

Popularity-Aware GreedyDual-Size Web Proxy Caching Algorithms*

Shudong Jin and Azer Bestavros

Computer Science Department
Boston University
111 Cummington St, Boston, MA 02215
{jins,bestavros}@cs.bu.edu

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Abstract

Web caching aims to reduce network traffic, server load, and user-perceived retrieval delays by replicating “popular” content on proxy caches that are strategically placed within the network. While key to effective cache utilization, *popularity* information (e.g. relative access frequencies of objects requested through a proxy) is seldom incorporated *directly* in cache replacement algorithms. Rather, other properties of the request stream (e.g. temporal locality and content size), which are easier to capture in an on-line fashion, are used to *indirectly* infer popularity information, and hence drive cache replacement policies. Recent studies suggest that the correlation between these secondary properties and popularity is weakening due in part to the prevalence of efficient client and proxy caches (which tend to mask these correlations). This trend points to the need for proxy cache replacement algorithms that directly capture and use popularity information.

In this paper, we (1) present an on-line algorithm that effectively captures and maintains an accurate popularity profile of Web objects requested through a caching proxy, (2) propose a novel cache replacement policy that uses such information to generalize the well-known GreedyDual-Size algorithm, and (3) show the superiority of our proposed algorithm by comparing it to a host of recently-proposed and widely-used algorithms using extensive trace-driven simulations and a variety of performance metrics.

Keywords: Web access characterization; Web caching protocols; distributed proxy caching; cache replacement algorithms; trace-driven simulations.

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1 Introduction

Web caching aims to reduce network traffic, server load, and user-perceived retrieval delay by replicating “popular” content on proxy caches [1, 14] that are strategically placed within the network—at organizational boundaries or at major AS exchanges, for example.

Importance of Efficient Cache Management: It may be argued that the ever decreasing prices of RAM and disks renders the optimization or fine tuning of cache replacement policies a “moot point”. Such a conclusion is ill-guided for several reasons. First, recent studies have shown that Web cache hit rates (HR) and byte hit rates (BHR) grow in a *log-like* fashion as a function of cache size [2, 7, 8, 9]. Thus, a better algorithm that increases hit rates by only several percentage points would be equivalent to a several-fold increase in cache size. Second, the growth rate of Web content is much higher than the rate with which memory sizes for Web caches are likely to grow. The only way to bridge this widening gap is through efficient cache management. Finally, the benefit of even a slight improvement in cache performance may have an appreciable effect on network traffic, especially when such gains are compounded through a hierarchy of caches.

Factors Affecting Cache Replacement Policies: There are many factors that affect the performance of a given cache replacement policy. Among others, these factors include object size, miss penalty, temporary locality, and long-term access frequency.

- Unlike traditional caching in memory systems, Web caches are required to manage objects of *variable* sizes. Caching smaller (and thus more) objects usually results in higher hit rates, especially given the preference for small objects in Web access [8]—though this preference seems to be weakening [5].
- The miss penalty (i.e. retrieval cost of missed objects from server to proxy) varies significantly. Thus, giving a preference to objects with a high retrieval latency can achieve high latency saving [23].
- Web traffic patterns were found to exhibit temporal locality [2, 9, 17] (i.e., recently accessed objects are more likely to be accessed again in the near future). This has led to the use of LRU cache replacement policy and generalizations thereof [9]. More recent studies have documented a weakening in temporal locality [5].
- The popularity of Web objects was found to be highly variable (i.e. bursty) over short times scales, but much smoother over long time scales [4, 13], suggesting the significance of *long-term* measurements of access frequency in cache replacement algorithms.

Motivation and Key Contributions: While key to effective cache utilization, *popularity* information (e.g., the relative access frequencies of objects requested through a proxy) is seldom maintained and rarely utilized *directly* in the design of cache replacement algorithms. Rather, other properties of the request stream (e.g., temporal locality and object size), which are easier to capture in an on-line fashion, are used to *indirectly* infer popularity information, and hence drive cache replacement policies.

To elaborate on this point, consider two widely used cache replacement policies: Least-Recently-Used (LRU) and Largest-File-First (LFF). LRU capitalizes on the temporal locality in a request stream, namely access recency, whereas LFF capitalizes on the negative correlation between popularity and object sizes. Both of these properties—namely, recency of a repeat access and size of requested object—are assumed to be indicative of the future popularity of the object, and hence reflective of the merit of keeping such an object in the cache. Recent studies [5] suggest that such relationships are weakening and hence may not be effective in indirectly capturing the popularity of Web objects.

In this paper, we (1) present an on-line algorithm that *effectively* captures and maintains an accurate popularity profile of Web objects requested through a caching proxy, (2) propose a novel cache replacement policy (termed GDSP) that directly uses such information to generalize the well-known GreedyDual-Size algorithm, and (3) show the superiority of our proposed GDSP algorithm by comparing it to a host of recently-proposed and widely-used algorithms with extensive trace-driven simulations using large DEC and NLANR proxy traces.

Our implementation of GDSP addresses a number of important problems, namely (a) How to capture the temporal locality exhibited in Web access streams? (b) How to avoid *cache pollution*—i.e., the tendency of previously popular objects to linger in the cache? (c) How to maintain the popularity profile of a large working set of web objects efficiently? and (d) How to accurately use such a profile to estimate access frequency?

The remainder of this paper is organized as follows. First, we describe our generalization of the GreedyDual-Size algorithm. Next, we review earlier work on Web proxy cache replacement algorithms. Next, we evaluate the performance of our proposed algorithm by comparing it to alternative techniques. We conclude with a summary and a discussion of future work.

2 Related Work

There is a large body of work on caching in general and on Web caching research in particular. In this section, we restrict our presentation to cache replacement policies for Web proxies.

Basic Policies: Simple Web cache replacement policies leverage on *a single basic* property of the reference stream. Least-Recently-Used (LRU) leverages on temporal locality of reference—namely, that recently accessed objects are likely to be accessed again. Least-Frequently-Used (LFU) leverages on the skewed popularity of objects in a reference stream—namely, that objects frequently accessed in the past are likely to be accessed again in the future.¹ Largest-File-First (LFF) leverages on the negative correlation that exists between object sizes and likelihood of access—namely, that small objects accessed in the past have a higher probability of being accessed again in the future.

Early characterizations of Web access patterns suggested the presence of strong temporal locality of reference [2]. However, more recent studies have concluded that this temporal locality is weakening [5]. One reason for this trend is effective client caching. To understand this, it suffices to note that the request stream generated by a client using an efficient caching policy is precisely the set of requests that missed in the client cache. Such a request stream is likely to exhibit weak temporal locality of reference—in particular, a recently accessed object is *unlikely* to be accessed again in the future! This trend suggests that LRU is not an adequate policy for cache replacement at proxies.

Early characterizations of Web access patterns suggested a strong preference for small objects [8]. However more recent studies have concluded that this preference is significantly weakening [5, 7]. Again, this weakening could be related to the presence of more efficient caching at clients, which tend to mask the correlation between size and frequency of access. It suggests that LFF is not an adequate policy for cache replacement at proxies.

Unlike LRU and LFF, LFU infers object popularity *directly* from the reference history.² While caching the most popular objects would yield optimal performance, recent studies of Web access patterns suggest that the popularity of Web objects is highly bursty [4, 13]. Objects that are popular over short time scales are not necessarily popular over longer time scales (and vice-versa). This property limits the performance of LFU (due to the cache pollution phenomenon to which we alluded earlier).

To summarize, the unique characteristics of Web accesses patterns observed at caching proxies (e.g., variable-size objects, variable-cost requests, burstiness of access stream, weakening temporal locality, etc.) limits the effectiveness of basic cache replacement algorithms.

Hybrid Policies: Several studies have generalized LRU to make it more sensitive to the variability in object size and retrieval delays. The GreedyDual algorithm [24] was proposed to deal with variable-cost (but uniform-size) page caching problem. Cao and Irani [9, 15] generalized the

¹Previous studies [7] indicate that the independent reference model [10] explains well the distribution properties of Web access, supporting the use of of frequency-based policies.

²This is in contrast to *indirectly* inferring popularity through locality of reference or object size.

GreedyDual algorithm to deal with the variability in size of Web objects. The resulting algorithm, GreedyDual-Size (GDS), enables a cache replacement strategy to be sensitive to the variability in Web object sizes and retrieval costs (miss penalty). The GDS implementation described in [9] uses $cost/size$ as the *utility value* of an object. This value is deflated over time to dynamically “age” objects in the cache. GDS was proven to possess an *optimal competitive ratio*—meaning that its cost of cache misses is within K times that of an off-line optimal algorithm, where K is the ratio of the cache size to the size of the smallest object in the trace.

Other generalizations of LRU have attempted to incorporate access frequency information into LRU. LRU-K computes the average reference rate of the last K accesses. In [20], LRU-K was shown to outperform LRU for database disk buffering applications. LNC-W3 is another generalization that incorporate object size, retrieval costs, and the average reference rate into LRU [21, 22]. LNC-W3 uses these aspects to compute the *profit* of caching an object. In simulations, LNC-W3 achieved higher delay savings when compared to LRU and LRU-K.

The Hybrid algorithm presented in [23] is aimed at reducing total latency by estimating the utility of retaining an object in the cache based on the object size, load delay, and frequency. The LRV algorithm presented in [17] uses the cost, size, and last access time of an object to calculate a utility value. The calculation is based on extensive empirical analysis of trace data that attempts to compute the probability of future accesses as a function of past access count, recency, object size, and server information. In [19], another policy MIX is proposed. It combines network latency, object size, access frequency, and the elapsed time since the last reference in a uniform formula for choosing victims. There are several drawbacks to these algorithms. First, they are heavily parameterized, requiring extensive tuning and parameter estimation. This makes them susceptible to changes in access patterns and to the location of the proxy cache (in relationship to other proxy caches in the network).

In another attempt to leverage on access frequency information, Arlitt *et al* proposed and evaluated two replacement policies—GDSF and LFU-DA [3]. GDSF simply incorporates access count into GDS. It uses $\frac{access_count \times cost}{size}$ as its base value. LFU-DA is a special case of GDSF in which $cost$ is proportional to $size$. Simulations show that GDSF(1), which assumes $cost$ is a constant for all objects, obtains the highest hit rate while LFU-DA obtains the highest byte hit rate. A recent paper [16] studied the inclusion of frequency of resource use in replacement and coherency policies. The combination of a simple GD-LFU policy, the same as GDSF(1), and a Hybrid coherency policy obtains the lowest average cost.

3 GDSP: Popularity-Aware GDS Cache Management

One of the weaknesses of GDS is its inability to capture (and leverage on knowledge of) the *long-term access frequencies* of Web objects. Recent studies [5, 7, 8] have shown the prevalence of Zipf-like distributions in Web access characteristics. One such distribution is found when characterizing object *popularity* (P) as a function of object *rank* (ρ). In particular, $P \sim \rho^{-\alpha}$, $0 < \alpha < 1$. This leads to the following property: *The number of objects accessed at least k times is proportional to $k^{-1/\alpha}$.* This implies that the probability of future references is dependent on past access frequencies—suggesting the relevance of taking into consideration long-term access frequencies in cache replacement strategies. In this section we present GDS-Popularity (GDSP) a generalization of GDS that enables it to leverage on knowledge of the skewed popularity profile of Web objects.

3.1 Overview of GDSP

We incorporate access frequency into the GDS algorithm through the use of a new *utility value* for a given object. The utility value $u(p)$ for an object p is defined as the expected normalized cost saving as a result of having p in the cache.

$$u(p) = \frac{f(p) \times c(p)}{s(p)},$$

where $s(p)$ is the size of p , $c(p)$ is its retrieval cost (or miss penalty), and $f(p)$ is the access frequency. Thus, $u(p)$ represents the cost saved per byte of p as a result of all accesses to it in a given period of time.

To captures access recency and to avoid pollution by previously popular objects, we use a dynamic aging mechanism similar to that used by GDS. In particular, we represent the *cumulative value* of an object p by $H(p)$. The cumulative value of the object last evicted from the cache is denoted by L . Thus, an invariant of our algorithm is that $H(p) \geq L$ for any object p the cache.

The general steps of the algorithm, called GDS-Popularity or GDSP, are described in Figure 1. The GDPS algorithm has nearly the same time and space cost as GDS. The object meta data can be maintained with a priority queue with key $H(p)$. The processing overhead on each hit or replacement is $O(\log n)$. Another element of overhead comes from maintaining the popularity profile and estimating frequency. The next section shows that the space and time requirements for doing so is very low.

3.2 Capturing Object Popularity in GDSP

GDSP maintains “meta” information for a subset of the objects in the request stream. Such information includes the object size, the retrieval cost, the last access time, and the estimated

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Algorithm GDS-Popularity
 $L \leftarrow 0.0$ 
for each request for object  $p$  do
  if  $p$  is in cache
    then  $H(p) \leftarrow L + f(p) \times c(p)/s(p)$ 
    else while there is not enough free cache for  $p$ 
      do  $L \leftarrow \min\{H(q)|q \text{ is in cache}\}$ 
      Evict the minimum  $q$ 
    fetch  $p$ 
     $H(p) \leftarrow L + f(p) \times c(p)/s(p)$ 

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Figure 1: Pseudo-code of GDSP Algorithm

access frequency relative to other Web objects. All but the last of these quantities are readily available from the request stream (e.g. HTTP headers, etc.)³

Relative Access Frequency Computation: One (simplistic) way of computing the relative access frequency of Web objects is to keep track of an access count of every Web object requested through the proxy. This is obviously unrealistic due to the huge scale of the Web. Instead, our solution keeps the access frequency of only a small fraction of all Web objects requested through the proxy. This method allows us to bound the space used to maintain access frequency information. In particular, in our implementation, we bound the space by satisfying two conditions: (1) less than (say) 1% of the cache is used to keep the access frequencies, and (2) the total number of objects for which access frequencies are kept is no more than (say) 20% of the total number of objects expected in a given access stream. Under such conditions, and for the NLANR and DEC traces we considered (discussed later), the total space requirement (including the auxiliary space for hash table and links), is only few MegaBytes.

It is important to note the necessity of keeping access frequency information for cached *and* evicted objects alike. This is necessary not only to improve the accuracy of access frequency estimation, but also to avoid the pollution phenomenon, to which we alluded earlier. This phenomenon is analogous to thrashing whereby a popular, newly cached object is evicted before building up enough “inertia” (in terms of access frequency) to resist eviction due to a burst of references to an object that is popular only over a shorter time scale [4, 13]. The situation is exacerbated further as cached objects age—the longer the request stream, the larger the “inertia” needed to resist evic-

³If the cost is defined as the latency, then it is not readily available. It can be estimated in a similar way as that of [23].

tion. Since the access frequency of a new popular object always starts from scratch, it has no fair chance to stay in the cache *unless* its access frequency is maintained even when the object itself is temporarily evicted.

In the remainder of this paper, we use the term “Popular Objects” to refer to the set of objects for which access frequencies are maintained at the proxy at any particular point in time. Also, we use the term “Cached Objects” to refer to the set of objects cached at the proxy at any particular point in time. Note that “Cached Objects” are a subset of “Popular Objects”, which are in turn a subset of all objects in the request stream.

Efficient Management of Meta Information: To support an efficient search for meta information associated a given URL, a hash table (on the URL) can be used. As explained earlier, we maintain entries in this hash table for only Popular Objects. To that end, we employ a replacement policy that evicts the least frequently accessed entry. A faithful implementation of such a policy would require the maintenance of a queue with access frequency as the key. This results in an $O(\log n)$ time cost for each replacement, which is expensive. Fortunately, since there is a significant number of entries with identical frequency, a more efficient replacement policy is possible. Namely, by aggregating entries with the lowest frequency, our implementation selects the oldest such entry as a candidate for eviction. This implementation needs only $O(1)$ time for each replacement.

Frequency Computation: As described earlier, we need to keep track of the access frequency for Popular Objects. Keeping a reference count, while simple, may result in some inaccuracies. Below, we discuss two such inaccuracies and present the refinements adopted in our implementation.

We denote by $f_i(p)$ the access frequency estimate for object p after being accessed i times since its inclusion as a Popular Object.

Access frequency estimates are time varying. To account for this, a mechanism must be adopted to give preference to more recent references in predicating future ones. In our implementation, we use a decay function to de-emphasize the significance of past accesses. In particular, on the $(i + 1)$ -th reference to an object p , its frequency is iterated as:

$$f_{i+1}(p) = f_i(p) \times 2^{-t/T} + 1,$$

where t is the elapsed time since the last reference and T is a time constant that controls the rate of decay. In our experiments, we set $T = 2$ days.⁴

⁴The frequency value reflects the merit of keeping an object over a long period. The significance of past accesses should not decay too fast. As for the traces considered in our experiments, it is usually suitable to half the effect of a reference every at least one day.

The Zipf-like nature of the popularity distribution implies that there can be arbitrarily many accessed-once objects in a request stream. The probability of future accesses to such objects is very low. To account for this, a mechanism must be adopted that deemphasizes accesses made to unpopular objects. In our implementation, we discount the significance of the *first* access to an object. In particular, the weight of a first reference is set to $f_1 = 1/3$. This value was chosen because, in the traces we considered in our experiments, the fraction of objects that were referenced twice or more was around $1/3$.

4 Performance Evaluation

In this section we present the results of extensive trace-driven simulation experiments that we have conducted to evaluate the performance of GDSP.

4.1 Traces Used

In our trace-driven simulation experiments we used traces from DEC⁵ [12] and NLANR⁶ [18]. Some of the characteristics of these traces are shown in Table 1.

Traces	All requests	All unique files	HR_∞	BHR_∞
DEC: 29/8-4/9, 1996	3,543,968(44.9GB)	1,354,996(21.9GB)	48.7%	35.8%
NLANR site UC: 7/4-10/4, 1999	4,278,480(62.4GB)	1,464,799(30.7GB)	55.8%	50.1%

Table 1: Traces used in our simulations

Preprocessing on DEC Traces: Our preprocessing of the DEC traces followed the same procedures described in [7, 9]. In particular, we have excluded non-cache-able requests, including cgi-bin requests and queries. In addition, in our experiments, we count a request as a hit if the last modification times of the cached object and the actual reply to users are the same when both are known, or if the object size has not changed when both last modification times are unknown.

Preprocessing on NLANR Traces: Our preprocessing of the NLANR traces was more elaborate. The NLANR traces include many IMS (If-Modified-Since) and REFRESH requests with a

⁵In this paper we only present the results we obtained from the first week of the DEC trace (results from the other weeks were identical).

⁶We have run our simulations with traces from a multitude of NLANR proxy sites from April to July, 1999. Since the results of our simulations were similar across all sites, in this paper we only present the results we obtained from the UC trace.

reply code of “304” (Not Modified). In order to include such requests in the workload, we had to find the sizes of the objects of such requests. We do so through a 2-pass scanning of the entire trace.⁷ In addition to this preprocessing, we have also excluded non-cache-able requests, including cgi-bin requests and queries.

4.2 Algorithms and Performance Metrics

Our performance evaluation metrics reflect the various objectives of the proxy caching algorithms.

Performance Metrics: We considered three metrics: Hit Rate (HR), Byte Hit Rate (BHR), and Latency. Optimizing HR aims to maximize the fraction of all requests found in the cache. Optimizing BHR aims to minimize the total traffic between the proxy and servers. Optimizing latency aims to minimize the average response time perceived by end-users. To achieve these objectives, one must tune what a proxy perceives as the miss penalty (i.e., the “cost” of a miss). In particular, to optimize HR, one should treat all misses as having identical cost. We refer to this by the *constant cost* assumption. To optimize BHR, one should relate the miss penalty to the size of the missed object (in number of packets, defined as $2 + \frac{\text{size}}{536}$). We refer to this by the *packet cost* assumption. To optimize latency, one should relate the miss penalty to the latency of retrieving the missed object from the server. We refer to this by the *latency cost* assumption.

Simulated Algorithms: In our simulations, we compared GDSP to LRU, LFU, GDS, and GDSF algorithm. LRU and LFU were selected because they represent widely used policies that exploit fundamental characteristics of the request stream—LRU capitalizes on temporal locality of reference (i.e. recency of access) and LFU capitalizes on popularity (i.e. access frequency). In our simulations, we have elected to exclude algorithms that were known to be inferior to GDS as established in [9]. These include the SIZE-based, Hybrid [23], and LRV [17] algorithms. Given that GDSF [3] (like our proposed GDSP algorithm) is an extension of GDS, which enables it to account for access frequency, we have also included comparisons of GDSF and GDSP.

An important aspect of LFU is the policy used for eviction when two objects have the same access count. To that end, a *tie breaker* is necessary. In our simulations, the last access time is used as the tie breaker. This also means that to some extent the LFU algorithm considers access recency.⁸

⁷This process was 96%-successful in identifying cache-able requests. The remaining 4% were IMS and Refresh requests for which we were unable to identify the object sizes.

⁸It is not clear whether different tie breakers lead to the different performance between the LFU algorithms in [7] and this paper(both are In-Cache LFU). Even if no tie breaker is used, the hit rates of LFU in our experiments were not as low as those in [7].

GDS is a family of algorithms, each with a different definition of *cost*. Three versions of the GDS algorithm, GDS(1), GDS(packets), and GDS(latency) are simulated, reflecting the constant cost, packet cost, and latency cost assumptions described above. Clearly, if the cost of transferring each byte is the same (i.e. retrieval cost is proportional to object size), then the GDS algorithm degenerates into LRU. This implies that the performance of GDS(packets) will be close to that of LRU since the number of packets is roughly proportional to the object size.

Similar to GDS, we also consider three versions of our GDSP algorithm—namely, GDSP(1), GDSP(packets), and GDSP(latency), and of the GDSF algorithm—namely, GDSF(1), GDSF(packets), and GDSF(latency).

4.3 Performance under the Constant Cost Assumption

First, assume that objects have the same cost. We compare LRU, LFU, GDS(1), and GDSP(1). Figure 2 gives the hit rates (y-axis) for these algorithms as a function of the cache size (x-axis, logarithmic scale). We show HR_∞ and BHR_∞ as an upper bounds on performance when the cache size approaches ∞ .

For the DEC trace, LFU and LRU have the lowest HR. Their performance is far worse than GDS(1) and GDSP(1)—e.g. when cache size is 1GB, LRU’s HR is 35.4% and LFU’s HR is 36.0% while both GDS(1) and GDSP(1) obtain about 44%. This is because LRU and LFU are not sensitive to object sizes. The BHR of LFU is low when the cache size is small; it increases the fastest when cache size increases. This may be due to two reasons: (1) when cache size is larger, frequently accessed objects have a better chance of being hit again, thus increasing their likelihood of staying in the cache, and (2) Since LFU uses the last access time as a tiebreaker, a larger cache allows LFU to benefit from temporal locality of reference.

GDSP(1) is consistently better than GDS(1), especially when the cache is small. GDS(1) has a lower BHR. This is not surprising since GDS(1) favors small files independent of their popularity—thus, a large popular object stands no chance of being cached under GDS(1). GDSP(1), on the other hand, achieves superior HR without significant degradation in BHR. This is the result of GDSP’s sensitivity to access frequency, which enables it to cache large popular files.

For the NLANR trace, the results are similar.⁹ The HR of GDSP(1) is consistently the highest. Its BHR is lower than LFU only when the cache is very large, but much higher than GDS(1). The disadvantage of GDS(1) in BHR is more obvious for this trace. Another difference is the consistently better performance of LFU when compared to LRU. This is probably due to the

⁹For the NLANR trace, we do not count a REFRESH request as a hit since the proxy must contact the server. However, we count the bytes hit since a server’s 304 reply does not lead to an object transfer. This assumption does not change the relative performance of the algorithms in simulations.

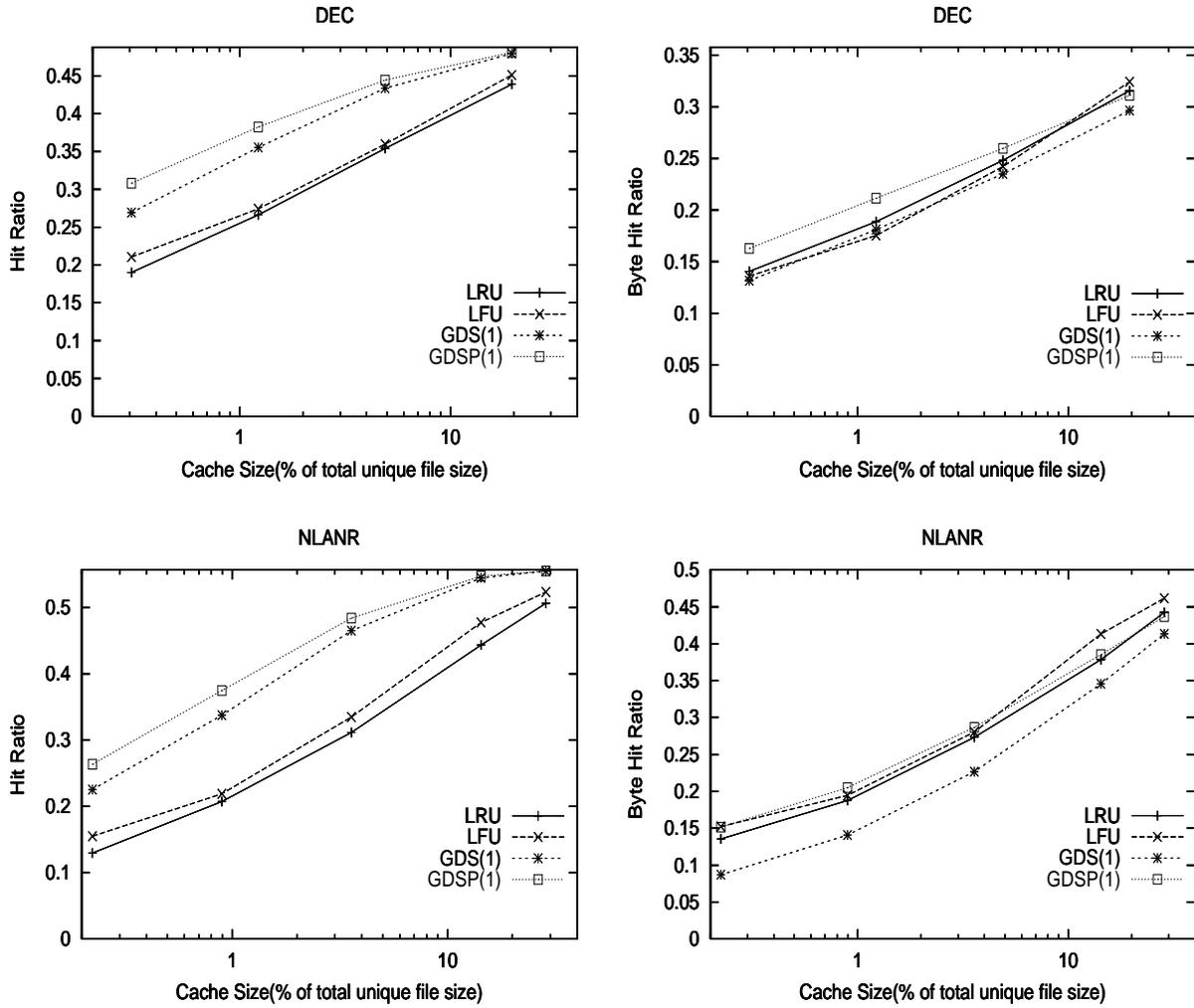


Figure 2: Hit rates of the algorithms under the constant retrieval cost assumption

weaker temporal locality in the NLANR trace (compared to the DEC trace). This weakening in temporal locality (from 1996 to 1999) is in line with the findings in [5]. Also, this weakening may be due to the diversity of users of upper-level NLANR proxies (such as the UC proxy).

To summarize, when HR is the main objective, GDSP(1) outperforms GDS(1) without significantly compromising BHR.

4.4 Performance under the Packet Cost Assumption

Figure 3 shows the hit rates when the cost is the number of packets transferred. Figure 4 shows the number of packet transfers due to the various algorithms. We compare LRU, LFU, GDS(packet),

and GDSP(packets).¹⁰

For the DEC trace, the hit rates for both GDS(packets) and LRU are close. This is because when the cost is roughly proportional to object size, GDS(packets) is nearly equal to LRU. GDSP(packets) consistently outperforms the others—both in terms of hit rates and packet transfers. The relative BHR improvement of GDSP(packets) over GDS(packets) and LRU is as much as 15%. The relative HR improvement is as much as 30% (when the cache is small).

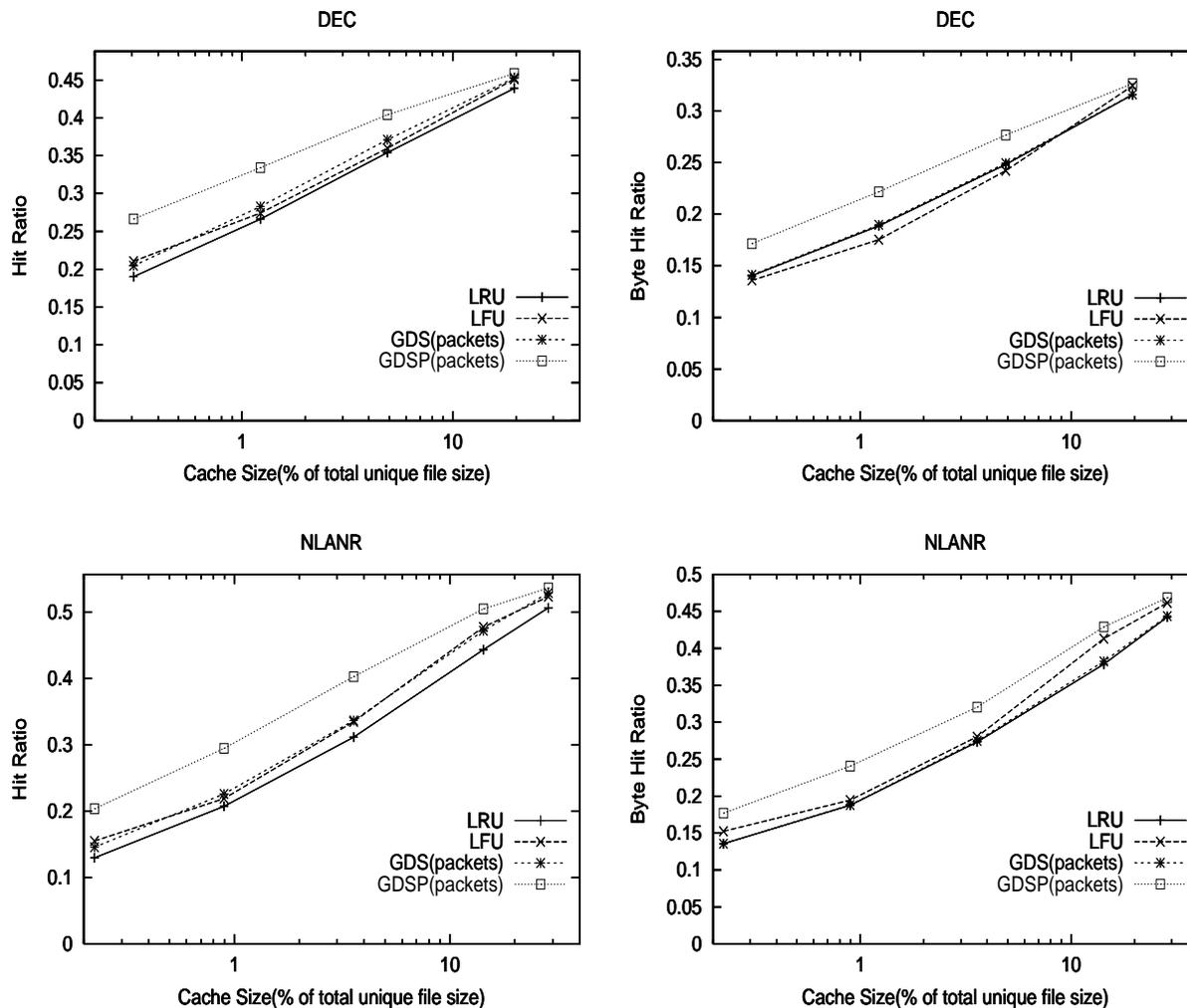


Figure 3: Hit rates of the algorithms under the packet cost assumption.

For the NLANR trace, the results are similar. The BHRs of GDS(packets) and LRU are nearly equal. GDS(packets) outperforms LRU slightly with respect to HR. This difference is due to the fact that $\frac{cost}{size}$ is not an exact constant and GDS(packets) slightly favors small objects, resulting in increased hits. LFU is closest to GDSP(packets) when the cache is large. LFU does well due to the weak temporal locality.

¹⁰The curves of LRU and LFU are actually the same as those in Figure 2.

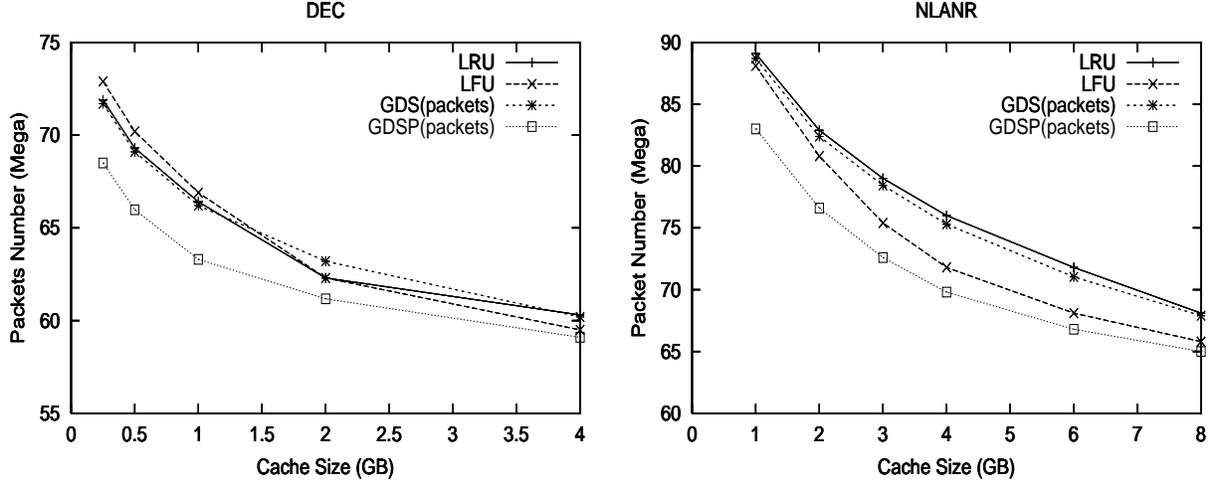


Figure 4: Number of Packets Transferred

When cache size is larger than 4% of the total unique file size, GDSP(packets) is superior to GDS(packets) along several performance metrics. The relative improvement with respect to HR and BHR is 20% and 17%, respectively.¹¹ GDS(packets) needs a significantly larger cache to obtain the same HR and BHR of GDSP(packets).¹² GDS(packets) produces 8% more packets on the network for the same traces and same cache size as shown in Figure 4 (right).¹³

4.5 Performance under the Latency Cost Assumption

The retrieval delay for fetching an object from a remote server can be modeled by $c(p) = t_{conn} + t_{byte} \times s(p)$, where t_{conn} is the time to establish the connection and t_{byte} is the average time to transfer a byte. We simply estimate these two parameters for all servers in the trace, instead of determining these parameters for each server separately.¹⁴ We do so by computing the average delay for objects of different sizes and estimating the parameters with *least square fit*. For the DEC trace, we computed $t_{conn} \approx 1.5secs$, and $t_{byte} \approx 0.00021sec/byte$. For the NLNR trace, we computed $t_{conn} \approx 1.7secs$, and $t_{byte} \approx 0.00013sec/byte$.

Figure 5 shows the latency reduction for both the DEC and NLNR traces under LRU,

¹¹For example, for the NLNR trace, when cache size is 1GB, the HR and BHR of GDS(packets) are 33.7% and 27.5%, respectively, whereas those of GDSP(packets) are 40.3% and 32.1%, respectively; When cache size is 4GB, the BHR of our algorithm is 42.9%, compared with 38.2% of GDS(packets).

¹²GDS(packets) needs 2.1GB cache to obtain HR 40.3% and 1.8GB cache to obtain BHR 32.1%.

¹³When cache size is 1GB, GDS(packets) needs 88.6M packets while GDSP(packets) needs 83.0M packets; when cache size is 4GB, GDS(packets) needs 75.2M packets while GDSP(packets) needs only 69.8M packets.

¹⁴We had originally attempted to compute these parameters on a per-server basis using the techniques proposed in [23] and used in [9]. However, our findings revealed wide inaccuracies. We suspect that these inaccuracies are due to the variability in network conditions as observed in [11] and server load conditions as observed in [6].

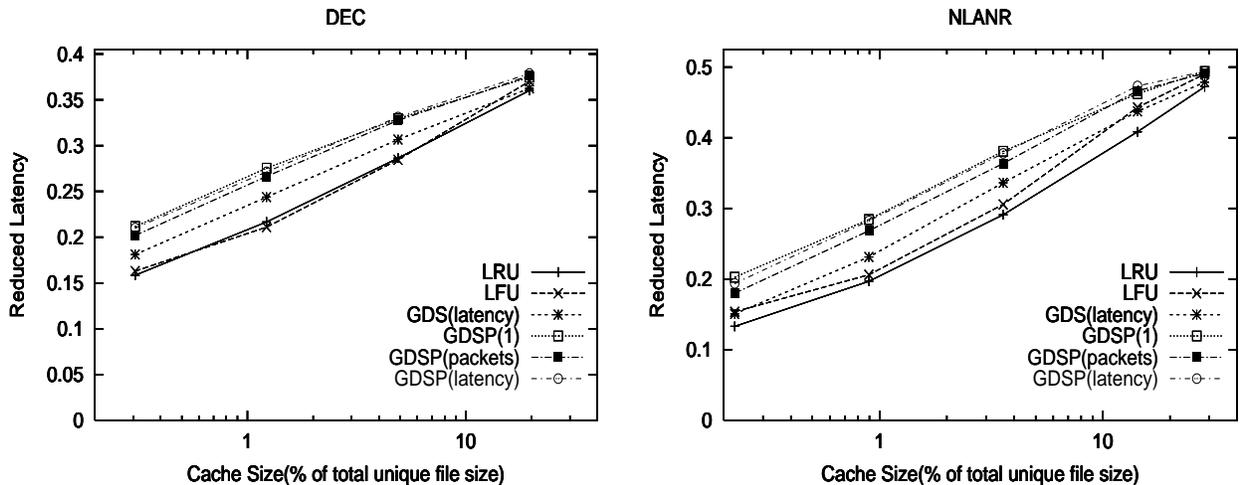


Figure 5: Latency reduction versus cache size for various cache replacement algorithms

LFU, GDS(latency), and the three versions of GDSP. The results show that latency reduction is minimal for LRU and LFU. All three versions of GDSP clearly outperform GDS(latency). The three versions have nearly the same performance except that GDSP(packets) is slightly worse.

4.6 Comparison to GDSF

As suggested in [3] and [16], a simple generalization of the GDS algorithm uses the exact access count as $f(p)$ in our algorithm and does not maintain a popularity profile for accurate frequency computation. This algorithm is called GDSF in [3] and GD-LFU in [16]. Studies have shown that this algorithm outperforms GDS. In this section we compare GDSF and GDSP.

Figure 6 gives the hit rates of GDSF(1), GDSF(packets), GDSP(1), and GDSP(packets) for the NLNR trace. The results are similar for the DEC trace and are not included here for space limitations. As evident from Figure 6, the GDSP algorithms consistently outperform the corresponding GDSF algorithms, which in turn are only slightly better than the corresponding GDS algorithms. These findings confirm the value of GDSP’s popularity profile maintenance techniques.

5 Summary

Popularity information is an important factor for effective Web cache replacement policies. In this paper, we presented an on-line policy that effectively captures and maintains an accurate popularity profile of Web objects requested through a caching proxy and designed a novel cache replacement algorithm that utilizes such information. To exploit temporal locality exhibited in the Web traffic as well as to avoid cache pollution by previously popular objects, the algorithm

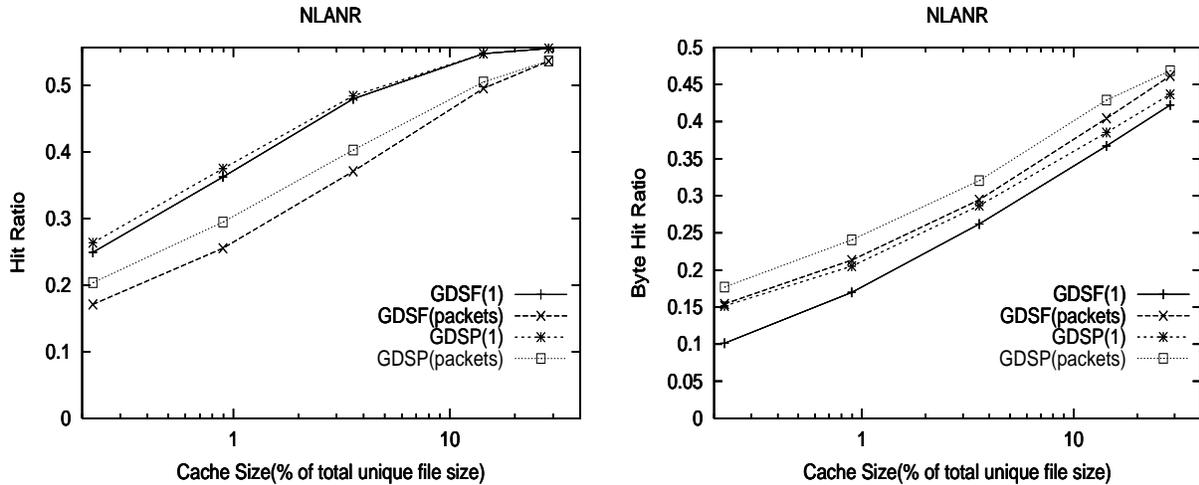


Figure 6: Performance of GDSP versus GDSF

generalizes GreedyDual-Size by incorporating frequency information. A popularity profile of Web objects requested through the proxy is maintained effectively, which makes it possible to accurately estimate the long-term access frequency. Our performance evaluation using extensive trace-driven simulations quantified the benefits and established the superiority of our proposed algorithm.

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