compared with ARC, and up to 6.7% compared with MQ.

Figure 7 depicts the variation of average response time in the whole process. In each figure, SOPA made the decision at the first and second points. It can be observed that at the first two points, the average response times of different policies were almost the same, since the warm-up process had not finished. SOPA could successfully reduce the average response time after selecting an appropriate policy.

5.2 TPC-C Workload

In this experiment, trace T1 was played on the initiator machine. The cache size was set to 256 M and 512 M. The average response times were shown in Table III.

The evaluation results showed that on T1, SOPA could reduce the average response time by up to 13.6% compared with LRU, up to 11.9% compared with ARC, and up to 10.5% compared with MQ.



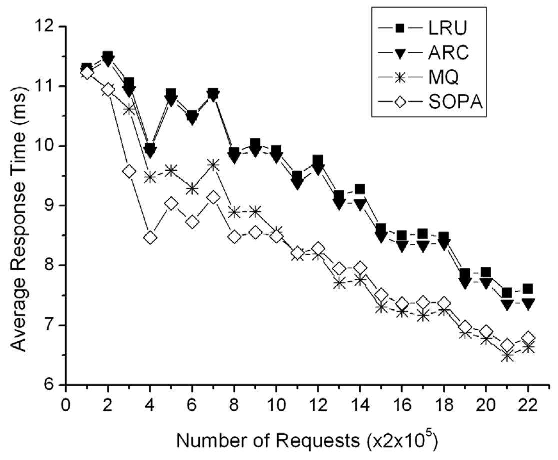


Fig. 7. The variation of average response time on (W3, 3G) and (W3, 1G). Each point is the average response time of 200,000 requests. For example, point 2 is the average response time of the 400,001st to the 600,000th requests.

Table III. Average Response Time (ms) of Different Policies on T1

	LRU	ARC	MQ	SOPA
T1, 256M	6.5	6.3	6.5	6.1
T1, 512M	6.4	6.3	6.2	5.5

Figure 8 depicts the variation of average response time on T1. Similarly, after the policy decision at the first point, SOPA could successfully reduce the average response time.

In these two evaluations, LIRS was selected as the optimal policy. In fact, LIRS "will work well for stable workloads drawn according to the IRM, but not for those LRU-friendly workloads drawn according to the SDD" [Megiddo and Modha 2003], and our simulation also showed that LIRS performed well on Websearch and TPC-C traces, but not on Financial and Cello99 traces. Thus,

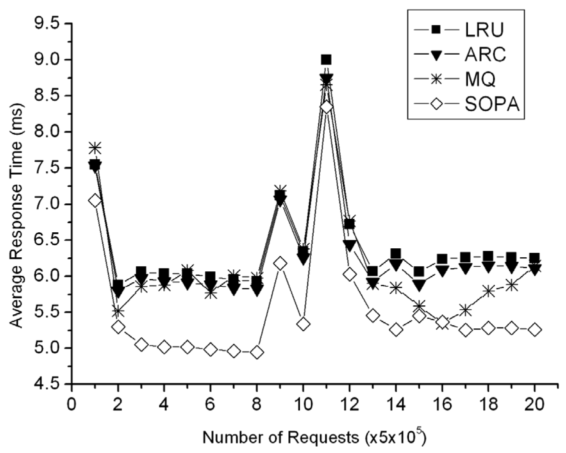


Fig. 8. The variation of average response time on (T1, 512M). Each point is the average response time of 500,000 requests.

it is not a policy that can be adaptive to many workloads. But SOPA could overcome this drawback, since SOPA only selected LIRS when it was good for the decision process.

These evaluations showed that by automatically choosing and switching among multiple policies, SOPA could adapt to different workloads and achieve lower average response time.

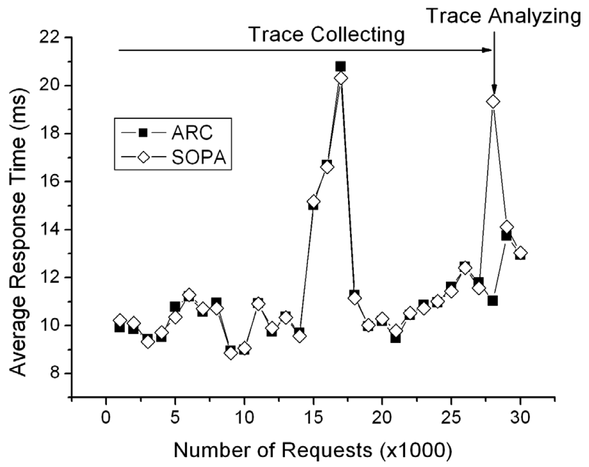
5.3 Overhead of Trace Collecting and Analyzing

In this section, we presented the overhead of the trace collecting and analyzing process.

Figure 9 depicted the overhead of the first round of the decision process on W3 and T1, where in Figures 7 and 8, this process was compressed into several points. Since the initial policy of SOPA was ARC, the average response time of SOPA and ARC at the same period of time were compared. In Figure 9, it can be observed that the overhead of trace collecting was almost negligible. Analyzing the trace was CPU-intensive work. On T1, where the workload was light at the time of trace analyzing, the overhead of trace analyzing was also negligible. On W3, where the workload was heavier, this process introduced a large average response time at point 28. However, the time for trace analyzing was very short, thus even a large average response time at a single point had little influence on the overall performance. Compared with the benefit gained by the decision-making, this overhead was worthwhile.

6. CONCLUSIONS AND FUTURE WORK

This article presents SOPA, a framework that can select the policy matched with the current workload adaptively for a cache system. It encapsulates the functions of a caching policy into a module, and by policy reconstruction, it allows dynamic switching from one caching policy to another one as well as



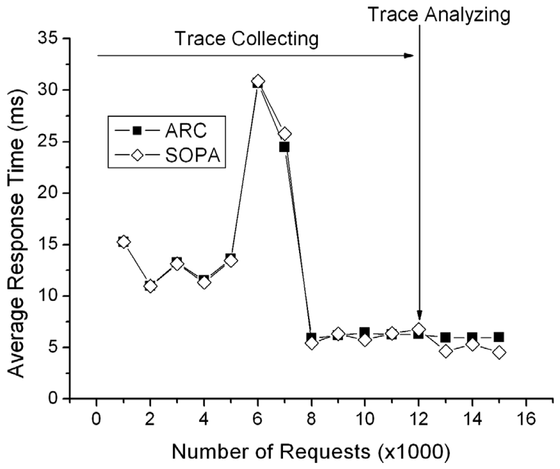


Fig. 9. The variation of average response time on (W3, 1G) and (T1, 256M). Each point is the average response time of 1000 requests.

the online deployment of new caching policies. It can select a caching policy matched with varying workloads.

The simulation evaluation showed that no single caching policy could perform well under all the different workloads. By choosing and switching among multiple policies, SOPA could achieve hit rates higher than any single caching policy. The real system evaluation on an IPSAN system shows that SOPA can reduce the average response time by up to 20.3% compared with LRU and up to 11.9% compared with ARC.

Our future work will focus on building a decision-making system based on experience. The Trace Analyzer stores the past decision results as experience and when a new workload comes, it can make a decision based on its experience. This can shorten the decision-making time needed and reduce the overhead of the trace analyzing.

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