A Data-Mining-Based Prefetching Approach to Caching For Network Storage Systems

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Abstract:

The need for network storage has been increasing at an exponential rate owing to the widespread use of the Internet in organizations and the shortage of local storage space due to the increasing size of applications and databases. Proliferation of network storage systems entails a significant increase in the amount of storage objects (e.g., files) stored, the number of concurrent clients, and the size and number of storage objects transferred between the systems and their clients. Performance (e.g., client perceived latency) of these systems becomes a major concern. Previous research has explored techniques for scaling-up of the number of storage servers involved to enhance the performance of network storage systems. However, adding servers to improve system performance is an expensive solution. Moreover, for a WAN-based network storage system, the bottleneck for its performance improvement typically is not caused by the load of storage servers but by the network traffic between clients and storage servers. This paper introduces an Internet-based network storage system named NetShark and proposes a caching-based performance enhancement solution for such a system. The proposed performance enhancement solution is validated using a simulation. Three major contributions of this paper are: (1) we have built a caching-based network storage system to expand storage capacities and to enhance access performance of system users; (2) we have proposed and shown that a data-mining-based prefetching approach outperformed other popularly applied caching approaches; (3) we have developed a network storage caching simulator to test the performance of different caching approaches.

(*Caching*; *Data Mining*; *Simulation*; *Network Storage System*)

1. Introduction

The need for network storage has been increasing at an exponential rate owing to the widespread use of the Internet in organizations and the shortage of local storage space due to the increasing size of applications and databases (Gibson and Meter 2000). Proliferation of network storage systems entails a significant increase in the amount of storage objects (e.g., files) stored, the number of concurrent clients, and the size and number of storage objects transferred between the systems and their clients. Performance (e.g., client perceived latency) of these systems becomes a major concern.

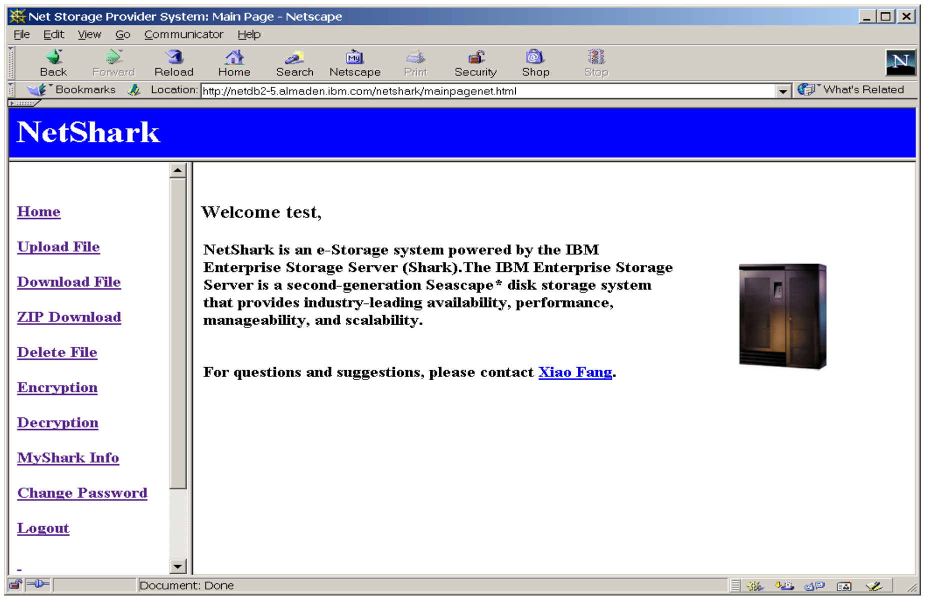
Previous research (Lee and Thekkath 1996, Thekkath et al. 1997) has explored techniques for scaling-up of the number of storage servers involved to enhance the performance of network storage systems. These techniques worked well for LAN-based network storage systems as increasing storage servers decreased the load for each server. However, adding servers to improve system performance is an expensive solution. Moreover, for a WAN-based network storage system, the bottleneck for its performance improvement typically is not caused by the load of storage servers but by the network traffic between clients and storage servers. A cost-effective way to improve its performance is to distribute storage servers and cache copies of storage objects at storage servers near the clients who request them (i.e., migrate copies of storage objects from storage servers that store them to storage servers near the clients who request them) (Gwertzman and Seltzer 1995, Barish and Obraczka 2000). This paper introduces an Internet-based network storage system named NetShark and proposes a caching-based performance enhancement solution for such a system. Three major contributions made by this paper are:

- We have built a caching-based network storage system to expand storage capacities and to enhance access performance of system users.
- We have proposed and shown that a data-mining-based prefetching approach outperformed other popularly applied caching approaches. Applications of the proposed caching approach include network storage caching as well as general-purposed web caching.
- We have developed a network storage caching simulator based on general and proven characteristics of trace logs (e.g., FTP logs) to test the performance of different caching approaches. Applications of this simulator are not limited to network storage caching. The simulator can be easily adapted to test different web caching algorithms.

The rest of the paper is organized as follows. Features, implementation, architecture and performance measurements of NetShark are briefly described in Section 2. We review related research in Section 3 and propose a data-mining-based prefetching approach in Section 4. Section 5 presents the simulator used to evaluate the performance of the proposed caching approach. We summarize and discuss the simulation results in Section 6 and conclude the paper with a summary and suggested future directions in Section 7.

2. Overview of NetShark

In this section, we briefly introduce features, implementation, architecture and performance measurements of NetShark. Shark is a second generation IBM Enterprise Storage Server[1] with a maximum storage capacity of 11TB. NetShark is an Internet-based network storage system built on Sharks and provides storage services to users at both IBM and the University of Arizona. By providing university users with extra storage space through Internet, NetShark strengthens the shared IBM and university goals of providing better supports for online learning communities. Besides routine functionalities, such as file transfer, file management and user management, NetShark also provides file compression functionality, which allows users to compress files before transferring them, and file encryption functionality, which enables users to encrypt critical files. Figure 1 shows a screen shot of NetShark installed at the IBM Almaden Research Center.


Net Storage Provider System: Main Page - Netscape
File Edit View Go Communicator Help
Back Forward Reload Home Search Netscape Print Security Shop Stop
Bookmarks Location: http://netdb2-5.almaden.ibm.com/netshark/mainpagenet.html
What's Related
NetShark
Home
Upload File
Download File
ZIP Download
Delete File
Encryption
Decryption
MyShark Info
Change Password
Logout
Document: Done

Welcome test,

NetShark is an e-Storage system powered by the IBM Enterprise Storage Server (Shark).The IBM Enterprise Storage Server is a second-generation Seascape* disk storage system that provides industry-leading availability, performance, manageability, and scalability.

For questions and suggestions, please contact Xiao Fang.

Figure 1: A Screen Shot of NetShark

[1] IBM Enterprise Storage Server is a copyrighted IBM product.

As shown in Figure 2, the implementation of NetShark consists of three layers: presentation layer, application layer, and storage layer. NetShark was designed to be accessed easily anywhere in the world. Therefore, we chose web browsers (e.g., Netscape) as its presentation tool. Apache web server was selected as the web server of NetShark for handling HTTP requests from clients and delivering HTTP responses to clients. The application layer consists of Java servlets managed by WebSphere[2] and a database maintained by DB2[3], namely Log-DB. The application layer is responsible for user authentication, transaction processing and session management. In addition to web logs collected by the Apache web server, all transactions between clients and NetShark are recorded in Log-DB. Some critical information missing in web logs (Colley et al. 1999), such as session identification, are stored in Log-DB. Log-DB provides an ideal source for the data-mining-based prefetching approach to be described in Section 4. The storage layer is located in Sharks and communicates with the application layer through SCSI protocol.

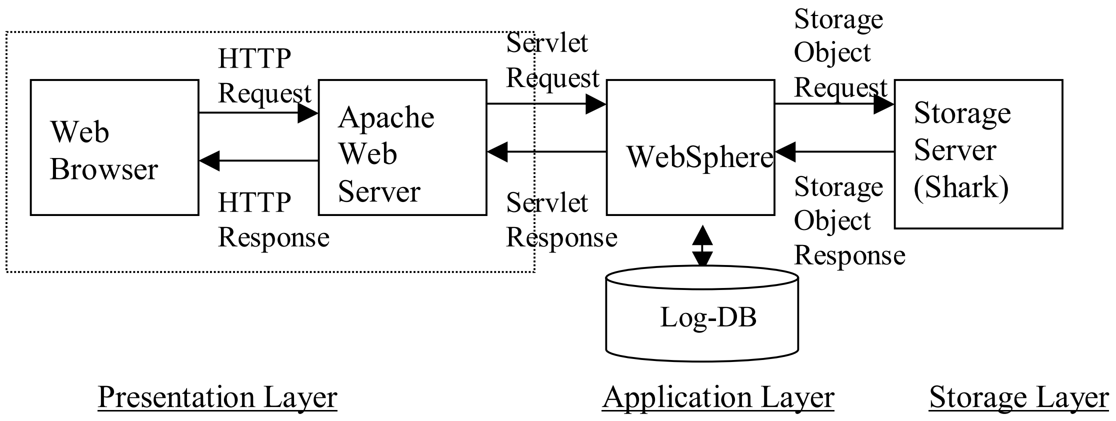


Figure 2: The Three-Layer Implementation Structure of NetShark

[2,3] WebSphere and DB2 are copyrighted IBM products.

NetShark employs a geographically distributed network storage architecture in which Sharks are distributed in several geographically separated regions where their clients reside. We name a Shark placed in a client's region the Home Shark of the client. To reduce client perceived latency and to balance workloads among Sharks, clients' requests are always routed to and responded from their Home Sharks. If a storage object requested is not stored in a client's Home Shark, a copy of the object will be cached to the Home Shark from the Shark that contains the object (hereafter called the Storage Shark).

Figure 3 offers an example of the NetShark architecture. In this example, NetShark hosts a Knowledge Management System (KMS) which consists of modular knowledge objects in various file and storage formats. Clients of the KMS are distributed in three geographically separated regions, New York, San Jose and Tucson. Sharks distributed in New York, San Jose and Tucson are denoted as Shark NYC, Shark SJC and Shark TUS respectively. A logical scenario of storage distribution could allocate the operating system knowledge objects to Shark NYC, the database knowledge objects to Shark SJC and the storage server knowledge objects to Shark TUS. In addition to serving as the Storage Sharks of the KMS, these three Sharks are also the designated Home Sharks for the clients in their located regions. When clients in Tucson request remote objects stored at Shark SJC, the requested objects will be cached from Shark SJC to the clients' Home Shark, Shark TUS, and remain in Shark TUS until other cached objects replace them. In this example, clients connect to their Home Sharks through Intranet/Internet and Sharks are connected using Public Switched Data Network (PSDN), a popular and high-performance way to connect servers in different regions.

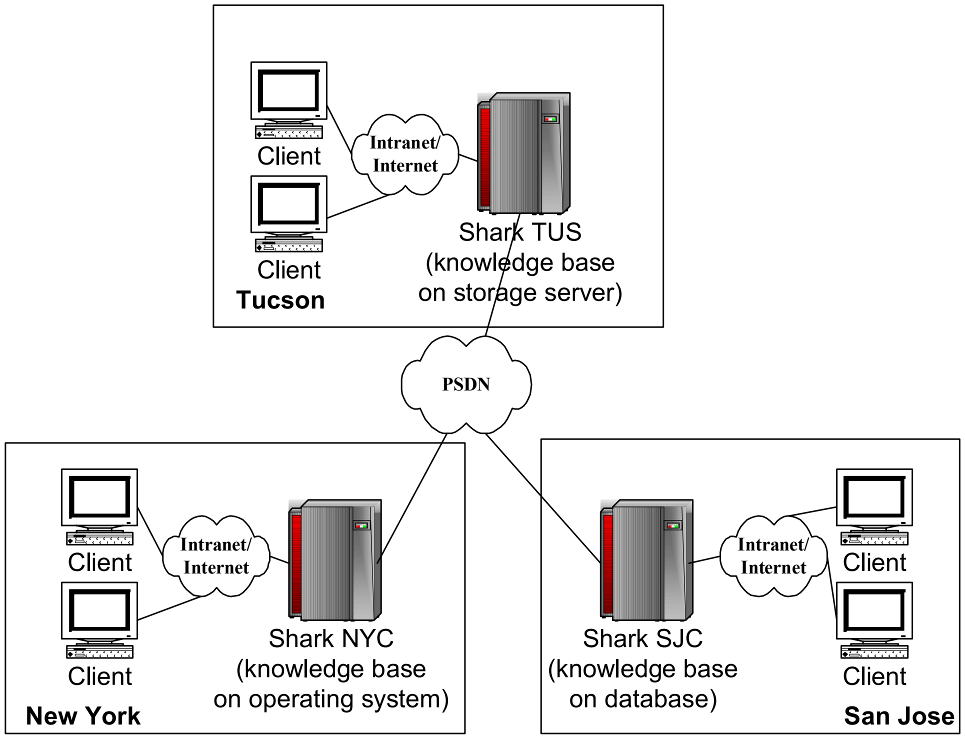

Client
Intranet/ Internet
Client
Shark TUS (knowledge base on storage server)
Tucson
PSDN
Client
Intranet/ Internet
Client
Shark NYC (knowledge base on operating system)
New York
Shark SJC (knowledge base on database)
Intranet/ Internet
Client
Client
San Jose

Figure 3: The Geographically Distributed Network Storage Architecture of NetShark

To compare different caching approaches for NetShark, we introduced three performance measurements for NetShark: client perceived latency, hit rate and Shark-Shark response time. Client perceived latency and hit rate are popular performance measurements for web caching.

Measurement 1: Client perceived latency[4] refers to the delay between the time when a client submits a storage object request and the time when the storage object is received by the client.

Retrieving storage objects directly from clients' Home Sharks saves the time of transferring these storage objects from their Storage Sharks to clients' Home Sharks.

[4] Client perceived latency is equivalent to response time in the distributed computing literatures.

Therefore, increasing the number of storage object requests that can be directly fulfilled from Home Sharks reduces client perceived latency.

Measurement 2: Hit rate, $hr = \frac{n_{\mathrm{home}}}{n_{req}}$, is used to measure the capability that Home Sharks can directly respond to storage object requests. Here n_{home} is the number of storage object requests that can be directly fulfilled from Home Sharks and n_{req} is the total number of storage object requests.

Measurement 3: To measure the impact of network traffic between Sharks, Shark-Shark response time is the length of the interval between the time when a Shark submits a storage object request to a remote Shark and the time when the storage object is received by the requesting Shark.

3. Related Work

In this section, we review research on web caching[5] on which our caching solution is based. Web caching is the temporary storage of web objects for later retrieval (Barish and Obraczka 2000). Major issues in web caching include what web objects need to be cached, how to replace old web objects when there is not enough space for newly cached web objects and how to keep consistency among copies of web objects. According to the aforementioned issues, web caching research can be divided into three parts: caching, replacement and consistency.

[5] There have been research on file migration for hierarchical storage management and distributed systems since 1970s (e.g., Liu Sheng 1992). Lots of past research results have been incorporated into web caching. Here, we present a review on web caching research related to this paper.

Caching

A simple caching approach, namely caching on demand, only caches currently requested web objects. More efficient caching approaches, prefetching approaches, cache both currently requested web objects and web objects predicted to be requested in the near future (Kroeger et al. 1997). Popularity-based prefetching approaches (Dias et al. 1996, Markatos and Chronaki 1998, Kim et al. 2000) predicted and prefetched future requested web objects based on their past request frequencies. Another type of prefetching approaches discovered and utilized access relationships between web objects in making prefetching decisions (Padmanabhan and Mogul 1996, Horng et al. 1998, Fan et al. 1999). For example, Padmanabhan and Mogul (1996) modeled access relationships between web objects using a dependency graph. In the dependency graph, nodes represented web objects and arcs between nodes represented access relationships between web objects (i.e., how likely one web object will be requested after another web object). Chinen and Yamaguchi (1997) proposed a different approach to predicting and prefeching future requested web objects based on structural relationships between web objects. The proposed approach parsed HTML files and prefetched embedded images and web objects pointed to by embedded links. However, the approach greatly increased network traffic between servers and proxies and it is not practical to prefetch web objects solely using the approach.

It had been shown in (Padmanabhan and Mogul 1996, Crovella and Barford 1998) that prefetching approaches increased network traffic between servers and proxies, which could impact client perceived latency negatively. However, none of the past prefetching approaches has addressed the network traffic increase problem. In (Padmanabhan and

Mogul 1996, Horng et al. 1998, Fan et al. 1999), access relationships between web objects were extracted based on an arbitrarily chosen look-ahead window and these approaches neglected session – a natural unit to extract access relationships between web objects. Aware of the limitations of the past prefetching approaches, the proposed prefetching approach will:

- predict and prefetch future requested objects based on sequential object request patterns within sessions and between sessions;
- divide future requested objects into two categories, urgent and wait, and cache objects in the urgent category immediately while cache objects in the wait category when the network traffic is below a user-defined threshold.

Replacement

Least-Recently-Used (LRU) and Least-Frequently-Used (LFU) are two widely used cache replacement approaches. LRU is concerned with recency of object requests, while LFU is concerned with frequency of object requests. LRU, which was previously used for page replacement in memory management (Tanenbaum and Woodhull 1997), is based on the observation that web objects that have been heavily requested recently will probably be heavily requested in the near future. Conversely, web objects that have not been used for ages will probably remain unused for a long time. Hence, the web object that have not been used for the longest time is replaced by LRU. LFU replaces the web object with the least request frequency. Cache replacement approaches proposed in (Cao and Irani 1997, Jin and Bestavros 2000) considered the cost of transferring a copy of web object from a server to a proxy, namely cache cost. Obviously, it is desirable to replace the web object with the lowest cache cost, if everything else is equal. We adopt LRU, a widely used replacement approach, in NetShark. Description of LRU can be found in lots of literatures, such as (Tanenbaum and Woodhull 1997), and is not included.

Consistency

There are two types of cache consistency approaches: weak cache consistency and strong cache consistency (Cao and Liu 1998). Weak cache consistency approaches might return stale web objects to users while strong cache consistency approaches guarantee to return up-to-date web objects to users. Client polling and TTL (i.e., time to live) are weak cache consistency approaches (Barish and Obraczka 2000). With client polling, cached objects are periodically compared with their original copies. Out-of-date cached objects are dumped and their newest versions are fetched. In TTL, each cached object has a time to live (TTL). When expired, these objects are discarded and their newest versions are fetched. Invalidation callback is a strong cache consistency approach (Barish and Obraczka 2000). It requires a server to keep track of all the cached objects. The server will notify all the proxies to invalidate their copies if the original object has been modified in the server. It has been shown in (Cao and Liu 1998) that strong cache consistency approaches can be realized with no or little extra cost than weak cache consistency approaches. We adopt a strong cache consistency approach, the invalidation callback approach, to maintain consistency among storage objects in NetShark. Description of the approach can be found in (Barish and Obraczka 2000) and is not included.

4. A Data-Mining-Based Prefetching Approach

Similar to web caching, major issues in network storage caching include what storage objects need to be cached (i.e., caching), how to replace old storage objects when there is not enough space for newly cached storage objects (i.e., replacement) and how to keep consistency among copies of storage objects (i.e., consistency). For NetShark, we propose a data-mining-based prefetching approach as the caching approach and we adopt LRU and invalidation callback as replacement and consistency approaches respectively.

The proposed prefetching approach consists of two algorithms: offline learning and online caching. Client request patterns are extracted from Log-DB periodically, using the offline learning algorithm. Based on the patterns extracted, the online caching algorithm caches storage objects. Table 1 summarizes the important notations to be referenced in Sections 4 and 5.

Table 1: Notation Summary

Notation	Description
$p_{\text{int}ra}$, $p^i_{\text{int}ra}$	an intra-session pattern
$P_{\text{int}ra}$	a set of intra-session patterns, where $p_{\text{int}ra} \in P_{\text{int}ra}$
$S(p_{\text{int}ra})$	the set of all storage objects in $p_{\text{int}ra}$
$p_{\text{int}er}$, $p^i_{\text{int}er}$	an inter-session pattern
$P_{\text{int}er}$	a set of inter-session patterns, where $p_{\text{int}er} \in P_{\text{int}er}$
$S(p_{\text{int}er})$	the set of all storage object sets in $p_{\text{int}er}$
SO, SO_i	a set of storage objects
so_d	the storage object on demand
so_r	a related storage object of so_d, predicted from intra/inter-session patterns
SO_S	the set of storage objects requested so far in a session , where $so_d \in SO_S$
$pattern(SO_S)$	an intra/inter-session pattern that contains SO_S

$Pattern(SO_S)$	the set of all intra/inter-session patterns that contain SO_S
$ti(so_r)$	the predicted time interval between so_d and so_r
$\sup(so_r)$	the support of so_r, which measures how likely so_r will be requested after so_d
$nw(so)$	the network over which a storage object, so, is transferred
$transfer(so, nw(so))$	the time to transfer a storage object, so, over network $nw(so)$, which can be calculated using (1)
$HD(nw(so))$	the average hop delay of network $nw(so)$
$HN(nw(so))$	the number of hops on network $nw(so)$
$D(nw(so))$	the distance of network $nw(so)$
$v(nw(so))$	the signal velocity of network $nw(so)$
$B(nw(so))$	the bandwidth of network $nw(so)$
$size(so)$	the size of a storage object, so
$slack(so_r)$	the slack value of so_r, which can be calculated using (2)
n_{NS}	the total number of storage objects in NetShark
SO_{NS}	the set of all storage objects in NetShark
$fre(so_i)$	the request frequency rate of so_i, where $so_i \in SO_{NS}$ for $i = 1,2,\cdots n_{NS}$
$fanout(so_i)$	the fan-out number of so_i, where $so_i \in SO_{NS}$ for $i = 1,2,\cdots n_{NS}$
$random(so_i)$	the random factor of so_i, where $so_i \in SO_{NS}$ for $i = 1,2,\cdots,n_{NS}$

4.1 The Offline Learning Algorithm

We briefly illustrate the structure of Log-DB before introducing the offline learning algorithm. A record in Log-DB has the following fields: ClientID, ClientIP, SessionID, FileName, FileType, FileSize and RequestTime. As shown in Table 2, critical fields for offline learning include ClientID, SessionID, FileName, and RequestTime, which respectively specify who requested which storage object (e.g., file) at what time and in which session. Here, a session is a sequence of storage object requests between a client's log-in and log-out of NetShark. It can be easily seen from Table 2 that a client (e.g., *CT1*) may have several sessions (e.g., *SN1* and *SN2*) and a session (e.g., *SN1*) may include several storage object requests (e.g., *A*, *B* and *C*).

Table 2: Critical Fields in Log-DB

ClientID	SessionID	FileName	RequestTime
CT1	*SN1*	*A*	*09:19:34 07/25/2001*
CT1	*SN1*	*B*	*09:20:34 07/25/2001*
CT1	*SN1*	*C*	*09:24:34 07/25/2001*
CT1	*SN2*	*F*	*10:57:34 07/25/2001*
CT1	*SN2*	*E*	*11:01:34 07/25/2001*
CT2	*SN3*	*F*	*09:57:34 07/25/2001*
CT2	*SN3*	*D*	*10:00:34 07/25/2001*
CT3	*SN4*	*A*	*09:29:34 07/25/2001*
CT3	*SN4*	*B*	*09:30:34 07/25/2001*
CT3	*SN4*	*C*	*09:32:34 07/25/2001*
CT3	*SN5*	*D*	*11:07:34 07/25/2001*
CT3	*SN5*	*E*	*11:09:34 07/25/2001*

Instead of an arbitrarily chosen lookahead window used in (Padmanabhan and Mogul 1996), the offline learning algorithm uses session as the basic processing unit to discover client request patterns. Two types of the patterns can be extracted from Log-DB: intra-session patterns P_{intra} and inter-session patterns P_{inter}.

Definition 1: An intra-session pattern, p_{intra}, where $p_{intra} \in P_{intra}$, reflects a request behavior within a session. It has the format: $\left\langle so_1 \xrightarrow[\text{time interval}]{} so_2 \cdots\cdots so_{n-1} \xrightarrow[\text{time interval}]{} so_n \ \text{support} \right\rangle$. Here $so_1, so_2, \cdots, so_n$ are storage objects requested within the same session. The time interval between two storage objects is the average time interval between the requests of the two storage objects in sessions where the pattern can be found. The support of an intra-session pattern is the fraction of sessions in which the pattern can be found.

For an intra-session pattern, p_{intra}, with the format $\langle so_1 \xrightarrow[\text{time interval}]{} so_2 \cdots\cdots so_{n-1} \xrightarrow[\text{time interval}]{} so_n \text{ support}\rangle$, we denote $S(p_{intra})$ as the set of all storage objects in it, i.e., $S(p_{intra}) = \{so_i\}$ for $i = 1,2,\cdots,n$.

Example 1: An intra-session pattern, $p_{intra} = \langle A \xrightarrow[\text{1 minute}]{} B \xrightarrow[\text{3 minutes}]{} C \ 0.4 \rangle$, can be discovered from the Log-DB example in Table 2. According to this pattern, storage objects A , B and C are sequentially requested within a session; such a pattern can be found in 40% (i.e., *SN1* and *SN4*) of the total sessions; and the average time intervals between the requests of A and B and between the requests of B and C are 1 minute and 3 minutes respectively. In this example, $S(p_{intra}) = \{A, B, C\}$.

Definition 2: An inter-session pattern, p_{inter}, where $p_{inter} \in P_{inter}$, reveals a request behavior between sessions. It has the format: $\langle SO_1 \xrightarrow[\text{time interval}]{} SO_2 \cdots\cdots SO_{n-1} \xrightarrow[\text{time interval}]{} SO_n \text{ support}\rangle$. Here $SO_1, SO_2 \cdots, SO_n$ are storage object sets requested in different sessions by the same client. The time interval between two storage object sets is the average time interval between the requests of the two storage object sets among clients demonstrating such a pattern. The support of an inter-session pattern is the fraction of clients demonstrating such a pattern.

For an inter-session pattern, p_{inter}, with the format $\langle SO_1 \xrightarrow[\text{time interval}]{} SO_2 \cdots\cdots SO_{n-1} \xrightarrow[\text{time interval}]{} SO_n \text{ support}\rangle$, we denote $S(p_{inter})$ as the set of all storage object sets in it, i.e., $S(p_{inter}) = \{SO_i\}$ for $i = 1,2,\cdots,n$.

Example 2: An inter-session pattern, $p_{inter} = \langle \{A, B\} \xrightarrow[\text{100 minutes}]{} \{E\}\, 0.66 \rangle$, can be learned from the Log-DB example in Table 2. According to this pattern, storage object sets *{A,B}* and *{E}* are sequentially requested in different sessions by the same client; 66% (i.e., *CT1* and *CT3*) of total clients demonstrate such a pattern; and the average time interval between the request of *{A,B}* and the request of *{E}* is 100 minutes (i.e., the average time interval between the request of B, the last requested storage object in *{A,B}*, and the request of *E*, the first requested storage object in *{E}*). In this example, $S(p_{inter}) = \{\{A, B\}, \{E\}\}$.

Both intra-session patterns and inter-session patterns can be extracted from Log-DB using sequential pattern mining. Agrawal and Srikant (1995) used a database of customer transactions to define sequential pattern mining. In this database, a customer had *k* transactions, where $k \geq 1$, and a transaction included the purchases of *m* items, where $m \geq 1$. As shown in the example in Table 3, each record in the database consists of customer-id, transaction-id, item-id and transaction-time. The database is sorted by increasing customer-id and then by increasing transaction-time.

Table 3: Customer Transactions For Sequential Pattern Mining

customer-id	transaction-id	item-id	transaction-time
CUST1	*T1*	*1*	*09:19:34 07/25/2001*
CUST1	*T1*	*2*	*09:19:34 07/25/2001*
CUST1	*T1*	*4*	*09:19:34 07/25/2001*
CUST1	*T2*	*5*	*11:21:34 07/26/2001*
CUST1	*T2*	*3*	*11:21:34 07/26/2001*
CUST2	*T3*	*1*	*09:29:34 07/25/2001*
CUST2	*T3*	*2*	*09:29:34 07/25/2001*
CUST2	*T4*	*6*	*10:21:34 07/28/2001*
CUST2	*T4*	*3*	*10:21:34 07/28/2001*
CUST3	*T5*	*8*	*13:21:34 07/30/2001*
CUST3	*T5*	*3*	*13:21:34 07/30/2001*

In sequential pattern mining, an itemset is a non-empty set of items. A sequence is an ordered list of itemsets and it reveals an inter-transaction purchasing behavior among customers. For example, $\{1,2\}$ is an itemset and $\langle\{1,2\},\{3\}\rangle$ is a sequence with the meaning that item 3 was purchased in a transaction after a transaction that had purchased items 1 and 2. A customer supports a sequence if and only if the sequence can be found in the transactions of the customer. The support of a sequence is defined as the fraction of total customers who support the sequence. For example, sequence $\langle\{1,2\},\{3\}\rangle$ is supported by customers *CUST1* and *CUST2* in the example given in Table 3 and its support is 66%. Sequential pattern mining is conducted to discover all large sequences, which are sequences with support larger than a user-defined threshold.

Before extracting intra/inter-session patterns from Log-DB, the database is sorted first by increasing ClientID and then by increasing RequestTime. Table 2 gives an example of a sorted Log-DB. To extract inter-session patterns from Log-DB, large sequences are discovered using sequential pattern mining. In this case, ClientID, SessionID and FileName in Log-DB (see Table 2) correspond to customer-id, transaction-id and item-id (see Table 3) respectively. Every large sequence discovered from Log-DB is an ordered list of storage object sets and it reveals an inter-session request behavior among clients. During the process of discovering large sequences, time intervals between storage object sets in sequences are calculated and incorporated into these sequences. The discovered large sequences with calculated time intervals are inter-session patterns.

To discover intra-session patterns, we create pseudo-transactions by assigning a Pseudo-TransactionID for each storage object request (i.e., each record) in Log-DB, as shown in Table 4. Similarly, large sequences are discovered using sequential pattern mining. In this case, SessionID, Pseudo-TransactionID and FileName in Log-DB (see Table 4) correspond to customer-id, transaction-id and item (see Table 3) respectively. Every large sequence discovered is an ordered list of storage object sets with only one element because each pseudo-transaction has only one storage object request. Large sequences discovered reveal inter-pseudo-transaction request behaviors among sessions (i.e., intra-session request behaviors). Similarly, time intervals between storage objects in sequences are calculated and incorporated into these sequences. The discovered sequences with calculated time intervals are intra-session patterns.

Table 4: Add the Pseudo-TransactionID Field Into Log-DB

ClientID	**SessionID**	**Pseudo-TransactionID**	**FileName**	**RequestTime**
CT1	*SN1*	*1*	*A*	*09:19:34 07/25/2001*
CT1	*SN1*	*2*	*B*	*09:20:34 07/25/2001*
CT1	*SN1*	*3*	*C*	*09:24:34 07/25/2001*
CT1	*SN2*	*4*	*F*	*10:57:34 07/25/2001*
CT1	*SN2*	*5*	*E*	*11:01:34 07/25/2001*
CT2	*SN3*	*6*	*F*	*09:57:34 07/25/2001*
CT2	*SN3*	*7*	*D*	*10:00:34 07/25/2001*
CT3	*SN4*	*8*	*A*	*09:29:34 07/25/2001*
CT3	*SN4*	*9*	*B*	*09:30:34 07/25/2001*
CT3	*SN4*	*10*	*C*	*09:32:34 07/25/2001*
CT3	*SN5*	*11*	*D*	*11:07:34 07/25/2001*
CT3	*SN5*	*12*	*E*	*11:09:34 07/25/2001*

We summarize the offline learning algorithm in Figure 4. We denote the number of records in Log-DB as n_{rec}. The offline learning algorithm includes four parts: sorting Log-DB, assigning Pseudo-TransactionID, discovering P_{inter} and discovering P_{intra}. Sorting Log-DB needs $O(n_{rec} \log n_{rec})$ time. Assigning Pseudo-TransactionID requires $O(n_{rec})$. During the discovery of P_{inter}, sequential pattern mining goes through Log-DB

α rounds, where α is determined by the maximum size of storage object sets and the maximum size of large sequences (Agrawal and Srikant 1995) [6]. Therefore, the time complexity of discovering P_{inter} is O($n_{rec} \times \alpha$). Usually, α is much less than n_{rec}. Hence, the time complexity of discovering P_{inter} is O(n_{rec}). Similarly, the time complexity of discovering P_{intra} is O(n_{rec}). Combining the time complexities of all these parts, the time complexity of the offline learning algorithm is $O(n_{rec} \log n_{rec})$. The main I/O cost of the algorithm is the I/O of Log-DB. Hence, the I/O cost of the algorithm is determined by such factors as the maximum size of storage object sets and the maximum size of large sequences.

```
Input:   Log-DB
Output: $P_{intra}$: intra-session patterns,
        $P_{inter}$: inter-session patterns.

sort Log-DB by increasing ClientID and then by increasing RequestTime;
assign a Pseudo-TransactionID for each storage object request (i.e., record) in Log-DB;
apply sequential pattern mining to Log-DB to discover $P_{inter}$;
apply sequential pattern mining to Log-DB to discover $P_{intra}$;
```

Figure 4 : The Offline Learning Algorithm

4.2 The Online Caching Algorithm

A storage object on demand, so_d, is one that currently has been requested by a client. The online caching algorithm caches so_d as well as its related storage objects, $\{so_r\}$, predicted from intra-session patterns (e.g., storage objects predicted to be requested right

[6] The maximum size of storage object sets and the maximum size of large sequences are determined by the minimum support threshold picked for sequential pattern mining.

after so_d within a session) and inter-session patterns (e.g., storage objects predicted to be requested in a session after the session requesting so_d). Although prefetching algorithms are more efficient than caching on demand (Kroeger et al. 1997), these algorithms have a well-known shortcoming of increasing network traffic between servers and proxies (e.g., between Sharks in NetShark) compared with caching on demand (Padmanabhan and Mogul 1996). The online caching algorithm addresses the network traffic increase problem by dividing related storage objects $\{so_r\}$ into two categories, urgent and wait, based on time intervals in intra/inter-session patterns. Related storage objects in the urgent category, denoted as $\{so_{r_u}\}$, where $\{so_{r_u}\} \subseteq \{so_r\}$, are cached immediately, while related storage objects in the wait category, denoted as $\{so_{r_w}\}$, where $\{so_{r_w}\} \subseteq \{so_r\}$, are cached when the network traffic between Home and Storage Sharks is below a user-defined threshold.

As shown in Figure 5, the online caching algorithm consists of five parallel procedures: Process_Requests, Predict_Related_Objects, Process_Urgent_Objects, Process_Wait_Objects and Transfer_Objects.

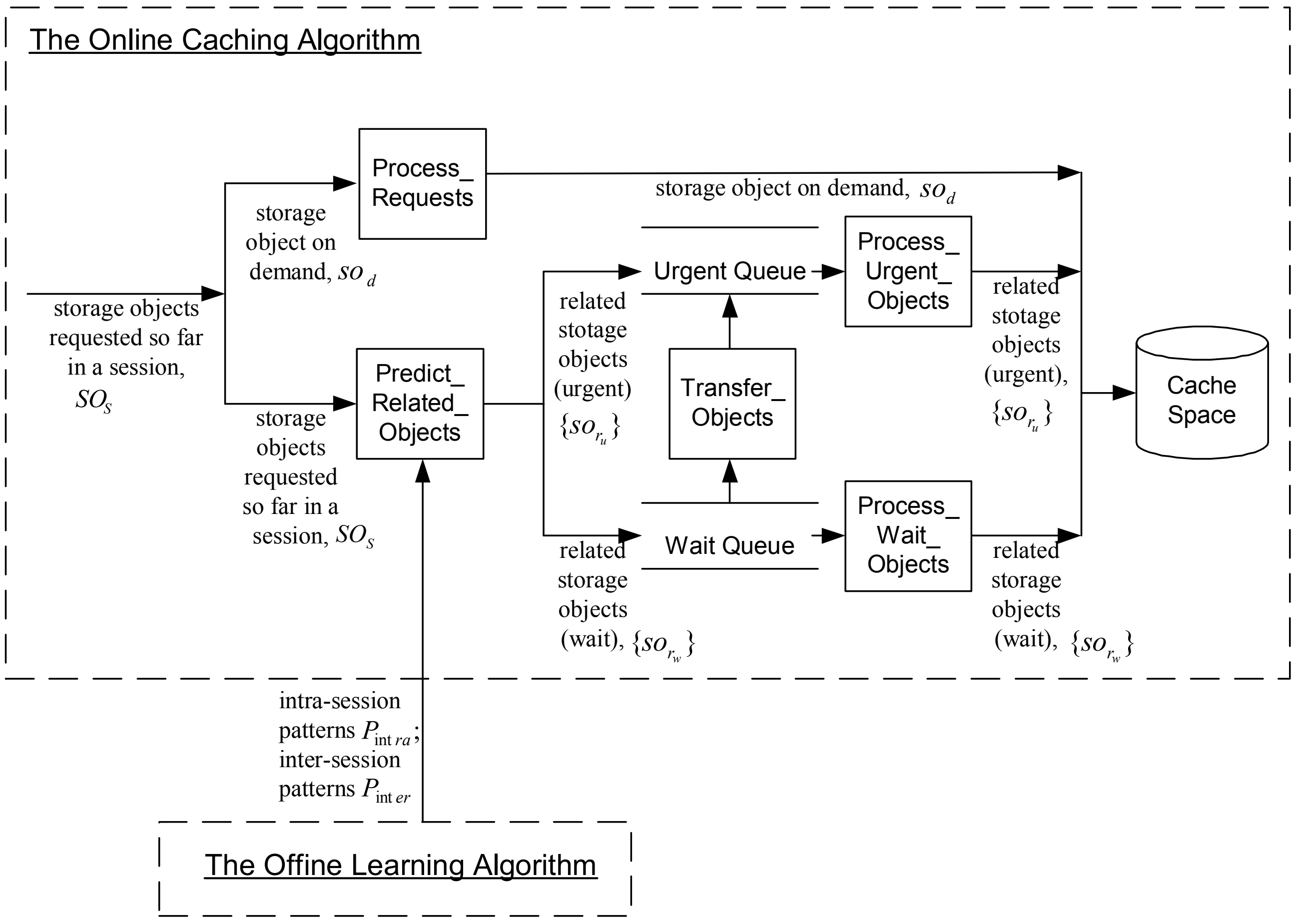

The Online Caching Algorithm
Process_ Requests
storage object on demand, so_d
storage objects requested so far in a session, SO_S
storage object on demand, so_d
Predict_ Related_ Objects
storage objects requested so far in a session, SO_S
related stotage objects (urgent) $\{so_{r_u}\}$
Urgent Queue
Process_ Urgent_ Objects
Transfer_ Objects
Wait Queue
Process_ Wait_ Objects
related storage objects (wait), $\{so_{r_w}\}$
related stotage objects (urgent), $\{so_{r_u}\}$
related storage objects (wait), $\{so_{r_w}\}$
Cache Space
intra-session patterns P_{intra}; inter-session patterns P_{inter}
The Offline Learning Algorithm

Figure 5: The Online Caching Algorithm

Procedure Process_Requests is triggered whenever there is a storage object request. It is responsible for returning the storage object on demand, so_d, to the requesting client. It also caches so_d if it is not in the Home Shark of the requesting client.

Procedure Predict_Related_Objects is also triggered by a storage object request. Input of the procedure includes the set of storage objects requested so far in a session, SO_S, which contains the storage object on demand, so_d, i.e. $so_d \in SO_S$, intra-session patterns P_{intra} and inter-session patterns P_{inter}. The procedure first predicts related storage objects

$\{so_r\}$ of so_d by searching for intra-session patterns $P_{\text{int}ra}$ and inter-session patterns $P_{\text{int}er}$ that contain SO_S.

Definition 3: SO_S is *contained* in an intra-session pattern, $p_{\text{int}ra}$, iff,

- $SO_S \subset S(p_{\text{int}ra})$;
- and the request sequence of storage objects in SO_S is the same as their request sequence in $p_{\text{int}ra}$.

Definition 4: SO_S is *contained* in an inter-session pattern, $p_{\text{int}er}$, iff $SO_S \in S(p_{\text{int}er})$.

We denote an intra/inter-session pattern that contains SO_S as $pattern(SO_S)$ and the set of all intra/inter-session patterns that contain SO_S as $Pattern(SO_S)$. The storage objects requested right after SO_S in $Pattern(SO_{cs})$ are related storage objects $\{so_r\}$ of so_d. Two attributes of a related storage object, so_r, $ti(so_r)$ and $\sup(so_r)$, can also be predicted from $Pattern(SO_S)$. $ti(so_r)$ is the predicted time interval between so_d and so_r, which is the time interval between so_d and so_r in the $pattern(SO_S)$ that includes so_r. $\sup(so_r)$ is the support of so_r, which measures how likely so_r will be requested after so_d. $\sup(so_r)$ is the support of the $pattern(SO_S)$ that includes so_r.

Example 3: Given the following intra/inter-session patterns:

$p^0_{\text{int}ra} : \langle B \xrightarrow[\text{2 minutes}]{} A \xrightarrow[\text{5 seconds}]{} I \;\; 0.08 \rangle$,

$p^1_{\text{int}ra} : \langle A \xrightarrow[\text{1 minute}]{} B \xrightarrow[\text{5 seconds}]{} C \xrightarrow[\text{1 minute}]{} K \; 0.12 \rangle$,

$p^2_{\text{int}ra} : \langle A \xrightarrow[\text{1 minute}]{} B \xrightarrow[\text{4 minutes}]{} F \;\; 0.1 \rangle$,

$p^0_{\text{int}er} : \langle \{A, B\} \xrightarrow[\text{100 minutes}]{} \{E, H\} \;\; 0.12 \rangle$, and

$p^1_{\text{int}er} : \langle \{D, F\} \xrightarrow[\text{10 minutes}]{} \{G\} \;\; 0.1 \rangle$,

if $SO_S = \{A, B\}, so_d = B$ and the request sequence of storage objects in SO_S is first A then B (i.e., $A \rightarrow B$), then SO_S is contained in $p^1_{\text{int}ra}$ by Definition 3, as,

- $SO_S \subset S(p^1_{\text{int}ra})$, where $S(p^1_{\text{int}ra}) = \{A, B, C, K\}$;
- the request sequence of storage objects in SO_S, $A \rightarrow B$, is the same as their request sequence in $p^1_{\text{int}ra}$.

Similarly, SO_S is also contained in $p^2_{\text{int}ra}$ by Definition 3. SO_S is contained in $p^0_{\text{int}er}$ by Definition 4, as $SO_S \in S(p^0_{\text{int}er})$, where $S(p^0_{\text{int}er}) = \{\{A, B\}, \{E, H\}\}$. Therefore, $Pattern(SO_S) = \{p^1_{\text{int}ra}, p^2_{\text{int}ra}, p^0_{\text{int}er}\}$. The storage objects requested right after SO_S in $p^1_{\text{int}ra}$, $p^2_{\text{int}ra}$ and $p^0_{\text{int}er}$ are *C*, *F*, *E* and *H*. Hence, $\{so_r\} = \{C, F, E, H\}$. From $Pattern(SO_S)$, we also get,

so_r	$ti(so_r)$	$\sup(so_r)$
C	5 seconds	0.12
F	4 minutes	0.1
E	100 minutes	0.12
H	100 minutes	0.12

Related storage objects $\{so_r\}$ are distributed into the urgent queue or the wait queue based on their slack values $slack(so_r)$. We introduce the follows before defining $slack(so_r)$. We denote $nw(so)$ as the network over which a storage object, so, is transferred. The time to transfer so over network $nw(so)$, $transfer(so, nw(so))$, can be calculated using the following formula (Dalley 2001).

$$transfer(so, nw(so)) = HD(nw(so)) \times HN(nw(so)) + \frac{D(nw(so))}{v(nw(so))} + \frac{size(so) \times 8}{B(nw(so))} \qquad (1)$$

Here $HD(nw(so))$ is the average hop delay of network $nw(so)$, $HN(nw(so))$ is the number of hops on network $nw(so)$, $D(nw(so))$ is the distance of network $nw(so)$, $v(nw(so))$ is the signal velocity of network $nw(so)$ (see Table 5 for some examples of $v(\cdot)$), $B(nw(so))$ is the bandwidth of network $nw(so)$ and $size(so)$ is the size of so.

Table 5: Signal Velocity of Different Media (Steinke 2001)

Medium	**Signal velocity (km/second)**
Phone line	160935
Copper (category 5)	231000
Optical fiber	205000
Air	299890

$slack(so_r)$ is defined using the following formula.

$$slack(so_r) = ti(so_r) - transfer(so_r, nw(so_r)) \qquad (2)$$

$nw(so_r)$ is the network over which so_r is transferred. In (2), $nw(so_r)$ refers to the network between the Storage Shark of so_r and the Home Shark of the client who could request so_r. $slack(so_r)$ reflects the degree of urgency to cache a related storage object so_r. Related storage objects with slack values less than or equal to 0 are placed in the urgent queue and need to be cached immediately; related storage objects with slack values larger than 0 are placed in the wait queue and cached when the network traffic between Home and Storage Sharks is below a user-defined threshold. Related storage objects in both urgent queue and wait queue are sorted by their descending supports (i.e., $\sup(so_r)$) then by their ascending slack values (i.e., $slack(so_r)$).

Example 4: For related storage objects, *C*, *E*, *F* and *H*, predicted in Example 3, $size(C) = 500\text{k bytes}$, $size(E) = 50\text{k bytes}$, $size(F) = 100\text{k bytes}$, $size(H) = 100\text{k bytes}$. Given the network over which these storage objects transferred, $nw(so_r)$, and its characteristics: $HD(nw(so_r)) = 0.015\text{ second}$, $HN(nw(so_r)) = 18$, $D(nw(so_r)) = 1000\text{ km}$, $v(nw(so_r)) = 231000\text{ km/second}$, $B(nw(so_r)) = 500\text{k bps}$, slack values of these storage objects can be calculated as follows:

$$transfer(C, nw(so_r)) = 0.015 \times 18 + \frac{1000}{231000} + \frac{500\text{k} \times 8}{500\text{k}} = 8.2743\text{ seconds}$$

$$slack(C) = ti(C) - transfer(C, nw(so_r)) = 5 - 8.2743 = -3.2743\text{ seconds}$$

Similarly,

$$slack(E) = ti(E) - transfer(E, nw(so_r)) = 5998.926\text{ seconds}$$

$$slack(F) = ti(F) - transfer(F, nw(so_r)) = 238.1257\text{ seconds}$$

$$slack(H) = ti(H) - transfer(H, nw(so_r)) = 5998.126\text{ seconds}$$

According to the slack values calculated, related storage object *C* is placed in the urgent queue while related storage objects *E*, *F* and *H* are put in the wait queue.

Procedure Predict_Related_Objects is summarized in Figure 6 below. The time complexity of the procedure is $O(n_{\text{intra}} + n_{\text{inter}})$, where n_{intra} is the number of intra-session patterns and n_{inter} is the number of inter-session patterns.

```
Event:  a storage object request /* event that triggers the procedure*/
Input:  $P_{\text{intra}}$ : intra-session patterns,
        $P_{\text{inter}}$ : inter-session patterns,
        $SO_S$ : the set of storage objects requested so far in a session,
            where $so_d \in SO_S$.

For each intra-session pattern $p_{\text{intra}}$, where $p_{\text{intra}} \in P_{\text{intra}}$
    If ( $SO_S$ is contained in $p_{\text{intra}}$ )
        $so_r$ = the storage object in $p_{\text{intra}}$ requested right after $SO_S$;
        If ( $so_r$ not in clients' Home Shark)
            calculate $slack(so_r)$;
            If ( $slack(so_r) \le 0$ ))
                urgent.add( $so_r$ ); /* add $so_r$ into the urgent queue */
            else
                wait.add( $so_r$ ); /* add $so_r$ into the wait queue */
            End if
        End if
    End if
End for
For each inter-session pattern $p_{\text{inter}}$, where $p_{\text{inter}} \in P_{\text{inter}}$
    If ( $SO_S$ is contained in $p_{\text{inter}}$ )
        $\{so_r\}$ = the storage object set in $p_{\text{inter}}$ requested right after $SO_S$;
        For each $so_r$, where $so_r \in \{so_r\}$
            If ( $so_r$ not in clients' Home Shark)
                calculate $slack(so_r)$;
                If ( $slack(so_r) \le 0$ ))
                   urgent.add( $so_r$ );/*add $so_r$ into the urgent queue*/
                else
                   wait.add( $so_r$ ); /* add $so_r$ into the wait queue */
                End if
            End if
        End for
    End if
End for
```

Figure 6 : Procedure Predict_Related_Objects

Procedure Process_Urgent_Objects is triggered whenever the urgent queue is not empty. The procedure caches related storage objects in the urgent queue, $\{so_{r_u}\}$. Procedure Process_Wait_Objects is triggered if the wait queue is not empty and the network traffic between Sharks is below a user-defined threshold. The procedure caches related storage objects in the wait queue, $\{so_{r_w}\}$. Procedure Transfer_Objects transfers a related storage object in the wait queue, so_{r_w}, to the urgent queue whenever its wait expiration time, $wet(so_{r_w})$, has passed the current system time. Here, $wet(so_{r_w})$ is calculated as:

$$wet(so_{r_w}) = \text{time}(so_d) + slack(so_{r_w}) \tag{3}$$

where $\text{time}(so_d)$ is the request time for the storage object on demand, so_d.

5. The Network Storage Caching (NSC) Simulator

Simulation is a major tool to evaluate different caching approaches (Davison 2001). Simulations used in previous caching research, such as (Kroeger et al. 1997), and simulators developed for caching performance evaluation, such as NCS (Davison 2001) and PROXIM (Feldmann et al. 1999), are trace-driven simulations based on specific trace logs. Using trace-driven simulations, it is hard to isolate, examine and explain the impacts of such system characteristics as the size of cache space on the performance of different caching approaches. Unlike trace-driven simulators, the NSC simulator is based on general and proven characteristics of trace logs and provides researchers with flexibility to manipulate parameters of these characteristics. Implemented using Csim18[7], the NSC simulator simulates how NetShark provides storage services for clients distributed in *m*

[7] Csim18 is a process-oriented, discrete-event simulation tool developed by Mesquite Software, Inc.

geographically separated regions. At the beginning of a simulation run, storage objects are randomly allocated to *m* Sharks.

As shown in Figure 7, the NSC simulator simulates request generation and three types of servers: Client-Shark network, Shark and Shark-Shark network. There may be more than one server in each server type. These servers serve requests and deliveries of storage objects according to the First-Come-First-Served (FCFS) queuing discipline. In Section 5.1, we explain the request generation model and Section 5.2 describes the server queuing models.

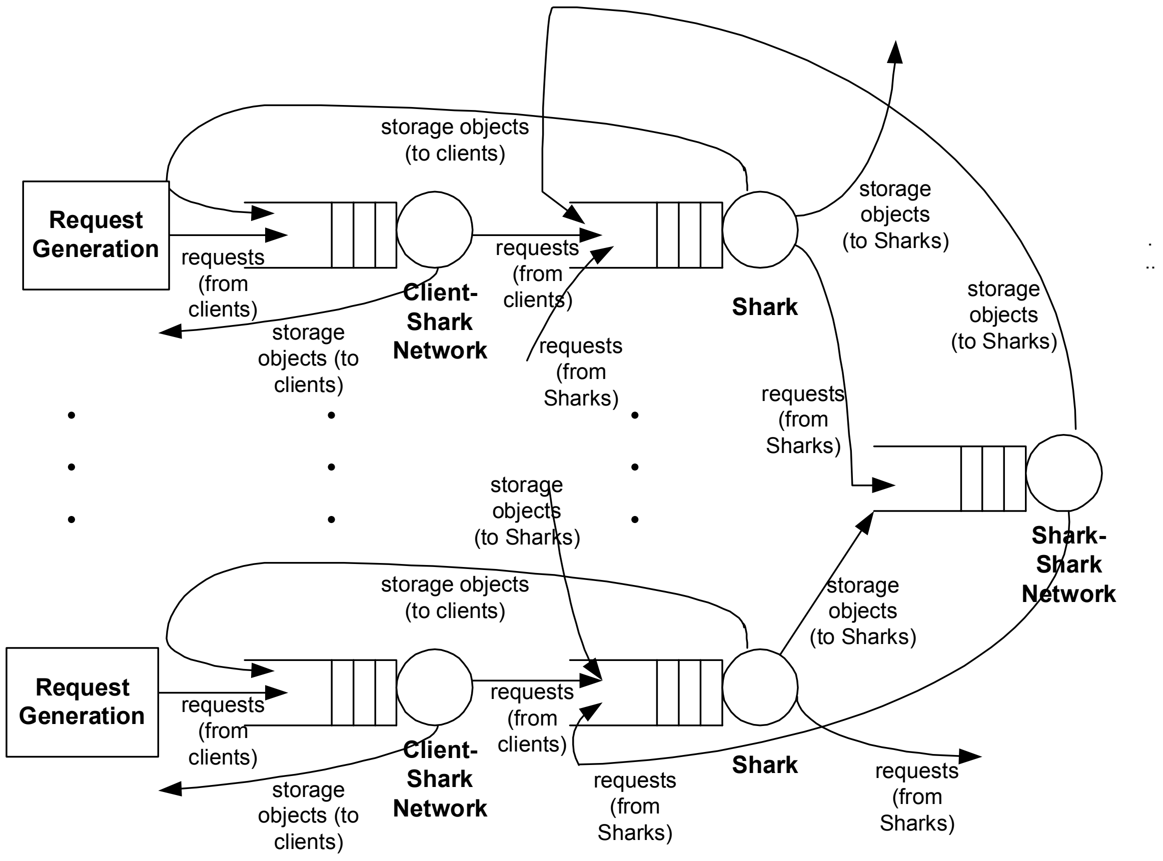


Figure 7: The NSC Simulator

5.1 The Request Generation Model

A request generation procedure consists of two steps: (1) generating session-begin messages and session-end messages; (2) generating requests within sessions. To generate session-begin/end messages, we assume the interarrival times between sessions and the durations of sessions to be exponentially distributed. Requests generation within a session begins as soon as the session-begin message has been generated and the requests generation stops as soon as the session-end message has been generated.

We call requests within a session as a request stream. We assume that the interarrival times between requests in a request stream follow a lognormal distribution (Paxson and Floyd 1995). As shown in Figure 8, a request stream is generated based on the request frequency rates of storage objects and the correlations between storage objects. Hence, the request frequency rates of storage objects and the correlations between storage objects need to be generated before a meaningful request stream can be generated.

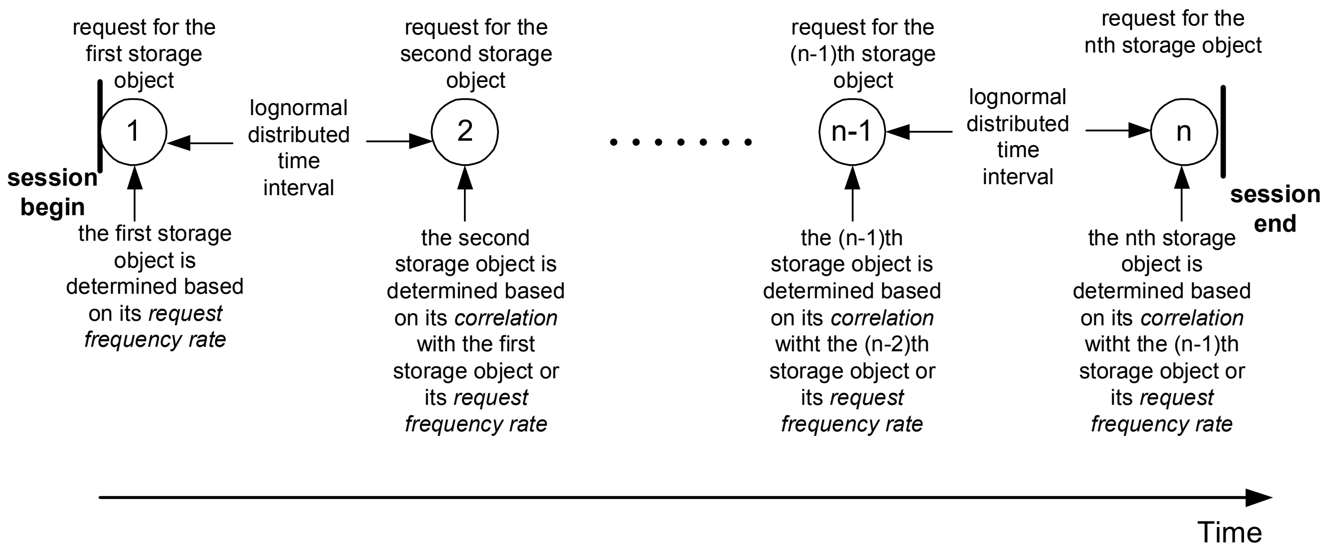

request for the first storage object
1
session begin
the first storage object is determined based on its *request frequency rate*
lognormal distributed time interval
request for the second storage object
2
the second storage object is determined based on its *correlation* with the first storage object or its *request frequency rate*
. . . .
request for the (n-1)th storage object
n-1
the (n-1)th storage object is determined based on its *correlation* witht the (n-2)th storage object or its *request frequency rate*
lognormal distributed time interval
request for the nth storage object
n
session end
the nth storage object is determined based on its *correlation* witht the (n-1)th storage object or its *request frequency rate*
Time

Figure 8: Request Stream Generation

The request frequency rates of storage objects approximately follow the Zipf's law in which the request frequency rate of the *k*th most frequently requested storage object is proportional to $\frac{1}{k}$ (Breslau et al. 1999). We denote the total number of storage objects in NetShark as n_{NS} and the set of all storage objects in NetShark as SO_{NS}, where $SO_{NS} = \{so_i\}$ for $i = 1,2,\cdots,n_{NS}$. For a storage object in NetShark, so_i, where $so_i \in SO_{NS}$ for $i = 1,2,\cdots,n_{NS}$, we denote $rank(so_i)$ as the rank of its request frequency rate among all storage objects in NetShark. Let $rank(so_i) = k$ if so_i is the *k*th most frequently requested storage object in NetShark. According to (Breslau et al. 1999), the request frequency rate of so_i, $fre(so_i)$, is defined below.

$$fre(so_i) = \frac{c}{rank(so_i)} \qquad \text{where } c = \frac{1}{\sum_{j=1}^{n_{NS}} \frac{1}{j}} \tag{4}$$

c in (4) can be approximated using the following formula.

$$c \approx \frac{1}{\ln(n_{NS}) + C + \frac{1}{2n_{NS}}} \tag{5}$$

Here, C is the Euler constant and $C \approx 0.577$. Using (4) and (5), the request frequency rates of storage objects can be generated by the NSC simulator.

To simulate a situation in which some storage objects are often requested together within sessions, the NSC simulator generates correlations between storage objects. For a storage object in NetShark, so_i, where $so_i \in SO_{NS}$ for $i = 1,2,\cdots,n_{NS}$, we name a storage object requested right after so_i within the same session as the next requested storage object of so_i. There are two types of the next requested storage object of so_i:

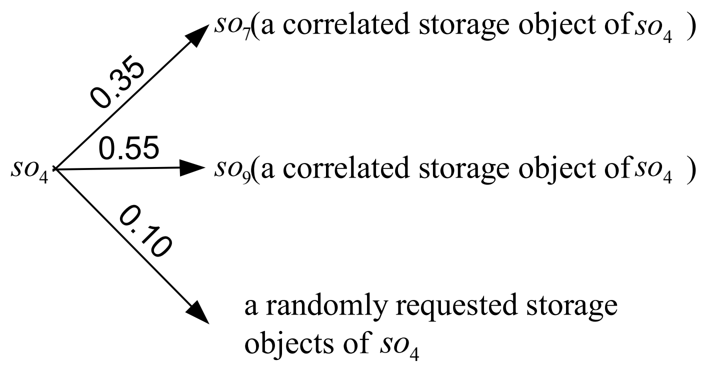
– a correlated storage objects of so_i: requested frequently right after so_i;

– a randomly requested storage object of so_i: requested infrequently right after so_i.

For a storage object, so_i, where $so_i \in SO_{NS}$ for $i = 1,2,\cdots,n_{NS}$, we denote $fanout(so_i)$, namely the fan-out number of so_i, as the number of the correlated storage objects of so_i. $c_j(so_i)$ denotes a correlated storage object of so_i and $\{c_j(so_i)\}$ denotes the set of all correlated storage objects of so_i, where $c_j(so_i) \in SO_{NS}$ for $j = 1,2,\cdots, fanout(so_i)$. $P(c_j(so_i) \mid so_i)$ denotes the correlation between $c_j(so_i)$ and so_i, which is the conditional probability of requesting $c_j(so_i)$ right after requesting so_i within the same session. We denote $random(so_i)$, namely the random factor of so_i, as the conditional probability of requesting a randomly requested storage object of so_i right after requesting so_i, where,

$$random(so_i) + \sum_{j=1}^{fanout(so_i)} P(c_j(so_i) \mid so_i) = 1 \tag{6}$$

Example 5: As shown in Figure 9, storage object so_4 has two correlated storage objects, so_7 and so_9, i.e., $fanout(so_4) = 2$, $c_1(so_4) = so_7$ and $c_2(so_4) = so_9$**.** The correlation between so_7 and $so_4, P(so_7 \mid so_4)$, is 0.35 and the correlation between so_9 and $so_4, P(so_9 \mid so_4)$, is 0.55. The conditional probability of requesting a randomly requested storage object of so_4 right after requesting $so_4, random(so_4)$, is 0.10.



so_7(a correlated storage object of so_4)
0.35
so_4
0.55
so_9(a correlated storage object of so_4)
0.10
a randomly requested storage objects of so_4

Figure 9: Correlations Between Storage Objects

Figure 10 gives an algorithm to generate all correlated storage objects of so_i, $\{c_j(so_i)\}$, and their correlations with so_i, $P(c_j(so_i) \mid so_i)$, where $c_j(so_i) \in SO_{NS}$ for $j = 1,2,\cdots, fanout(so_i)$, given the fan-out number of so_i, $fanout(so_i)$, and the random factor of so_i, $random(so_i)$. In the algorithm, $F(k)$ is denoted as the *k*th cumulative request frequency rate, where $k = 0,1,2,\cdots, n_{NS}$.

$$F(k) = \begin{cases} \sum_{m \le k} fre(so_m) & k = 1,2,\cdots, n_{NS},\ \ so_m \in SO_{NS} \text{ for } m = 1,2,\cdots, n_{NS} \\ 0 & k = 0 \end{cases} \tag{7}$$

In the NSC simulator, $fanout(so_i)$ is simulated using a Poisson random variable with parameter λ and $random(so_i)$ is simulated using a uniform random variable over the interval $(0, r)$, where $0 < r < 1$. λ and r can be manipulated to change correlations between storage objects. Running the algorithm for every storage object in NetShark, correlations between storage objects in NetShark can be generated.

```
Input:  $fanout(so_i)$ : the fan-out number of $so_i$
        $random(so_i)$: the random factor of $so_i$
Output: $\{c_j(so_i)\}$ : the set of all correlated storage objects of $so_i$,
                where $c_j(so_i) \in SO_{NS}$ for $j = 1,2,\cdots, fanout(so_i)$
        $P(c_j(so_i) \mid so_i)$ : the correlation between $c_j(so_i)$ and $so_i$,
                where $c_j(so_i) \in SO_{NS}$ for $j = 1,2,\cdots, fanout(so_i)$


$corr = 1 - random(so_i)$; /* probability of requesting correlated storage objects of $so_i$ */
$\{c_j(so_i)\} = \phi$;
While ( $fanout(so_i) \geq 1$ )
    $x = rand(0,1)$;   /* x ~ uniform distribution over (0,1)*/
    /*pick a storage object based on its request frequency rate*/
    select k, where $x \in [F(k-1), F(k))$;
    If $so_k \in \{c_j(so_i)\}$ /* $so_k$ has been selected before*/
        continue;
    End if
    $\{c_j(so_i)\} = \{c_j(so_i)\} \cup \{so_k\}$;
    If ( $fanout(so_i) > 1$ )
        $P(so_k \mid so_i) = rand(0, corr)$;
        $corr = corr - P(so_k \mid so_i)$;
    else
        $P(so_k \mid so_i) = corr$; /*last correlated storage object of $so_i$ */
    End if
    $fanout(so_i) --$;
End while
```

Figure 10: Generate Correlated Storage Objects Of A Storage Object

Figure 11 gives the request stream generation algorithm. In the algorithm, $F(t, so_i)$ denotes the *t*th cumulative correlation of so_i, where $t = 0,1,2,\cdots, fanout(so_i)$.

$$F(t, so_i) = \begin{cases} \sum_{j \leq t} P(c_j(so_i) \mid so_i) & t = 1,2,\cdots, fanout(so_i) \\ 0 & t = 0 \end{cases} \tag{8}$$

Example 6: For correlations given in Example 5, we have,

$F(1, so_4) = P(c_1(so_4) \mid so_4) = P(so_7 \mid so_4)$=0.55;

$F(2, so_4) = P(c_1(so_4) \mid so_4) + P(c_2(so_4) \mid so_4) = P(so_7 \mid so_4) + P(so_9 \mid so_4)$=0.9.

The request stream generation algorithm is triggered whenever there is a session-begin message. The first requested storage object in a request stream is generated based on its request frequency rate. The rest of the requested storage objects are generated using a loop that stops when a session-end message has been received. Within the loop,

– if a randomly generated number (i.e., uniformly distributed) is less than one minus the random factor (i.e., $random(\cdot)$) of the currently requested storage object , a storage object is generated based on its correlation with the currently requested storage object;

– otherwise, a storage object is generated based on its request frequency rate.

```
Event: a session-begin message has been generated

Input: $fre(so_i)$: request frequency rates of storage objects,
                    where $so_i \in SO_{NS}$ for $i = 1,2,\cdots,n_{NS}$,
       $P(c_j(so_i) \mid so_i)$: correlations between storage objects,
                    where $so_i \in SO_{NS}$ for $i = 1,2,\cdots,n_{NS}$ and
                    $c_j(so_i) \in SO_{NS}$ for $j = 1,2,\cdots, fanout(so_i)$.

Output: a request stream

/* generate the first requested storage object based on its request frequency rate*/
$x = rand(0,1)$;  /* x ~ uniform distribution over (0,1)*/
select k, where $x \in [F(k-1), F(k))$;
place the request for $so_k$ in the request stream;
current = $so_k$; /* currently requested storage object*/
While (session not end) /* not receiving a session-end message */
    $x = rand(0,1)$;
    If ( $x < (1 - random(\text{current}))$ )
    /*generate a correlated storage object of the currently requested storage object*/
        select t, where $x \in [F(t-1, \text{current}), F(t, \text{current}))$;
        place the request for $c_t(current)$ in the request stream;
        current = $c_t(current)$;
    else
    /* generate a randomly requested storage object based on its request frequency rate*/
        $x = rand(0,1)$;
        select k, where $x \in [F(k-1), F(k))$;
        place the request for $so_k$ in the request stream;
        current = $so_k$;
    End if
End while
```

Figure 11: The Request Stream Generation Algorithm

5.2 The Server Queuing Models

To simulate the servers, the sizes of storage objects need to be generated first. According to (Paxson and Floyd 1995), the sizes of storage objects follow a Pareto distribution, which is a type of heavy-tailed distribution with the following distribution function.

$$F(x) = 1 - \left(\frac{\alpha}{x}\right)^{\beta} \qquad x \geq \alpha \tag{9}$$

Here α is the location parameter, which is the minimum size of all storage objects, and β is the shape parameter with the value ranging from 0.9 to 1.4 (Paxson and Floyd 1995). Using (9), the sizes of storage objects can be generated.

5.2.1 Client-Shark/Shark-Shark Network Servers

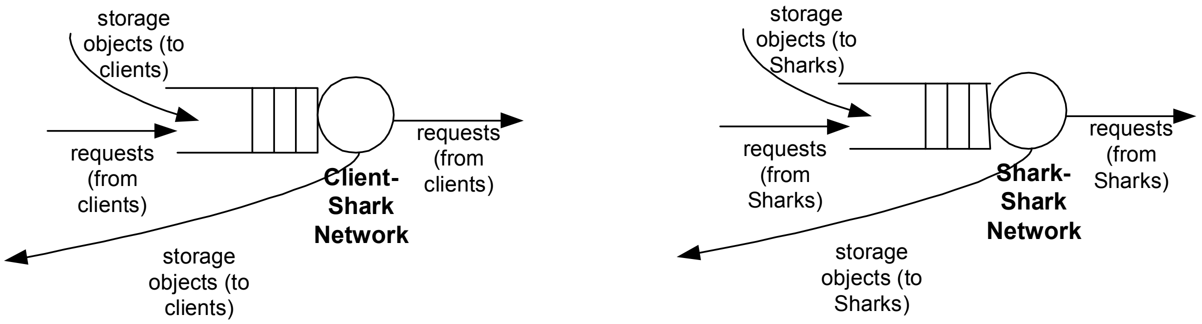


Figure 12: Client-Shark/Shark-Shark Network Servers

In the NSC simulator, Client-Shark network servers and Shark-Shark network servers are simulated using G/G/1 queues. As shown in Figure 12, both Client-Shark network servers and Shark-Shark network servers transfer requests and storage objects. The distribution of the request interarrival times at a Client-Shark network server is determined by such factors as the distributions of the session and request interarrival times at its connected request generation model. The distributions of the request interarrival times at a Shark-Shark network server is determined by such factors as the hit rates of its connected Shark servers. The request service times of Client-Shark and Shark-Shark network servers can be calculated using (1). In the NSC simulator, we assume request size to be a constant. Hence, for a given type of network, its request service time is deterministic.

The distributions of the storage object interarrival times at Client-Shark and Shark-Shark network servers are determined by such factors as the waiting times and service times of their connected Shark servers. The storage object service times of Client-Shark and Shark-Shark network servers can be calculated using (1). According to (Paxson and Floyd 1995), $size(so)$ follows a Pareto distribution with the distribution function listed in (9). To get the distribution of the storage object service times, we introduce random variables *Y* and *X*, where $Y = c + dX, c > 0, d > 0$, and *X* follows a Pareto distribution. We have,

$$F(y) = P\{Y \le y\} = P\{c + dX \le y\} = P\left\{X \le \frac{y-c}{d}\right\}$$

according to (9),

$$F(y) = 1 - (\frac{d\alpha}{y-c})^{\beta} \quad y \ge c + d\alpha \tag{10}$$

We denote a Client-Shark network as nw_{CS} and a Shark-Shark network as nw_{SS}. According to (1), by substituting *c* in (10) with $HD(nw) \times HN(nw) + \frac{D(nw)}{v(nw)}$ and *d* in (10) with $\frac{8}{B(nw)}$, the distribution function of the storage object service times is the following.

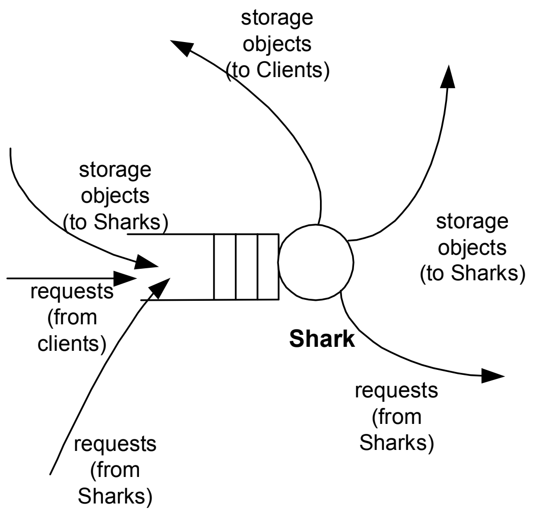
$$F(x) = 1 - \left(\frac{\frac{8\alpha}{B(nw)}}{x - HD(nw) \times HN(nw) - \frac{D(nw)}{v(nw)}} \right)^{\beta}$$

$$x \geq HD(nw) \times HN(nw) + \frac{D(nw)}{v(nw)} + \frac{8\alpha}{B(nw)}$$

$$\text{where } nw = \begin{cases} nw_{CS} & \text{for a Clinet - Shark network server} \\ nw_{SS} & \text{for a Shark - Shark network server} \end{cases} \tag{11}$$

Here α is the location parameter, which is the minimum size of all storage objects, and β is the shape parameter with the value ranging from 0.9 to 1.4 (Paxson and Floyd 1995).

5.2.2 Shark Servers



storage objects (to Clients)
storage objects (to Sharks)
storage objects (to Sharks)
requests (from clients)
Shark
requests (from Sharks)
requests (from Sharks)

Figure 13: A Shark Server

As shown in Figure 13, a Shark server receives requests from clients or other Shark servers and retrieve storage objects to fulfill these requests. Requests that cannot be fulfilled and requests for prefetched storage objects are sent to other Shark servers. A

Shark server also receives cached and prefetched storage objects from other Shark servers and store them. In the NSC simulator, a Shark server is simulated using a G/G/1 queue. The distributions of request and storage object interarrival times at a Shark server are determined by such factors as the distributions of request and storage object interarrival times at its connected Client-Shark/Shark-Shark network servers and request and storage object service times of these network servers. The service time of a Shark server consists of two parts: the computational time of the online caching algorithm running at the Shark server, which is considered as a constant in the NSC simulator; and the time to retrieve/store a storage object, *so*, from/to a Shark server, $IO(so)$, which is defined below.

$$IO(so) = \frac{size(so)}{dio} \tag{12}$$

Here *dio* is the disk I/O speed of Sharks. In the NSC simulator, we assume *dio* to be a constant. $size(so)$ follows a Pareto distribution with the distribution function given in (9). Similarly, we can derive the distribution function of $IO(so)$ as follows.

$$F(x) = 1 - \left(\frac{\alpha}{dio \times x}\right)^{\beta} \qquad x \geq \frac{\alpha}{dio} \tag{13}$$

Here α is the location parameter, which is the minimum size of all storage objects, and β is the shape parameter with the value ranging from 0.9 to 1.4 (Paxson and Floyd 1995).

6. Simulation Results

Using the NSC simulator described in Section 5, we compared three caching approaches: the data-mining-based prefetching approach described in this paper, caching on demand and a widely used prefetching approach – the popularity-based prefetching appraoch (Dias et al. 1996, Markatos and Chronaki 1998).

Before presenting the simulation results, we list values of major simulation parameters in Table 6. In this Table, mean of session interarrival times and mean of request interarrival times are calculated from a FTP log. By running a network routing software – VisualRoute, we found that the number of hops between clients and servers within the same region ranged from 3 (e.g., clients and servers are in an organization's Intranet) to 9 and the number of hops between clients and servers in different regions ranged from 14 to 22 or even more (e.g., clients and servers are in different countries). In the architecture of NetShark, clients and their Home Sharks are in the same region while Sharks are distributed into different regions. Hence, we set the number of hops between clients and their Home Sharks at 6 (i.e., average of 3 and 9) and the number of hops between Sharks at 18 (i.e., average of 14 and 22). In the simulator, we assume that clients and Sharks are connected using Intranet/Internet and Sharks are connected using ATM PSDN (i.e., Public Switched Data Network).

Table 6: Values of Major Simulation Parameters

Parameter	Value
The simulation time	12 hours
The number of regions	6
The number of Sharks	6
The number of storage objects	20000
The location parameter of the Pareto distribution for storage object size (α)	30 K bytes
The shape parameter of the Pareto distribution for storage object size (β)	1.06
Mean of session interarrival times	80.9844 seconds
Mean of request interarrival times	5.9894 seconds
The random factors of storage objects ($random(\cdot)$)	uniform distributed over (0, 0.3)
Mean of the fan-out numbers of storage objects ($fanout(\cdot)$)	100
The request size	50 bytes
The bandwidth of Client-Shark network ($B(nw_{CS})$)	500K bps
The bandwidth of Shark-Shark network ($B(nw_{SS})$)	155M bps
Average hop delay of Client-Shark/ Shark-Shark network ($HD(\cdot)$)	0.015 second
The number of hops on Client-Shark network ($HN(nw_{CS})$)	6
The number of hops on Shark-Shark network($HN(nw_{SS})$)	18
The distance of Client-Shark network ($D(nw_{CS})$)	20 Km
The distance of Shark-Shark network ($D(nw_{SS})$)	1000 Km
The signal velocity of Client-Shark network ($v(nw_{CS})$)	231000 Km/second
The signal velocity of Shark-Shark network ($v(nw_{SS})$)	205000 Km/second
The disk I/O speed of Sharks (*dio*)	43.1M bytes/second
Maximum cache size	10% of the total storage object sizes

To compare the three caching approaches on the same benchmark, we used the same replacement approach, LRU, when comparing them. Figure 14 and Figure 15 illustrate hit rates (Measurement 2) and client perceived latencies (Measurement 1) of the three caching approaches as the cache size increased from 22% of the maximum cache size to 100% of the maximum cache size with an 11% gap. Compared with caching on demand, the popularity-based prefetching approach increased hit rate by an average of 21.8% and the data-mining-based prefetching approach increased hit rate by an average of 32.8%.

Compared with caching on demand, the popularity-based prefetching approach reduced client perceived latency by an average of 5.1% and the data-mining-based prefetching approach reduced client perceived latency by an average of 7.7%.

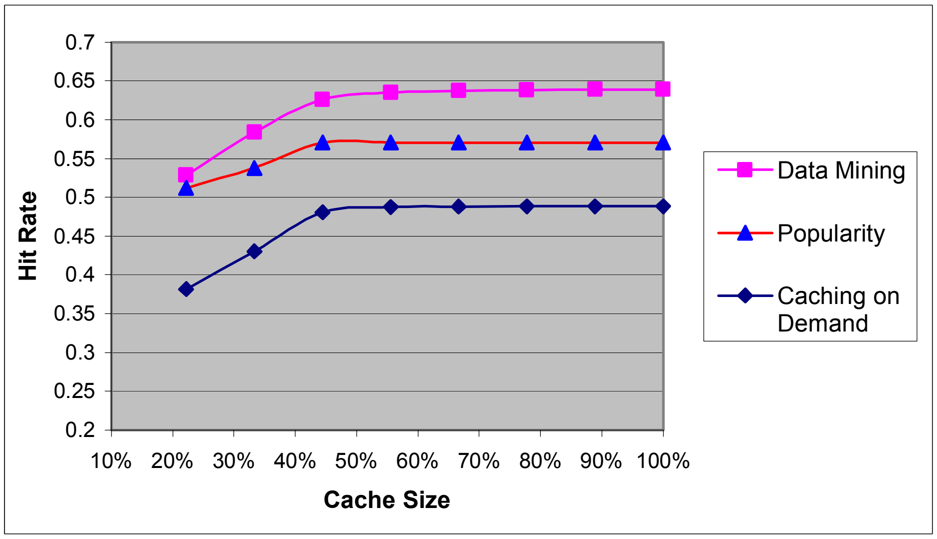


Figure 14: Hit Rate Comparison Between The Three Caching Approaches

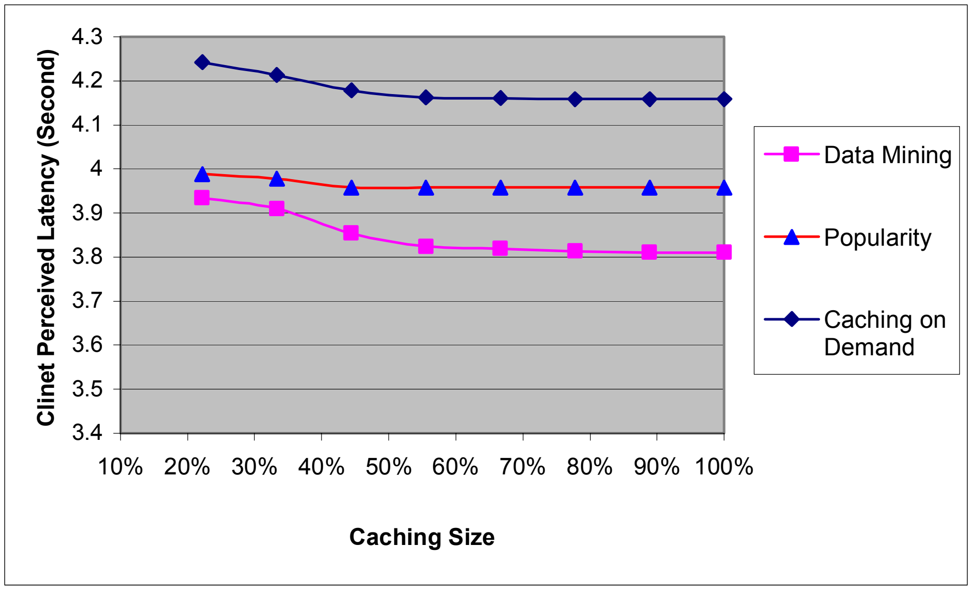


Figure 15: Client Perceived Latency Comparison Between The Three Caching Approaches

It is not surprising that both prefetching approaches outperformed caching on demand, as shown previously in (Kroeger et al. 1997). Between the two prefetching approaches, the data-mining-based prefetching approach outperformed the popularity-based prefetching approach for the following reasons. The popularity-based prefetching approach prefetches storage objects only based on their popularities (i.e., request frequencies) while the data-mining-based prefetching approach prefetches storage objects based on both their popularities (i.e., support of intra/inter-session patterns) and their correlations. Hence, the latter is more effective in prefetching storage objects that will be requested by clients. Furthermore, the data-mining-based prefetching approach considers the network traffic increase problem associated with prefetching approaches and tries to cache storage objects when the network traffic is not heavy. As shown in Figure 16, compared with caching on demand, the popularity-based prefetching approach increased Shark-Shark response time (Measurement 3) by an average of 2.3% while the data-mining-based prefetching approach increased Shark-Shark response time by an average of 1.13%

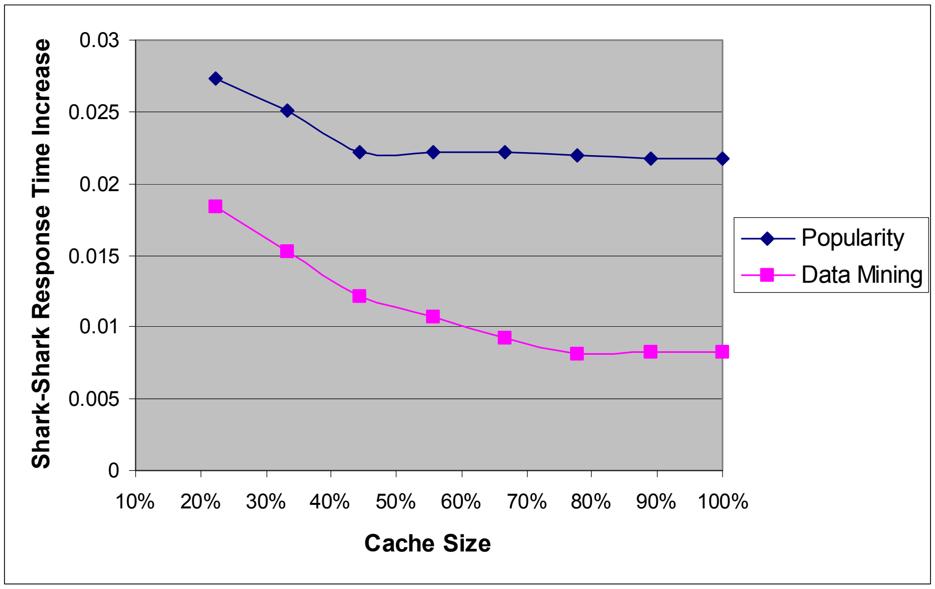


Figure 16: Network Traffic Increase Compared With Caching On Demand

7. Conclusion and Future Work

Network storage is a key technique to solve the local storage shortage problem and to realize storage outsourcing over the Internet. This paper has presented the implementation of a caching-based network storage system — NetShark and has proposed a caching approach – a data-mining-based prefetching approach. A simulator has been developed to evaluate the proposed caching approach. Simulation results have shown that the proposed caching approach outperforms other popularly used caching approaches.

Future work is needed in the following areas. First, we plan to evaluate the proposed caching approach using real world applications such as the Knowledge Management System mentioned in Section 2. Second, as NetShark is used continuously, data in Log-DB accumulate continuously. Hence, intra/inter-session patterns learned from offline data mining need to be refreshed accordingly. Refreshing patterns too often not only could inflict unbearable costs but also often result in repetitive patterns identical with previous mining while refreshing patterns too seldom may result in the missing of critical patterns (Ganti et al. 2001). We plan to apply and extend the research in (Fang and Sheng 2000) to design an efficient pattern refreshing algorithm. Third, we plan to incorporate structural relationships between storage objects (e.g., storage objects in the same directory) into the proposed caching approach. Finally, an analytical model based on the queuing theory needs to be developed to analyze the performance of different caching approaches mathematically.

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