The Case for Better Throughput Estimation

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Abstract

A Web proxy must accurately predict network performance between itself and its servers and clients in order to make good distillation decisions. In this paper, we show that the current approaches to make such predictions — either assuming the proxy is well-connected to all servers or using past observations — are insufficient. We propose a new prediction method, estimation with uncertainty, *that will play a crucial role in web proxies. This method can also be useful in domains such as distributed prefetching, distributed query planning, and cache replacement algorithms that take into account the cost of refetching evicted objects.*

1. Introduction

The diversity of speeds with which end users access network services is steadily increasing. Typical home users have network connectivity in the tens of Kb/s — several orders of magnitude slower than institutional users. Mobile users can experience connectivity that frequently varies over similar ranges. Web services are often optimized for those users connected by high-speed links; weakly-connected users are then forced to cope with poor performance when accessing those services. Rather than force services to optimize to the slowest potential customer, a proxy-based *distillation* architecture has been proposed [2].

In this architecture, shown in Figure 1, a proxy is placed at the border between weakly-connected clients and the rest of the network. The path from a server to the proxy will often be much faster than that from the proxy to the client. The proxy can then distill each object fetched from the server into a version that is smaller but of lower fidelity. When the server-proxy path is faster than the proxy-client path, the overhead of distillation is more than offset by the shortened transmission time along the slow link, improving response time for the client.

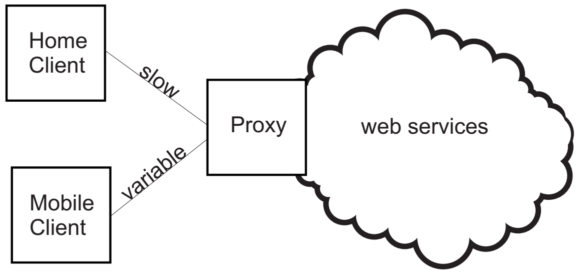


Figure 1. Proxy Architecture

Correct distillation requires good estimates of the speed along the server-proxy and proxy-client paths. For example, users connected by mobile links can have distillation decisions made for them *dynamically*. Objects are distilled little if at all when the bandwidth between proxy and client is high, and are aggressively distilled when that path is slow [9].

Unfortunately, proxies often assume that all remote services are *well-connected* to the proxy, and focus only on the speed of the path to the client. A Web server that is connected to the rest of the network by a slow modem line will never serve items quickly enough to justify distillation. More recently, a proxy that uses observations of recent performance to each destination for future predictions has been implemented [4]. This proxy can discover persistent performance limitations, but cannot predict short-term variations in performance due to transient load.

This paper argues that both of these approaches are inadequate as the basis for making distillation decisions. In order to show this, we have measured how each approach would affect the Web browsing of a small group of users at the University of Michigan. Section 2 describes how these measurements were collected. Section 3 quantifies the impact of assuming that connections are always fast or can be predicted by past behavior. In Section 4 we propose a new method, *estimation with uncertainty*, that will provide for better distillation decisions.

While we have focused primarily on Web proxies, a good bandwidth estimator is crucial to a number of important problems. For example, one needs good estimates of network performance for prefetching in a distributed system [13, 14]. Good estimates are also essential in distributed query planning [3, 7] and caches that consider the cost of refetching in replacement decisions [15].

The problem of predicting end-to-end application throughput — sometimes referred to as *goodput* — is related to the problem of estimating either bottleneck or available bandwidth along a path. Several variants of the *packet-pair* algorithm [5] have been proposed, some quite sophisticated [6]. However, bandwidth along a path is only one component of throughput. Latency, loss rate, and other factors can also have a substantial effect on the performance seen by applications.

2. Experimental Method

In order to explore the impact of various assumptions in distillation decisions, we measured the Web browsing of a small set of users in the EECS department of the University of Michigan. This traffic was measured at a proxy for all of our users' Web activity over one month. The proxy provided no distillation or other added services; it was used only to measure fetch throughput from remote servers.

The proxy generates an *access log* that records information about client requests, one line per request. When a request arrives at the proxy, it is forwarded to the remote web server, which provides a response. An HTTP response consists of a set of headers followed by the requested data. The proxy first receives the headers and sends them back to the client before reading and forwarding the data itself.

We have modified our proxy to record two timestamps for each fetch: one after fetching the headers, and one after fetching the end of the data. The log record for each fetch contains: client IP address, server IP address, URL, MIME type, request time, post-header timestamp, post-fetch timestamp, and the number of data bytes received. In order to guarantee privacy — and encourage as many people as possible to use our proxy — we log only the MD5 hashes [11] of the first three entries. Thus, we can correlate fetches to the same server, but cannot identify servers, clients, or fetched objects.

The throughput between the server and the proxy is defined as:

$$T = \frac{b}{t_f - t_h} \qquad (1)$$

Where b is the number of data bytes fetched, t_f is the timestamp taken after all data is obtained, and t_h is the timestamp taken after the headers have been fetched.

Browsers fetch a web page by first fetching the page's text and then issuing separate requests for each embedded object. In order to overlap connection set-up and tear-down with the transfer of useful data, browsers often issue requests for embedded objects concurrently. These requests often are to the same server; an example is shown in Figure 2.

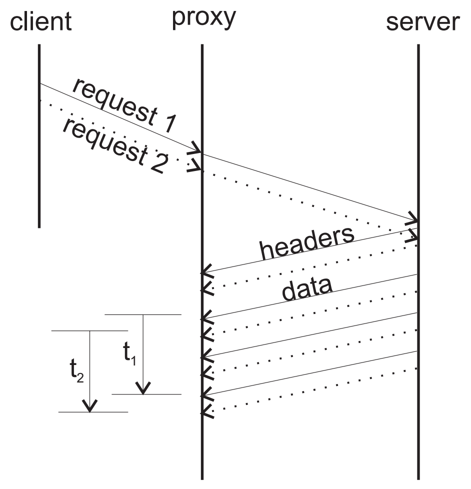


Figure 2. Parallel Requests for Web Objects

The times t_1 and t_2 denote the periods during which the proxy receives data from the server for the first and second request, respectively. In this example, the transmission of the two responses happens concurrently, and the available network capacity is divided between them. If we were to measure the throughput separately for each request, we would understate the aggregate throughput between the server and the proxy. Thus, whenever two log entries with the same endpoints overlap in time, we merge them into a single entry. The new entry has a size that is the sum of the size of the two merged entries. The first timestamp is the smaller of the post-header timestamps, while the second is the larger of the post-fetch timestamps. We found that 22% of logged responses experience such overlapping.

The proxy interleaves fetching pieces of an object from the remote server with forwarding those pieces to the client. If the path from the proxy to the client is the bottleneck, the measured throughput will again understate the capacity from server to proxy. Since our users almost always have excellent connections to the proxy, we do not log these extremely rare observations.

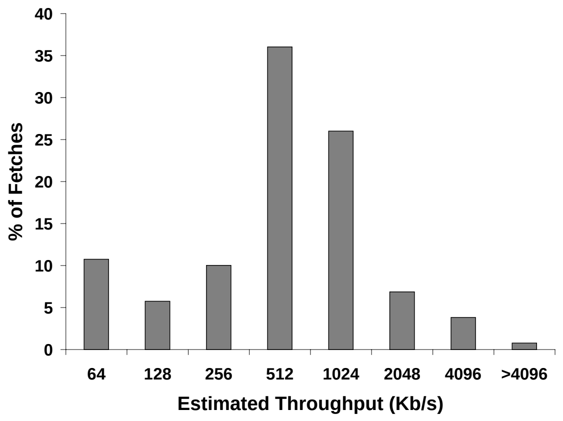
We modified Apache version 1.3.1 to act as our data collection proxy. It ran on a 300 MHz Pentium II machine with 64 MB of RAM running Linux 2.0.35. The log file was approximately 22 MB with an average of 4000 requests per day. There were 1660 distinct servers in the log. However, about 40 servers accounted for more than 50% of all the requests. The logged reponses include 76% *successful* responses, 17% *not modified* responses, and 7% other responses. We report only the successful responses.

3. Experimental Results

We used the collected data to answer two questions. First, what is the impact of assuming that the paths between the proxy and all servers are fast? Second, what is the impact of using past observations to predict individual fetch times?

3.1. Assuming Fast Links

The most common strategy used by distilling proxies is to assume that all remote services are well-connected to the proxy. In other words, the time for the proxy to fetch an object from a remote server is considered to be negligible compared to the time to distill and forward that same object.



This figure shows the distribution of the observed throughput for all images larger than 5KB in size. The X axis is in Kb/s, and the Y axis shows percentage of observed fetches. Each bin represents the percentage of fetches between the previous bin's X value and the current bin's. The final bin gives all fetches faster than 4Mb/s. Note that 10% of all fetches are at or below 64Kb/s.

Figure 3. Image Retrieval Throughput

Figure 3 shows the distribution of bandwidths observed by our proxy when fetching images from remote servers. Because TCP slow-start can have a dominant effect for transfers over paths with large round-trip times, smaller objects tend to have lower bandwidths. In this histogram, we consider only images that are 5KB or greater in size; most proxies distill only images, and those smaller than 5K in size are not likely to benefit from distillation. This number was selected to be conservative. Other work suggests distilling images larger than 1K [4]; using this size as the cutoff would shift the distribution in Figure 3 to the left.

There were 15,742 images over 5K fetched during data collection. Each bucket represents the percentage of observations that fell between that bar's X value and the previous one; for example, the second bar shows that almost 6% of all fetches were at bandwidths between 64 Kb/s and 128 Kb/s. The final bucket contains all fetches that were faster than 4 Mb/s.

The central message of this histogram is that more than one in ten images are fetched near or below typical modem speeds. A proxy that assumed all fetches were fast would distill these images rather than simply forwarding them. The user would then see a lower quality image without a corresponding reduction in response time; the server-proxy path is the constraining link, and distillation will not deliver the last byte of the image more quickly. In fact, response time would likely increase due to the added delay of distillation.

3.2. Using Short-Term Averages

Rather than simply assuming that all fetches are fast, the proxy must use some method of estimating the time it will take to fetch an object from a remote service. One suggested approach [4] has been to use a technique similar to SPAND [12] to make these predictions. In this approach, the proxy logs interactions with each server and client in protocol stubs. An off-line algorithm periodically summarizes these observations, grouped by endpoint and size. When each fetch is requested by the client, the proxy consults this summary to predict the time required to obtain the requested object. It bases this summary primarily on observations that are at most tens of minutes old [1].

The success of this approach depends on the degree to which such summaries can predict individual fetch times. To gauge the predictive power of past observations, we first selected the most popular server from our logs.[1] The traffic to this server is most likely to provide us with a history on which to base predictions; predictions to other servers are likely to be less accurate. We then predicted the times for one day's worth of fetches using the median of the observations from the previous 15 minutes, measuring the degree to which our predictions matched reality.

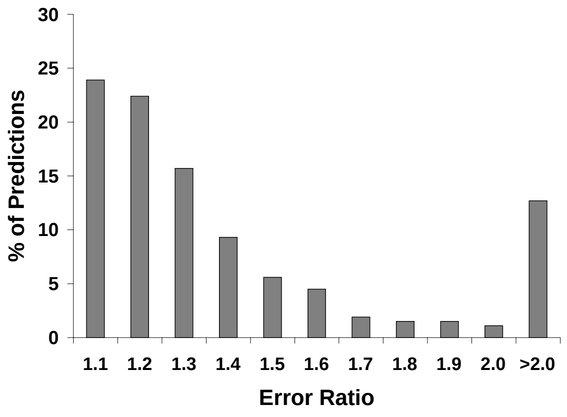
We used an *error ratio* metric to determine the accuracy of prediction. For the fetch of an object of size s, we first examine prior fetches to predict its performance. Over wide area links, TCP slow-start dominates the throughput of small transfers; therefore, we consider only those objects larger than $s/2$ and smaller than $2s$. We then take the median of those observations as the predicted fetch time, t_p.

[1]Since we record only the MD5 hashes of server names, we do not know what server this was.

We say that this predicted time is correct to within an error ratio, r, of the actual time, t_a, if it satisfies the following inequality:

$$\frac{t_p}{r} \le t_a \le r t_p \qquad (2)$$

We consider the error ratio of a particular prediction to be the smallest possible value.



This figure shows the distribution of error for predictions based on short-term observations. The X axis gives the error ratio, and the Y axis is in percentage of predicted fetches. Note that more than 12% of all predictions were off by a factor of 2 or more.

Figure 4. Error Ratio: Short-Term Predictions

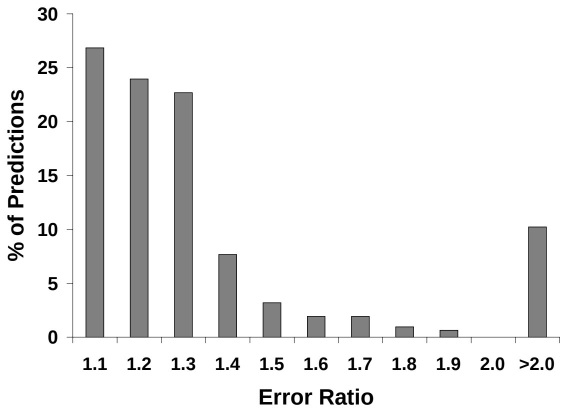
Figure 4 shows the distribution of prediction accuracy for fetches of all sizes. There were 313 fetches during the day; 14% of them did not have any applicable observations within the previous 15 minutes. The histogram depicts the remaining predictions. Each bucket represents the percentage of predictions that had error ratios between that bar's X value and the previous one. For example, the second bar shows that more than 22% of all predictions had error ratios between 1.1 and 1.2. The final bar gives the percentage of predictions with error ratios greater than 2.0.

While most predictions are quite good, more than one in eight of them are still off by a factor of two or more. This is much better than the performance reported in the paper describing SPAND [12], which claims less than 70% of predictions with an error ratio less than two. This is in part because they did not consider the impact of size on throughput, though they mention it as a mitigating factor and have corrected it in later work [4].

3.3. Using Long-Term Averages

The number of unpredictable fetches is quite high, especially given the fact that this is the most popular server in our access logs. Aggregating history information from several co-located hosts would improve this rate, as would serving a larger number of clients. However, even with substantially larger traffic rates, predictions with recent data will not always be possible.

One fallback strategy would be to use older observations to predict such fetches. To gauge the success of such a strategy, we re-ran the prediction experiment, using the past week's observations rather than those from only the most recent 15 minute period. The results are presented in Figure 5.



This figure shows the distribution of error for predictions based on long-term observations. The X axis gives the error ratio, and the Y axis is in percentage of predicted fetches. Note that 10% of all predictions were off by a factor of 2 or more.

Figure 5. Error Ratio: Long-Term Predictions

Surprisingly, the predictions are slightly better than those based on short-term observations. This is counter to the observation that network performance tends to be most stable over periods of tens of minutes [1]. We cannot fully explain this difference, though our observed traffic load was both smaller in scale and only to a single host. The question of what interval to use for prediction is one that we are pursuing in ongoing work.

However, even predictions based on long-term averages are still off by more than a factor of 2 in one out of ten cases. Such erroneous predictions can lead a proxy to make sub-optimal distillation decisions. The proxy will either throw away information needlessly or not distill aggressively enough to give good response times.

4. Towards a Better Estimator

In order for a proxy to make the best possible distillation decisions, it must accurately predict each individual fetch. However, it is unlikely that we will be able to build an oracular proxy that is always able to predict correctly. If two hosts are close together — as the client and the proxy are likely to be — performance observations are likely to be very stable. However, traffic performance between two widely separated Internet hosts shows significant variance [10], and observing a sequence of bandwidth observations can lead one to believe they are no more than noise.

In light of this, a proxy should have the following properties to be as useful as possible:

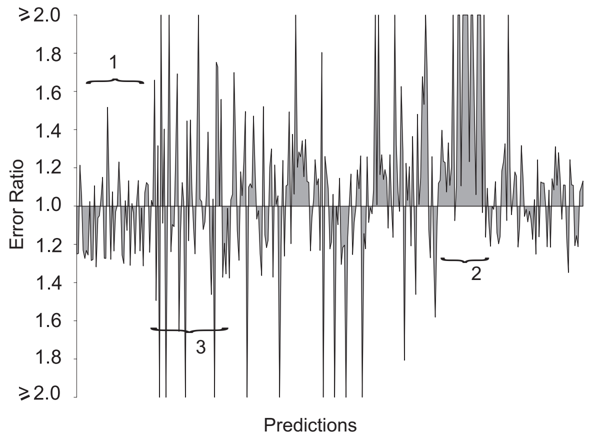
- It must accurately estimate transfer time from servers. These estimates must depend in part on short-term observations.
- Each estimate should be accompanied by a *degree of confidence*. This confidence should ideally be conservative.
- The proxy should take both the estimate and the confidence into account when making distillation decisions. When confidence is low, the proxy should be conservative in the prediction's use unless directed otherwise by user preferences.

As shown in Sections 3.2 and 3.3, past observations are not sufficient as predictors of bandwidth; the proxy must take into account transient variations. Simple approaches can work well for the short connection between client and proxy. For example, Odyssey uses:

$$p_i = \alpha b_{i-1} + (1-\alpha)p_{i-1} \qquad (3)$$

where p_i is the predicted bandwidth of the ith fetch, and b_i is the actual bandwidth during that fetch; α is 3/4, giving a heavy bias towards the most recent observation. This has been shown to have sufficient predictive power in realistic situations [8], while retaining good agility — the ability to react quickly to change in mobile environments.

However, since performance observations over wide-area connections carry much more noise, something more sophisticated is required to predict performance between the proxy and servers. To see why, consider Figure 6; it shows the same predictions as Figure 5, but in different form. Rather than a histogram of error ratios, it shows the error ratio for the long-term predictions to the most popular server, in sequence. Error ratios above the X axis represent estimates that were too high; those below the X axis are estimates that were too low. Points plotted at the extremes show error ratios of 2.0 or greater.



This figure shows the error for each prediction based on long-term observations. The X axis gives each prediction in sequence, and the Y axis shows error ratio. Predictions above the X axis are too optimistic. In region 1, predictions are accurate. In region 2, predictions are consistently too high. In region 3, throughput is unstable.

Figure 6. Error Ratio: Series of Predictions

On first glance, it appears that there is little predictive power in these observations. However, on closer inspection there is some opportunity for improvement. We have labeled three regions of interest in the graph. In region 1, the deviation from the prediction is fairly small; it could be used with a high degree of confidence.

In region 2, the predictions are consistently too high, often exceeding an error ratio of 2.0. During this period, the time to fetch objects from the server was much longer than usual. This could have been caused either by increased cross-traffic or by load at the server. During this period it would be possible to observe that the long-term average is too optimistic, and quickly adjust the estimates downward to meet reality.

In region 3, the predictions are alternately far too fast and far too slow. If estimates had confidences attached, the proxy would be able to determine that it was in a range of instability. In such cases, it would be best to conservatively assume that the object will arrive quickly at the proxy. If wrong, the proxy might throw away extra information through too-aggressive distillation. The alternative — assuming a lower bandwidth, and forwarding the item unchanged — might result in unnecessarily long response times when the assumption is unwarranted.

We plan to build an estimator that includes confidences to cope with situations similar to the three above. It is depicted in Figure 7, and is similar to a canonical feedback control system. At each fetch, the estimator will compare its predictions with the actual values. By designing an appropriate set of heuristics, one can identify consistent errors,

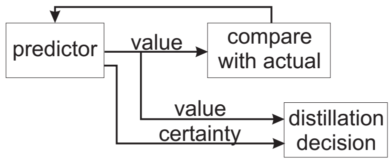


Figure 7. A Better Estimator

such as might happen in region 2, or noisy states, such as region 3. This is similar to the variance metric maintained by protocols such as TCP. However, the uncertainty bounds are also influenced by age of observations; older measurements are less certain than more recent ones. It is also exposed to all entities that make use of bandwidth estimates, rather than used only for internal bookkeeping.

5. Conclusion

Correct distillation decisions at a proxy require accurate predictions of the time to fetch an object from a remote service. Because the servers storing the original objects are often far away in the network topology, accurately estimating that time is an extremely difficult problem. As we have shown, simply assuming all fetches will be fast is incorrect, as is using only past average behavior and ignoring short-term fluctuations.

We propose to build an estimator framework that uses feedback control to both improve the accuracy of estimates as well as attach a certainty to them. When estimates are accurate, the proxy can make much better distillation decisions. When the estimates are very uncertain, the proxy must make some conservative assumptions in order to preserve good response time for the end users. In addition to distillation proxies, such an estimator would be invaluable in distributed prefetching, query planning, and cache replacement algorithms. We plan to investigate its use in these and other domains.

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