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System Design Issues for Internet Middleware Services: Deductions from a Large Client Trace

Steven D. Gribble and Eric A. Brewer
The University of California at Berkeley

For more information about USENIX Association contact:

1. Phone: 510 528-8649
2. FAX: 510 548-5738
3. Email: office@usenix.org
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System Design Issues for Internet Middleware Services: Deductions from a Large Client Trace

Steven D. Gribble and Eric A. Brewer
The University of California at Berkeley
{gribble,brewer}@cs.berkeley.edu

Abstract

In this paper, we present the analysis of a large client-side web trace gathered from the Home IP service at the University of California at Berkeley. Specifically, we demonstrate the heterogeneity of web clients, the existence of a strong and very predictable diurnal cycle in the clients' web activity, the burstiness of clients' requests at small time scales (but not large time scales, implying a lack of self-similarity), the presence of locality of reference in the clients' requests that is a strong function of the client population size, and the high latency that services encounter when delivering data to clients, implying that services will need to maintain a very large number of simultaneously active requests. We then present system design issues for Internet middleware services that were drawn both from our trace analysis and our implementation experience of the TranSend transformation proxy.

1 Introduction

The growth of the Internet, and particularly of web-oriented middleware services ([15], [3], [6]) within the Internet, has seen a recent explosion [31]. These middleware services, particularly the more popular services that experience extremely high load, must overcome a number of challenging system design issues in order to maintain fast response time, constant availability, and capacity. Services must be able to accommodate an increasingly varied client population (in terms of hardware, software, and network connectivity). They must be able to handle offered loads of hundreds of requests per second, and because of the often slow connectivity to clients and the implied lengthy delivery times, they must be able to handle hundreds of simultaneously outstanding tasks.

Previous work has explored the performance of operating system primitives and the relationship between OS performance and architecture ([29], [2]), and operating system design issues for busy Internet services ([19], [27]). In contrast, this paper raises a number of system design issues specifically for Internet middleware services. These issues were encountered during two separate but related efforts: the analysis of a set of extensive client-side HTTP [5] traces that we gathered from the University of California at Berkeley's dial-in modem banks during October and November of 1996, and the implementation and deployment experience we gained from the TranSend Internet middleware service [15].

Since nearly 70% of all Internet clients use dial-in modems of speeds of 28.8 Kb/s or less [18], we use the traces to make a number of observations about the Internet user population and the services with which they communicate. Section 2 discusses the gathering of the traces, including the tools used and the information gathered, and section 3 performs a detailed analysis of these traces, both in terms of observations made about the client population and the services themselves. In section 4, we discuss the middleware system design issues drawn from our experience with the TranSend transformation proxy service, and in section 5 we present related work. Finally, in section 6 we conclude.

2 Home IP Trace Gathering

During October and November of 1996, we gathered over 45 consecutive days worth of HTTP traces from the Home IP service offered by UC Berkeley to its students, faculty, and staff available to researchers. (Two and a half weeks worth of anonymized versions of these traces have been made available at http://www.acm.org/ita.) Home IP provides dial-up PPP/SLIP connectivity using 2.4 kb/s, 9.6 kb/s, 14.4 kb/s, or 28.8 kb/s wireline modems, or Metricom Ricochet wireless modems (which achieve approximately 20-30 kb/s throughput with a 500 ms RTT).

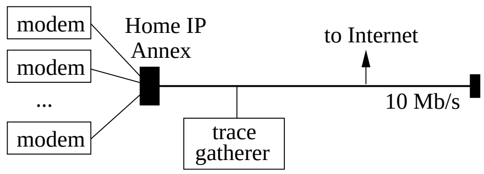


Figure 1: **The Home IP Tracing Environment**

2.1 IPSE

The HTTP client traces were unobtrusively gathered through the use of a packet sniffing machine placed on a 10 Mb/s Ethernet segment at the head-end of the Home IP modem bank through which all IP traffic flowed (figure 1). The trace gathering program that we used was a custom HTTP module written on top of the Internet Protocol Scanning Engine (IPSE)[17]. IPSE is a user-level packet filter that runs on Linux; IPSE allows filter modules to capture TCP segments and recreate the TCP streams observed by the endpoints of the TCP connection. The custom module was therefore able to parse each HTTP request as it was happening, and write out the salient features of each HTTP request to a log file on-the-fly. Only traffic destined for port 80 was traced; all non-HTTP protocols and HTTP connections to other ports were excluded. Each user of the Home IP service is assigned a static IP address, so we could track individual users over the entire duration of the tracing experiment.

2.2 The Trace Files

The 45 day trace contains approximately 24,000,000 HTTP requests, representing the web surfing behaviour of over 8,000 unique clients. The trace capture tool collected the following information for each HTTP request seen:

- the time at which the client made the request, the time that the first byte of the server response was seen, and the time that the last byte of the server response was seen,
- the client and server IP addresses and ports,
- the values of the **no-cache**, **keep-alive**, **cache-control**, **if-modified-since**, **useragent**, and **unless** client headers (if present),
- the values of the **no-cache**, **cache-control**, **expires**, and **last-modified** server headers (if present),
- the length of the response HTTP header and response data, and
- the request URL.

IPSE wrote this information to disk in a compact, binary form. Every four hours, IPSE was shut down and restarted, as its memory image would get extremely large over time due to a memory leak that we were unable to eliminate. This implies that there are two potential weaknesses in these traces:

1. Any connection active when the engine was brought down will have a possibly incorrect timestamp for the last byte seen from the server, and a possibly incorrect reported size.
2. Any connection that was forged in the very small time window (about 300 milliseconds) between when the engine was shut down and restarted will not appear in the logs.

We estimate that no more than 150 such entries (out of roughly 90,000-100,000) are misreported for each 4 hour period.

3 Trace Analysis

In this section, we present the results of our analysis of the Home IP traces. In section 3.1, we demonstrate the heterogeneity of the observed client population. Section 3.2 discusses the request rates and interarrival times generated by the client population. In 3.3, object type and size distributions are presented. Section 3.4 demonstrates the existence of locality of reference within the traces through the use of a number of cache simulations driven by trace entries. Finally, section 3.5 presents distributions of service response times, and argues that at any given time, a very large number of outstanding requests will be flowing through middleware or end services.

3.1 Client Heterogeneity

Table 1 lists the most frequently observed "User-Agent" HTTP headers observed within the Home IP traces. From this table, it is easy to make a common misconclusion about web clients, namely that the set of web clients in use is extremely homogeneous, as nearly all browsers observed in our traces are either the Netscape Navigator [28] or Microsoft Internet Explorer (MSIE) [26] browsers running on the Windows or Macintosh operating systems. However, there is significant heterogeneity arising from the many versions of these browsers and their widely varying feature sets. Furthermore, we observed a total 166 different UserAgent values within the traces, representing a wide range of desktop systems (MacOS, Win16, NetBSD, Linux, etc.) More significantly, however, we saw requests from a number of exotic clients such as Newton PDAs running the NetHopper [1] browser.

Browser	OS	% Seen
Netscape	Windows 95	55.1
	Macintosh	19.7
	Windows (other)	8.8
	Windows NT	3.5
	Linux	2.2
	Other	0.4
MSIE	Windows 95	7.6
	Macintosh	0.6
	Windows NT	0.7
	Windows (other)	0.1
Other		1.3

Table 1: **UserAgent HTTP headers:** this table lists the 10 most frequent UserAgent headers observed in the traces. "Other" browsers observed include PointCast, Cyberdog, Mosaic, Opera, Lynx, JDK, and NetHopper.

Internet services that do not want to limit the effective audience of their content must therefore be able to deliver content that suits the needs of all of these diverse clients. Either the services themselves must adapt their content, or they must rely on the emergence of middleware services (such as in [13], [14], and [7]) to adapt content on the fly to better suit the clients' particular needs.

3.2 Client Activity

As seen in figure 2, the amount of activity seen from the client population is strongly dependent on the time of day. The Berkeley web users were most active between 8:00pm and 2:00am, with nearly no activity seen at 7:00am. Services that receive requests from local users can thus expect to have widely varying load throughout the day; internationally used services will most probably see less of a strong diurnal cycle. Other details can be extracted from these graphs. For example, there is a decrease of activity at noon and at 7:00pm, presumably due to lunch breaks and dinner breaks, respectively.

The diurnal cycle is largely independent of the day of the week, but there are some minor differences: for instance, on Fridays and Saturdays, the traffic peaks are slightly higher than during the rest of the week. However, the gross details of the traces remain independent of the day of the week. We calculated the average daily cycle observed by averaging the number of events seen per minute for each minute of the day across 15 days of traffic. For our calculation, we picked days during which there were no anomalous trace effects, such as network outages. Figure 3 shows this average cycle, including a polynomial curve fit that can be used to calculate approximate load throughout a typical day.

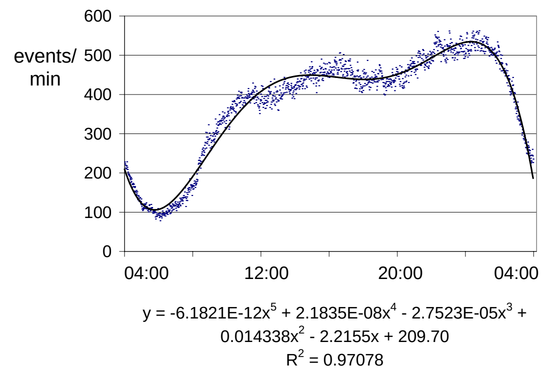


Figure 3: **Average diurnal cycle** observed within the traces - each minutes worth of activity shown is the average across 15 days worth of trace events. The y-axis shows the average number of observed requests per minute.

On shorter time scales, we observed that client activity was less regular. Figure 4 illustrates the observed request rate at three time scales from a one-day segment of the traces. At the daily and hourly time scales, traffic is relatively smooth and predictable - no large bursts of activity are present. At the scale of tens of seconds, very pronounced bursts of activity can be seen; peak to average ratios of more than 5:1 are common.

Many studies have explored the self-similarity of network traffic ([4], [16], [21], [22], [24], [30]), including web traffic [9]. Self-similarity implies burstiness at all timescales - this property is **not** compatible with our observations. One indicator of self-similarity is a heavy-tailed interarrival process. As figure 5 clearly shows, the interarrival time of GIF requests seen within the traces is exponentially distributed, and therefore not heavy tailed. (We saw similar exponential distributions for other data types' request processes, as well as for the aggregate request traffic.) These observations correspond to

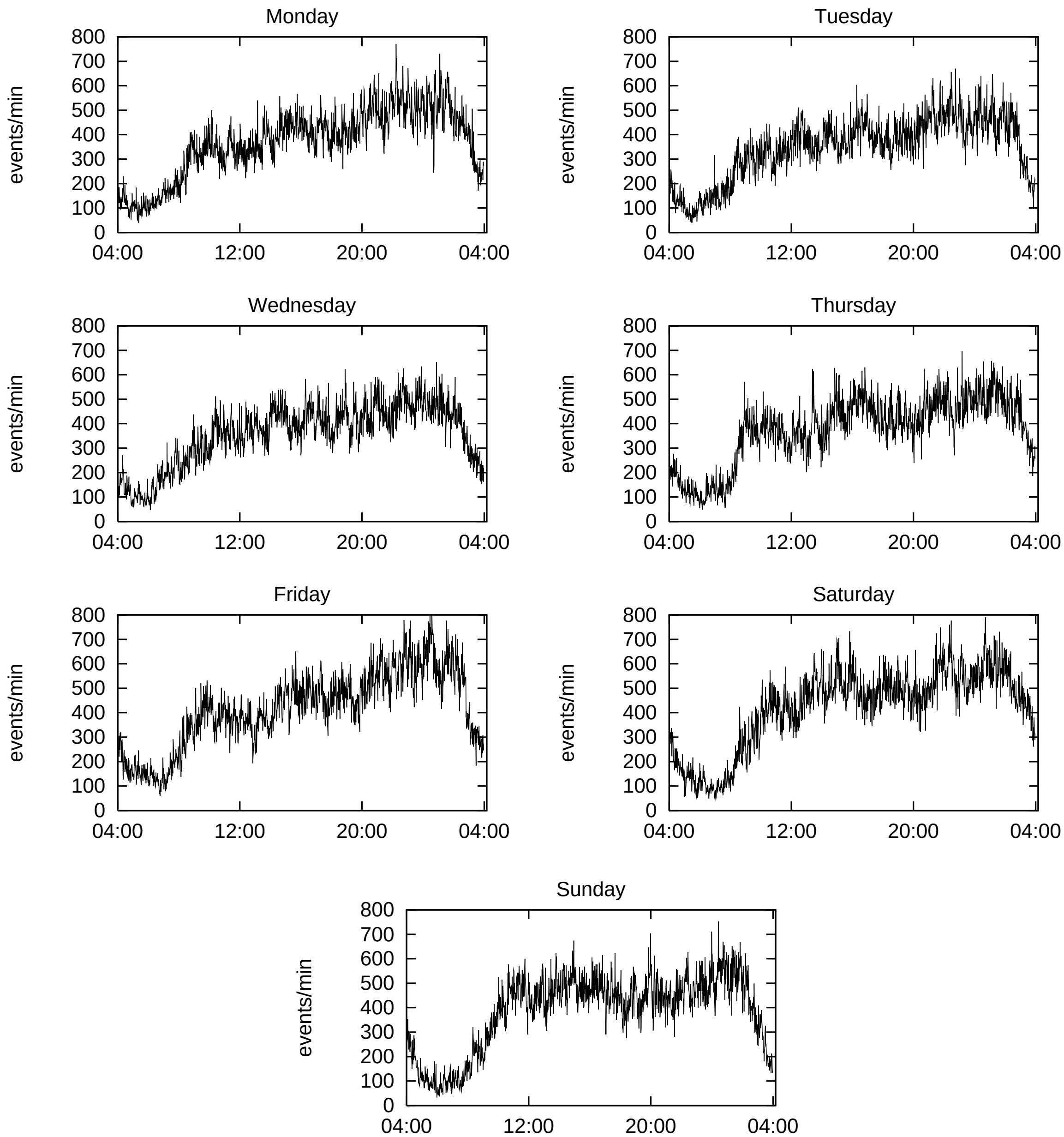


Figure 2: **Diurnal cycle** observed within the traces - each graph shows 1 day worth of trace events. The y-axis shows the number of observed requests per minute.

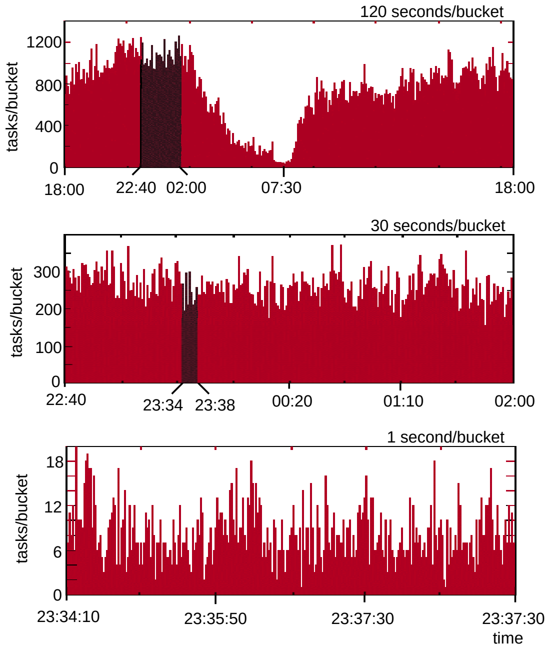


Figure 4: **Request rate** observed over a 24 hour, 3 hour, and 3 minute period of the traces.

requests generated from a large population of independent users.

Internet services must be able to handle rapidly varying and bursty load on fine time scales (on the order of seconds), but these bursts tend to smooth themselves out on larger time scales (on the order of minutes, hours, or days). The provisioning of resources for services is therefore somewhat simplified.

3.3 Reference type and size distributions

Section 3.1 answered the question of who is requesting data, and section 3.2 discussed how often data is requested. In this section, we inspect the nature of the data that is requested. Figure 6a shows the mime type breakdown of the transferred data in terms the number of bytes transferred, 6b shows this breakdown in term of files transferred.

From figure 6a, we see that most of the bytes transferred over the Home IP modem lines come from three predominant mime types: **text/html**, **image/gif**, and **image/jpeg**. Similarly, figure 6b shows that most files sent over the modem lines have the same three predominant mime types. Interestingly, however, we see that although most bytes transferred correspond to JPEG images, most files transferred correspond to GIF images. This means

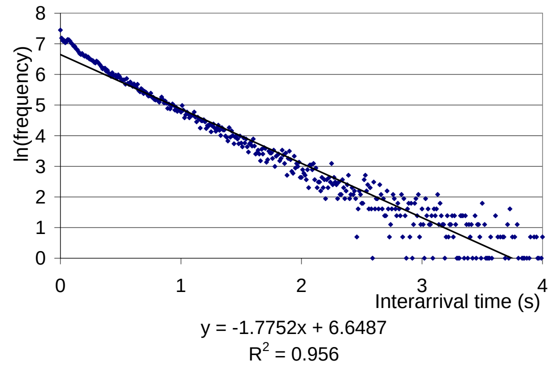


Figure 5: **Interarrival time distribution** for GIF data type requests seen within a day-long trace portion. Note that the Y-axis is on a logarithmic scale.

that, on average, JPEGs are larger than GIFs.

The fact that nearly 58% of bytes transferred and 67% of files transferred are images is good news for Internet cache infrastructure proponents. Image content tends to change less often than HTML content - images are usually statically created and have long periods of stability in between modification, in comparison to HTML which is becoming more frequently dynamically generated.

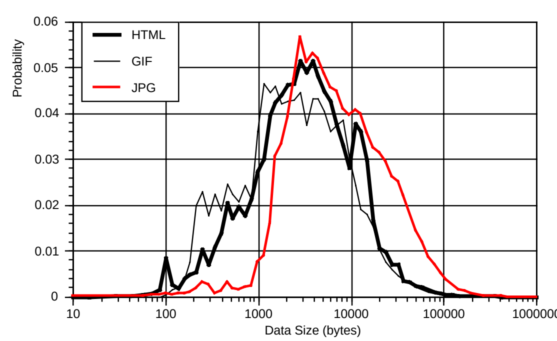
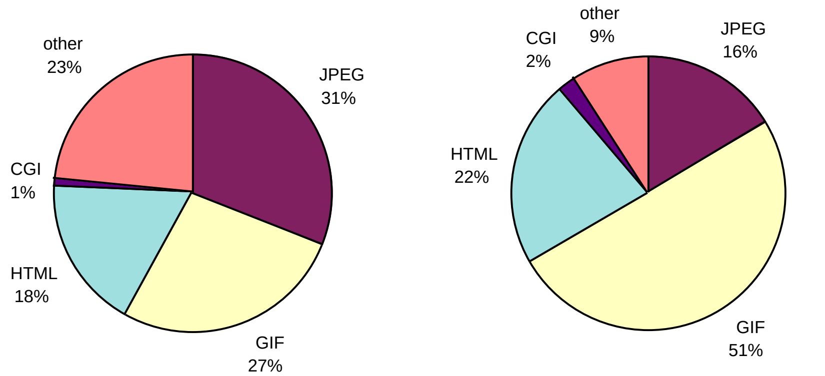


Figure 7: **Size distributions by MIME type**, shown on a logarithmic scale. The average HTML file size is 5.6 kilobytes, the average GIF file size is 4.1 kilobytes, and the average JPEG file size is 12.8 kilobytes.

In figure 7, we see the distribution of sizes of files belonging to the three most common mime type. Two observations can immediately be made: most Internet content is less than 10 kilobytes in size, and data type size distributions are quite heavy-tailed, meaning that there is a non-trivial number of large



(a) breakdown of bytes transferred, by mime type

(b) breakdown of files transferred, by mime type

Figure 6: **Breakdown of bytes and files transferred by MIME type**

data files on the web. Looking more closely at individual distributions, we can confirm our previous hypothesis that JPEG files tend to be larger than GIF files. Also, the JPEG file size distribution is considerably more heavy-tailed than the GIF distribution. There are more large JPEGs than GIFs, perhaps in part because JPEGs tend to be photographic images, and GIFs tend to be cartoons, line art, or other such simple, small images.

There are other anomalies in these distributions. The GIF distribution has two visible plateaus, one at roughly 300-1000 bytes, and another at 1000-5000 bytes. We hypothesize that the 300-1000 byte plateau is caused by small "bullet" images or icons on web pages, and the 1000-5000 byte plateau represents all other GIF content, such as cartoons, pictures, diagrams, advertisements, etc. Another anomaly is the large spike in the HTML distribution at roughly 11 kilobytes. Investigation revealed that this spike is caused by the extremely popular Netscape Corporation "Net Search" page.

3.4 Locality of Reference

A near-universal assumption in systems is that of locality of reference, and the typical mechanism used to take advantage of this locality of reference is caching ([11], [8]). The effectiveness of caching depends upon a number of factors, including the size of the user population that a cache is serving and the size of the cache serving that population.

To measure the effectiveness of infrastructure caching (as opposed to client-side or server-side caching) with respect to the HTTP references captured from the Home IP population, we imple-

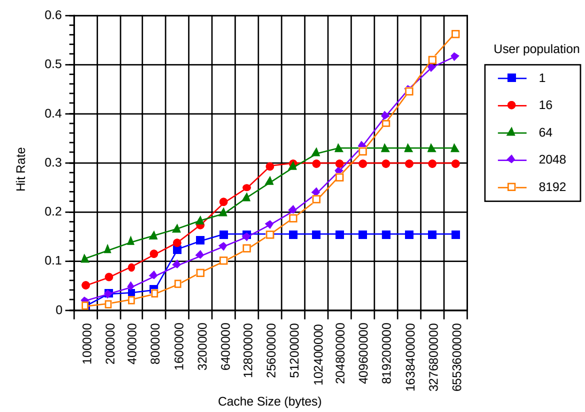


Figure 8: **Hit rate vs. Cache size** for a number of different user population sizes.

mented a cache simulator and played segments of the traces at these caches. We filtered out requests from all but a parameterizable set of client IP addresses in order to simulate client populations of different sizes. The cache simulator obeyed all HTTP cache pragmas (such as the no-cache pragma, the if-modified-since header, and the expiry header), and implemented a simple LRU eviction policy. Figure 8 shows measured cache hit rate as a function of cache size for different user population sizes, and figure 9 shows measured hit rate as a function of user population size for different cache sizes.

Figure 8 shows two trends: the first is that an increasingly large cache size results in an increasingly large cache hit rate. The second trend is that we observed that hit rate is a very strong function of the

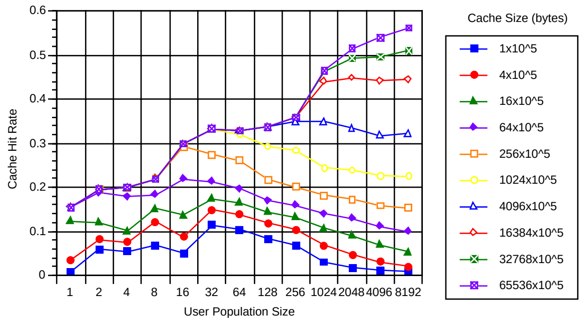


Figure 9: **Hit rate vs. User Population size** for a number of cache sizes.

user population size. As the population gets larger, the locality of reference within that population gets stronger, and caches become more effective. For a given population size, the cache hit rate as a function cache size plateaus at the working set size of that population. In figure 9, one additional trend can be observed: as the user population size grows, if the cache size does not also pace the increasingly large working set of that population, the cache hit rate will start to drop as the cache effectively begins to thrash from constant evictions.

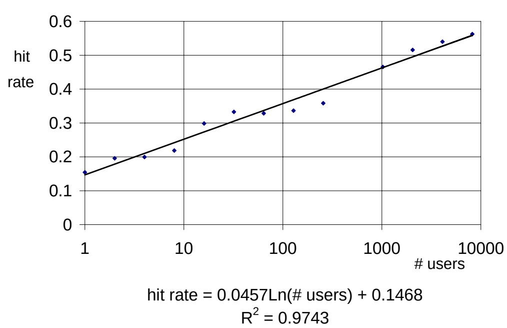


Figure 10: **Asymptotic Hit Rate vs. User Population Size**

An interesting question is: what is the maximum possible cache performance for a given user population size? In figure 10, we have plotted the asymptotic hit rate achieved in the limit of infinitely large cache size as a function of the user population size. In other words, this graph explicitly shows the cachable working set size of a given user population size. We see that for the range of population sizes that we can model from our traces, the asymptotic hit rate grows logarithmically with population size.

Obviously, this logarithmic increase cannot continue forever, as there is a maximum possible hit rate of 100%; unfortunately, our traces do not contain a large enough population size to see the logarithmic increase tail off.

A factor that can alter the performance of Internet caches is the increasingly prevalent use of cache pragmas in HTTP headers. To investigate this effect, we measured the percentage of HTTP client requests and server responses that contained relevant headers, namely:

no-cache: This header can be supplied by either the client or the server, and indicates that the requested or returned data may not be served out of or stored in a client-side or proxy cache.

cache-control This is a generic, extensible HTTP header whose value contains the real directive. Cache-control is intended to be used to supply additional caching directives that are interpreted by middleware caches, rather than by the end server or client.

if-modified-since This HTTP header allows a client to specify that a document should be returned only if it has been modified after a certain date. If it hasn't, then the client uses a locally cached version.

expires This HTTP header allows a server to supply an expiry date for returned content. Caches obey this directive by treating cached data as stale if the expiration date has occurred.

last-modified This HTTP header allows a server to indicate when a document has last been modified. This is typically used as a hint for caches when calculating time-to-live (TTL) values, or when returning HTTP headers in response to a client's HEAD request.

As can be seen in table 2, most HTTP headers that can affect cache performance are rarely used. The most frequently used header is the last-modified server response header; this header is now commonly returned by default from most HTTP servers. The presence of this header in data stored within a middleware cache or end server can be compared to the value of the if-modified-since client header to test whether or not cached data is stale. Unfortunately, only 1/4 of the client requests contained this header. Cache-control, no-cache, and expiry headers are extremely infrequent. These headers should become more commonly used once HTTP 1.1 compliant browsers and servers are deployed.

Pragma occurrence	11/8/96	4/28/97
(C) no-cache	7.2%	5.7%
(C) cache-control	0%	0.004%
(C) if-modified-since	22.8%	20.6%
(S) no-cache	0.2%	0.5%
(S) cache-control	0.1%	0.5%
(S) expires	4.7%	5.0%
(S) last-modified	54.3%	54.5%

Table 2: **HTTP header frequencies:** this table summarizes the percent of HTTP client requests (C) and server responses (S) that contained various HTTP headers that affect caching behaviour.

Internet services can benefit quite strongly from caching, as there is significant locality in a user population's references. Services must be careful to deploy an adequately large cache in order to capture the working set of that population.

3.5 Service Response Times

The recently emerging class of middleware services must take into consideration the performance of conventional content-providing Internet services as well as the characteristics of the client population. Middleware services retrieve and transform content on behalf of clients, and as such interact directly with content-providing services, relying in part on the services' performance to determine their own.

In figure 11, we present a breakdown of the time elapsed during the servicing of clients' requests. Figure 11a shows the distribution of the elapsed time between the first byte of the client request and the first byte of the server's response observed by the trace gatherer, shown using both a linear and a logarithmic y-axis. This initial server reaction time distribution is approximately exponentially decreasing, with the bulk of reaction times being far less than a second. Internet services are thus for the most part quite reactive, but there is a significant number of very high latency services.

Figure 11b shows the distribution of the elapsed time between the first observed server response byte and the last observed server response byte (as measured by when the TCP connection to the server is shut down).[1] From these graphs, we see that complete server responses are usually delivered to the clients in less than ten seconds, although a great number of responses take many tens of seconds to deliver. (Bear in mind that the response data is being delivered over a slow modem link, so this is not too surprising.)

A number of anomalies can be seen in this graph, for instance the pronounced spikes at 0, 4, 30, and roughly 45 seconds. The spike at 0 seconds corresponds to HTTP requests that failed or returned no data. The spike at 4 seconds remains a bit of a mystery - however, note that the 4 second delivery time corresponds to 14 KB worth of data sent over a 28.8 KB modem, which is almost exactly the size of the "home_igloo.jpg" picture served from Netscape's home page, one of the most frequently served pages on the Internet. We believe that the spikes at 30 and 45 seconds most likely correspond to clients or servers timing out requests. Finally, figure 11b shows the distribution of total elapsed time until a client request is fully satisfied. This distribution is dominated by the time to deliver data over the clients' slow modem connections.

From these measurements, we can deduce that Internet servers and middleware services must be able to handle very large amounts of simultaneous, outstanding client requests. If a busy service expects to handle many hundreds of requests per second and requests take tens of seconds to satisfy, there will be many thousands of outstanding requests at any given time. Services must be careful to minimize the amount of state dedicated to each individual request the overhead incurred when switching between the live requests.

3.6 Summary

This section of the paper presented a detailed analysis of the Berkeley Home IP traces. We demonstrated the heterogeneity of the user population, the burstiness of traffic a fine-grained time scales, the presence of a strong and predictable diurnal traffic cycle, locality in client web requests, and the heavy-tailed nature of web service response times. In the next section, we discuss how these observations relate to a real Internet middleware service designed at Berkeley, the TranSend distillation proxy.

4 System Design Experience from TranSend

The TranSend middleware service provides distillation ([13], [14]) services for the Berkeley Home IP modem user population, representing roughly 8,000

[1] Persistent HTTP connections were very uncommon in these traces, but these special cases were handled correctly - the elapsed time until the last byte from the server for a given request is seen is reported in these figures.

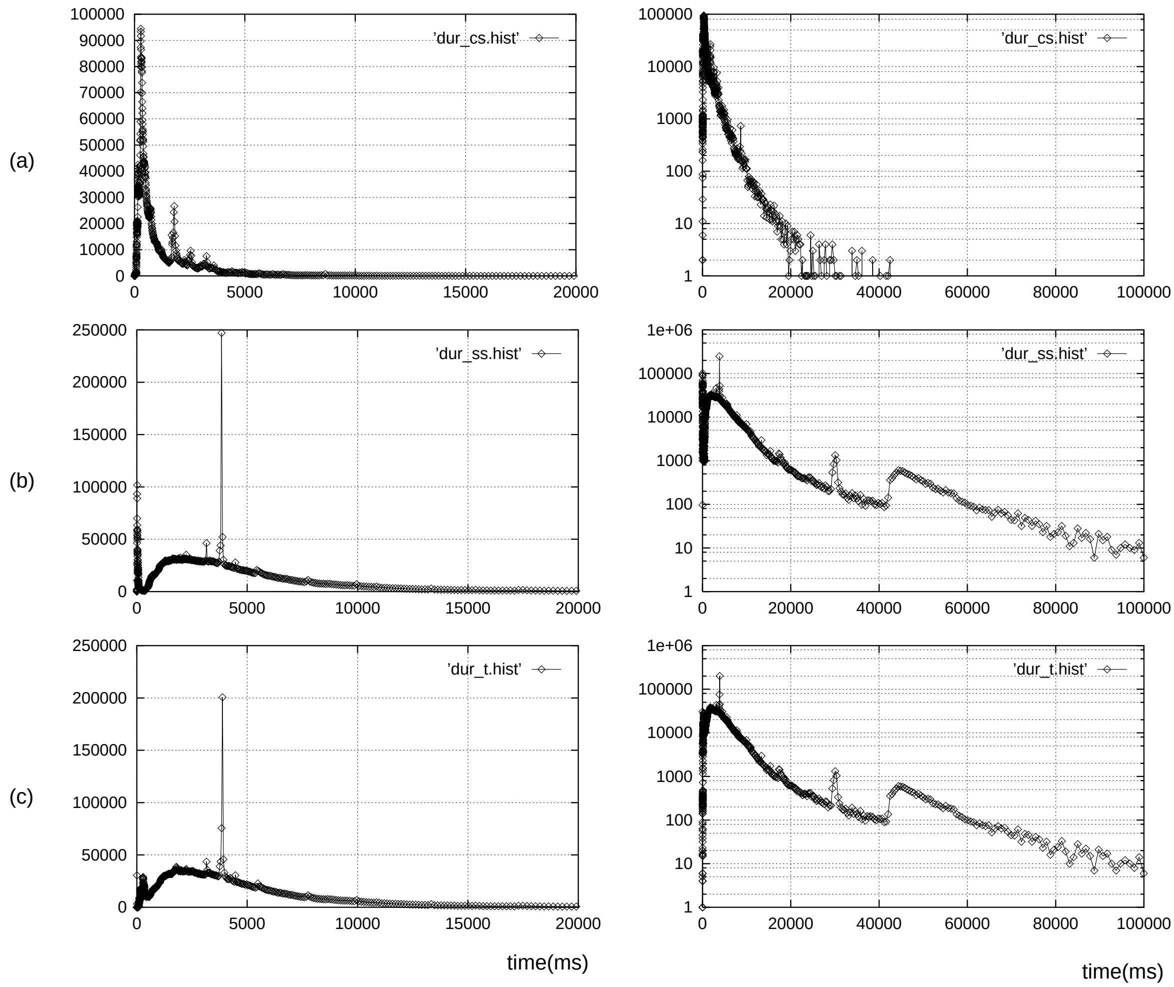


Figure 11: **Response time distributions** (a) elapsed time between the first observed byte from the client and the first observed byte from the server, (b) elapsed time between the first observed byte from the server and the last observed byte from the server, and (c) total elapsed time (between the first observed byte from the client and the last observed byte from the server). All distributions are shown with both a linear and a logarithmic Y-axis.

active users of a bank of 600-700 modems. Distillation is data-type specific, lossy compression - for example, a distilled image may have reduced resolution or color depth, sacrificing image quality for compactness of representation. Although a small additional latency is introduced by performing distillation, the byte-wise savings realized by the more compact distilled representations more than compensates for the latency of performing the distillation, resulting in a factor of 3-7 reduction in the end-to-end latency of delivering web content to users over their slow modem links. It was therefore an explicit design goal of TranSend to help mitigate the heterogeneity of Internet clients by adapting servers' content to clients' needs.

4.1 Burstiness

The TranSend service runs on a cluster of high performance workstations. Client requests are load balanced across machines in the cluster in order to maximize request throughput and minimize the end-to-end latency of each request through the system [15]. As observed in the Home IP traces, the load presented to TranSend is quite bursty on time scales on the order of seconds. Fortunately, the service time for an individual request is on the order of milliseconds; if a burst of traffic arrives at the system, it takes only a few seconds for the backlog associated with that burst to be cleared from the system.

Over longer time scales, we have indeed observed relatively stable, non-bursty load. Certain real-world events (such as the publication of an article in the campus newspaper about the service) did trigger temporary load bursts that persisted for hours, however these bursts were extremely rare (they have only occurred two or three times during the 4 months that TranSend has been active). Because of this long-term smoothness, we were able to allocate a fixed number of cluster nodes to TranSend. To handle the infrequent long-term bursts of activity, we designed TranSend to easily recruit "overflow nodes" in times of need.

4.2 Reference Locality

The TranSend service incorporates a large web cache. We have observed that there is locality in both the pre- and post- transformed representations of web content. In our experience, a 6 gigabyte web cache has been more than sufficient to serve the needs of the Home IP service, providing close to a 50% hit rate, as predicted by the cache simulations.

4.3 Service Response Times

The two largest components of end-to-end latency perceived by the end users of TranSend are the time that it takes TranSend to retrieve content from web services on a cache miss, and the time it takes TranSend to deliver transformed content to users over the slow modem lines. The time spent by TranSend actively transforming content is less than 100 milliseconds, but content retrieval and delivery latencies often exceed tens of seconds. This means that at any given time, there are many idle, outstanding tasks supported by TranSend, and a large amount of associated idle state.

We engineered TranSend to assign one thread to each outstanding task. Because of these high latencies, we have observed that there must be on the order of 400-600 task threads available. A large amount of the computational resources of TranSend is spent context switching among these threads. In retrospect, we concluded that a more efficient design approach would have been to use an event-driven architecture, although we would certainly lose the ease of implementation associated with the threaded implementation. Similarly, each task handled by TranSend consumes two TCP connections and two associated file descriptors (one for the incoming connection, and one for the connection within TranSend to the cache). We did not attempt to measure the overhead we incurred from this large amount of network state.

5 Related Work

A number of web client tracing efforts have been made in the past. One of the earliest was performed by Boston University [10], in which about a half million client requests were captured. These traces are unique in that the Mosaic browser was exclusively used by the client population; the Boston University researchers instrumented the browser source code in order to capture their traces. This research effort concentrated on analyzing various distributions in the traces, including document sizes, the popularity of documents, and the relationship between the two distributions. They used these measured distributions to make a number of recommendations to web cache designers.

Our traces are similar to the Boston University traces in spirit, although by using a packet snooper to gather the traces, we did not have to modify client software. Also, our traces were taken from a much larger and more active client population (8,000 users generating more than 24,000,000 requests over a 45 day period, as compared to the Boston University traces' 591 users generating 500,000 requests over a 6 month period).

In [20], a set of web proxy traces gathered for all external web requests from Digital Electronics Corporation (DEC) is presented. These traces were gathered by modifying DEC's two SQUID proxy caches. These traces represent over 24,000,000 requests gathered over a 24 day period. No analysis of these traces is given - only the traces themselves were made public. Only requests flowing through the SQUID proxy were captured in the traces - all web requests that flowed from DEC to external sites were captured, but there is a lack of DEC local requests in the traces.

Many papers have been written on the topic of web server and client trace analysis. In [32], removal policies for network caches of WWW documents are explored, based in part on simulations driven by traces gathered from the Computer Science department of Virginia Tech. In [9], WWW traffic self-similarity is demonstrated and in part explained through analysis of the Boston University web client traces. In [25], a series of proxy-cache experiments are run on a sophisticated proxy-cache simulation environment called SPA (Squid Proxy Analysis), using the DEC SQUID proxy traces to drive the simulation. A collection of proxy-level and packet-level traces are analyzed and presented in [12] to motivate a caching model in which updates to documents are transmitted instead of complete copies of modified documents. Finally, an empirical model of HTTP network traffic and a simulator called INSANE is developed in [23] based on HTTP packet traces captured using the *tcpdump* tool.

6 Conclusions

In this paper, we presented the results of an extensive, unintrusive client-side HTTP tracing efforts. These traces were gathered from a 10 Mb/s Ethernet over which traffic from 600 modems (used by more than 8,000 UC Berkeley Home IP users) flowed. Forty-five days worth of traces were gathered. We used a custom module written on top of the Internet Protocol Scanning Engine (IPSE) to perform on-the-fly traffic reconstruction, HTTP protocol parsing, and trace file generation. Being able to do this on the fly allowed us to write out only the information that interested us, giving us smaller and more manageable trace files.

We measured and observed a number of interesting properties in our Home IP HTTP traces, from which we have drawn a number of conclusions related to Internet middleware service design:

1. Although most web clients can be classified as accessing Internet services using a PC-based browsers and desktop machines, there is significant heterogeneity in the client population that Internet middleware services must be prepared to handle.

2. There is an extremely prominent diurnal cycle affecting the rate at which clients access services. Furthermore, clients' activity is relatively smooth at large time scales (on the order of tens of minutes, hours, or days), but increasingly bursty at smaller time scales (order of minutes or seconds). Internet middleware services can thus provision their resources based on the request rate observed over several hours if they can afford to smooth bursts observed over second-long time scales.

3. There is a very large amount of locality of reference within clients' requests. The amount of locality increases with the client population size, as does the working set of the client population. Thus, caches that take advantage of this locality must grow in size in parallel with the client population that they service in order to avoid thrashing.

4. Although Internet services tend to be very reactive, the latency of delivering data to clients is quite lengthy, implying that there could potentially be many hundreds or thousands of outstanding, parallel requests being handled by a middleware service. Services must thus minimize the amount of state and switching overhead associated with these outstanding, mostly idle tasks.

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