WebProphet: Automating Performance Prediction for Web Services

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Abstract

Today, large-scale web services run on complex systems, spanning multiple data centers and content distribution networks, with performance depending on diverse factors in end systems, networks, and infrastructure servers. Web service providers have many options for improving service performance, varying greatly in feasibility, cost and benefit, but have few tools to predict the impact of these options.

A key challenge is to precisely capture web object dependencies, as these are essential for predicting performance in an accurate and scalable manner. In this paper, we introduce WebProphet, a system that automates performance prediction for web services. WebProphet employs a novel technique based on timing perturbation to extract web object dependencies, and then uses these dependencies to predict the performance impact of changes to the handling of the objects. We have built, deployed, and evaluated the accuracy and efficiency of WebProphet. Applying WebProphet to the Search and Maps services of Google and Yahoo, we find WebProphet predicts the median and 95^{th} percentiles of the page load time distribution with an error rate smaller than 16% in most cases. Using Yahoo Maps as an example, we find that WebProphet reduces the problem of performance optimization to a small number of web objects whose optimization would reduce the page load time by nearly 40%.

1 Introduction

Software vendors and service providers are increasingly delivering services to users through the Internet. Large-scale web services, such as maps, search, and social networking, have proliferated, attracting hundreds of millions of users worldwide. On the client side, these services heavily leverage Asynchronous Javascript and XML (AJAX) to provide a seamless and consistent user experience across devices and form factors. Behind the scenes, significant amounts of data and computation are provided by servers in the cloud.

Many web services are extremely complex, since they aim to match or even exceed the rich user experience offered by traditional desktop application. For instance, the "driving directions" webpage of Yahoo Maps comprises about 110 embedded objects and 670KB of Javascript code. These objects are retrieved from many different servers, sometimes even from multiple data centers (DCs) and content distribution networks (CDNs). These dispersed objects meet only at a client machine, where they are assembled by a browser to form a complete webpage. Since service providers lack object-level measurements obtained from clients, it is hard for them to assess and study user-perceived performance. Moreover, there exist a plethora of dependencies between different objects. Many objects cannot be downloaded until some other objects are available. For instance, an image download may have to await a Javascript download because the former is requested by the latter. These multiple factors make it highly challenging to understand and predict the performance of web services.

The performance of web services has direct impact on user satisfaction. Poor page load times (PLT) result in low service usage, which in turn may undermine service income. For instance, a study by Amazon reported roughly 1% sales loss as the cost of a 100 ms extra delay. Another study by Google found a 500 ms extra delay in display search results may reduce revenues by up to 20% [16]. Even worse, users may simply abandon a service provider for another offering, as switching barriers are often low.

Ideally, service providers would like to predict the effects of potential optimizations before actual deployment. Yet it is seldom clear what benefits various possible options for improvement might bring a service provider – whether optimization to the object structure of the page, or optimizations in the manner in which content is placed and delivered over the Internet. User-perceived PLT is affected by the loading time of web objects and their dependencies. The loading time of each individual object is further affected by a variety of *delay factors*, including DNS lookup time, network round trip time (RTT), server response time, and client execution time.

One compelling way to predict performance is to first measure the PLT through experiments on the service itself (*e.g.*, A/B tests [16] by varying a given property of the service), and then to extrapolate estimates using some form of regression. However, such experiments can be difficult to setup and expensive to sustain. It is not uncommon for such experiments to run for days or even weeks, limiting the capacity for adding additional experiments. Furthermore, it is extremely challenging to sweep the space of all possible scenarios since the number of scenarios grows exponentially with the number of objects and delay factors. Without detailed knowledge of object dependencies, it is difficult to decide how many distinct scenarios need to be measured to attain accurate predictions.

Existing approaches for performance prediction generally fall into two broad categories: provider based *vs.* end-system based. In the first category, WISE [23] predicts performance based on server logs collected at the service provider's data centers. As a result, this approach has limited visibility into some client-side factors that are crucial for user-perceived PLT, such as page rendering time, object dependencies, and multiple data sources (crossing data centers and content providers). In the second category, Link Gradients [10] proposes to predict end-to-end response times of untested system configurations, assuming the effects of change in individual factors are completely independent of each other. While this assumption may hold in small-scale enterprise applications, it is inapplicable to complex web services in which inter-component dependencies are prevalent.

To overcome these challenges and shortcomings, this paper presents WebProphet, a tool that predicts the impact of various optimizations on user-perceived PLT of web services. First, WebProphet aims to be applicable to a diverse set of web services. Second, WebProphet aims to automatically produce accurate predictions. Given the number of web services and the churns in their implementations, a tool that involves manual effort can be overly burdensome and error prone.

WebProphet consists of a measurement engine, a dependency extractor, and a performance predictor. The dependency extractor employs a novel algorithm to infer dependencies between web objects by perturbing the download times of individual objects. Our key observation is the delay of an individual object will be propagated to all of its dependent objects. While others have noticed that timing perturbation can convey information (in particular, [20] uses such techniques to transmit data covertly), we are the first to apply it to systematically discovering web object dependencies. Given the dependency graph of a webpage, the performance predictor implements a simple and yet accurate method to simulate the page load process of a web browser. It can make fast and accurate PLT prediction under any combination of changes in objects and delay factors. It can also predict the statistical properties (*e.g.*, median or 95th-percentile) of a PLT distribution under a hypothetical scenario.

We applied WebProphet to four widely-used web services: Maps and Search of Google and Yahoo. We verified that our system successfully extracts the dependency graphs for all these services, even though some of the complex webpages comprise over 100 objects. We used WebProphet to predict PLT on real, popular web browsers using controlled experiments and the PlanetLab testbed. Our evaluation shows that the predictions of WebProphet are highly accurate, with error rates mostly under 16%. This is quite promising given the inherent noise (*e.g.*, different loss conditions) in these experiments. We then apply WebProphet to finding cost-effective optimization strategies for real applications. For instance, Yahoo Maps contains 110 objects and has a median PLT of 3.987 seconds measured from Northwestern University. By simply optimizing the client execution time of 14 objects and moving 5 static objects from Yahoo data centers to the Akamai CDN, the median PLT of Yahoo Maps can be cut by nearly 40%.

We continue to discuss the problem formulation and present an overview of WebProphet in §2. We describe dependency extraction in §3 and performance prediction in §4. The implementation is covered in §5. In §6 and §7, we show the results of dependency extraction and performance prediction respectively. We demonstrate how WebProphet helps to optimize the PLT of Yahoo Maps in §8. We evaluate the systems performance in §9. Finally, we review the related work in §10 and conclude in §11.

2 Problem Context

Many web services are delivered to users in form of webpages that can be rendered by a browser. Sophisticated webpages may contain many static and dynamic objects arranged hierarchically. To load a page, a browser typically first downloads a main HTML object that defines the structure of the page. Next, it may download a Cascading Style Sheets (CSS) object that describes the presentation of the page. The main HTML object may embed many Javascript objects that are executed locally to interact with a user. As the page is being rendered, an HTML or a Javascript object may request additional ob-

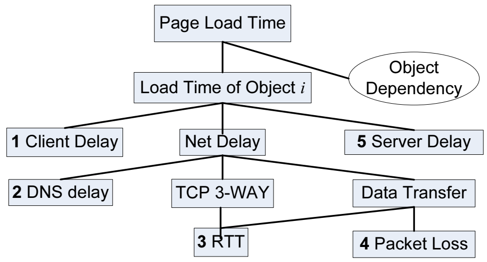


Figure 1: The page load time decomposition.

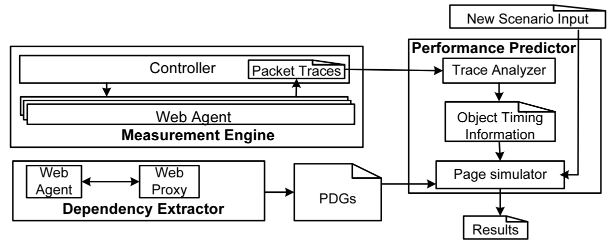


Figure 2: System architecture.

jects, such as images and Javascripts. This process continues until all relevant objects are loaded.

We define page load time (PLT) as the time between when the user triggers the page starting to load and when all the objects in the page are loaded. Sometimes, users do not care about all the objects in a page. For instance, a page may contain invisible images, advertisements, or user tracking services. Moreover, a user action may only trigger a few new objects to be loaded after the initial page load. Accordingly, we could also define PLT as the time to load a subset of objects in a page that are relevant to user-perceived performance. Note that there is a subtle difference between when objects are loaded and when objects are perceived by the user. While the latter is more directly related to user satisfaction, it is also harder to define and measure precisely. Therefore, we choose to focus on the former in this paper.

As illustrated in Figure 1, we may decompose the loading time of each object into client delay, network delay, and server delay. The client delay is due to various browser activities such as page rendering and Javascript execution. The network delay can be further decomposed into DNS lookup time, TCP three-way handshake time, and data transfer time. TCP handshake time and data transfer time are influenced by network path conditions such as RTT and packet loss. The server delay is produced by various server processing tasks such as retrieving static content or generating dynamic content.

Service providers have many different options to improve the PLT of a webpage. For instance, they may upgrade the back-end infrastructure to reduce server response time for dynamic objects. They may use a CDN service to reduce the network delay for static objects. They may also optimize the implementation code to reduce the client execution time for computation-intensive objects. While optimizing for an individual object or delay factor (or for a combination of multiple objects or delay factors) will bring some benefits, they may also incur significant costs in development and management. It is economically infeasible for a service provider to optimize for every object/delay factor, and is often unclear where to find the biggest bang for the buck. Our goal is to build an automated system that can accurately predict the PLT improvement under any combination of changes in object and delay factor. A service provider can easily use our system to narrow down the optimization strategies that could bring the most benefits.

For a web service, WebProphet predicts PLT based on a performance model extracted from client-side observations. Compared to server-side techniques [23], our approach can take into account a few important factors that are visible only at the client. First, a modern webpage usually contains many objects which have dependencies between each other. As a result, the PLT cannot be estimated simply based on the page size and TCP-level characteristics such as RTT, packet loss, and congestion window size. In fact, the dependencies will determine when an object can be loaded and which objects can be loaded in parallel. Second, many webpages comprise sophisticated HTML and Javascript objects to provide a rich user experience. Nonetheless, HTML rendering and Javascript execution may introduce significant client delay. Third, the objects in a page may come from multiple data centers and CDN nodes. For example, Yahoo Maps uses both the Akamai CDN and Yahoo data centers to deliver page content. Though the client side is the ideal place where we can measure the user-perceived PLT accounting for all these effects end-to-end, existing client browsers lack the measurement hooks needed.

As shown in Figure 2, WebProphet has three major components. Given a webpage, the *dependency extractor* infers the dependencies between objects by perturbing the download times of individual objects. The *measurement engine* controls multiple automated *web agents* which can drive a full-featured web browser (Firefox 3) to load the page. The measurement engine also collects one packet trace for each page load. Using the extracted dependency graph and the packet trace in a baseline scenario, the *performance predictor* estimates the PLT in a new scenario by simulating the page load process.

The PLT of a webpage will not be a constant due to the variations of network latency, server response time, and load on the client. WebProphet can predict the statistical properties (*e.g.*, median or 95th-percentile) of the PLT distribution under a new scenario. For this purpose, we first collect a reasonably large number of page load traces in a baseline scenario using a web agent. Then, for each of these traces, we run performance prediction to obtain the PLT in the new scenario, and therefore produce the PLT distribution in a new scenario.

Currently, we do not explicitly consider the effect of packet loss in our model. In other words, we assume the same loss condition in the baseline and new scenarios. Differences in loss conditions can change the number of round trips involved in loading an object, which in turn lead to prediction errors (§4.1). The impact of packet loss on PLT can be highly variable, and highly dependent on factors such as network transients, TCP congestion states, and specific TCP loss recovery mechanisms. In spite of this limitation, as shown in §7, WebProphet attains high prediction accuracy in both controlled and real-world experiments under normal loss conditions.

3 Dependency Extraction

In this section, we first present an overview of dependency relationships between web objects and describe the types of dependencies that we aim to discover. We then explain the details of our dependency extraction algorithm based on timing perturbation.

3.1 What are dependencies?

Modern webpages may contain many types of objects, including HTML, Javascript, CSS, and image. These embedded objects are downloaded via separate requests on potentially multiple TCP connections instead of all at once. For instance, the main HTML object may contain a Javascript object whose execution will lead to additional downloads of HTML and image objects. We say one object *depends* on the other if the former cannot be downloaded until the latter is available. Dependencies between objects can be caused by a number of reasons. Common ones include: i) The embedded objects in an HTML page will depend on the HTML page; ii) Since many objects are dynamically requested during Javascript execution, these objects depend on the corresponding Javascript; iii) The download of an external CSS or Javascript object may block the download of other types of objects in the same HTML page [22]; iv) Object downloads may depend on certain events in Javascript object or web browser. For instance, a Javascript object may download image B only after image A is loaded.

Given an object A, its dependent objects usually cannot be requested before A is *completely* downloaded. However, there are exceptions. Today's browsers render an HTML page in a streamlined fashion, by which we mean the HTML page can be partially displayed even before its download finishes. For example, if an HTML page has an embedded image, the image can be downloaded and displayed in parallel with the download of the HTML page. The image download may start once the tag `<img src=... />` (identified by a byte offset in the HTML page) has been parsed. We call an HTML object a *stream* object. We use *dependency* $offset_A(img)$ to denote the offset of the last byte of `<img src=... />` in the stream object A. We observed this streamlined processing behavior in major browsers including IE, Firefox and Chrome.

Given an object X, we use $descendant(X)$ to denote the set of objects that depend on X and use $ancestor(X)$ to denote the set of objects that X depends on. By definition, X cannot be requested until all the objects in $ancestor(X)$ are available. Among the objects in $ancestor(X)$, we are particularly interested in object Y which is the last to become available. We call Y the *last parent* of X. If Y is a stream object, its *available-time* is when the dependency $offset_Y(X)$ has been loaded. If Y is a non-stream object, its available-time is when Y is completely loaded. In §4.1, we will explain how to use the available-time of Y to estimate the start time of X's download. Essentially, this will allow us to predict the PLT of a webpage. While X only has one last parent in one particular page load, its last parent may change across different page loads due to variations in the available-time of its ancestors. We use $parent(X)$ to denote the subset of the objects in $ancestor(X)$ which may be the last parent of X.

Given a webpage, we use a *parental dependency graph (PDG)* to encapsulate the parental relationship between objects in the page. A $PDG = (V, E)$ is a Directed Acyclic Graph (DAG) and includes a set of nodes and directed links. Each node is a web object. Each link $Y \leftarrow X$ means Y is a parent of X.

3.2 How to extract dependencies?

WebProphet extracts the dependencies of a webpage by perturbing the download of individual objects. Our key observation is the delay of an individual object will be propagated to its descendants. While conceptually simple, the major challenge is to extract the stream parent of an object and the corresponding dependency offset. Suppose an object X has a stream parent Y. To discover this parental relationship and the dependency offset, the available-time of $offset_Y(X)$ must be later than that of all the other parents of X in a particular page load. This requires the ability to control the download of not only each non-stream parent of X as a whole but also each partial download of each stream parent of X. As we will see in §7.4, correctly extracting stream parents and dependency offsets is critical for accurate PLT prediction.

Discovering ancestors/descendants: Given a webpage and its embedded objects, we discover the descendants of each object iteratively. In each round, we reload the page and delay the download of an object X for τ seconds. Here, X is an object which has not been processed and τ is much greater than the normal loading time of any object. The descendants of X are the objects whose download is delayed together with X for at least τ seconds. We repeat this process until the descendants of all the objects are discovered. Note that the order by which we delay each object has no influence on the final result.

Our approach for dependency extraction makes two assumptions. First, we assume the dependencies of a webpage do not change during the discovery process. This may not hold in practice. When a page is reloaded, there could be some minor changes in the new page. For instance, there could be parameter changes in the Universal Resource Identifier (URI) of certain objects. We tackle this problem by matching similar URIs in different rounds according to *edit distance*. Moreover, there could be object changes due to reasons such as new advertisements. We find such changes tend to have limited impact on the overall structure of the page or the PDG. This is because the number of affected objects is small and they usually do not have any descendants. In § 7, we will show that our prediction results are highly accurate in spite of minor changes in webpages.

The second assumption we make is that the artificially injected delay will not change the dependencies in the page. Among the pages we studied, we found only one exception in the "driving directions" webpage of Google Maps. There are two Javascripts `A.js` and `B.js` which have the same parent `main.js`. We use `A` and `B` to represent the names of these two Javascripts, given their original names are very long. When `main.js` is severely delayed, `A.js` and `B.js` sometimes are combined into one single Javascript named `AB.js`. This probably reflects the fact that `main.js` attempts to adapt when it detects poor download speed. We identified this application behavior because it leads to inconsistencies in the extracted dependencies of the page. Among the applications we studied, only Google Maps exhibits this behavior which is handled with a simple heuristic. In the future, we plan to devise a more systematic solution to deal with such behavior.

Extracting non-stream parents: Given a non-stream object X and its descendant Z, we observe that X is the parent of Z if and only if there does not exist an object Y which is the descendant of X and the ancestor of Z. On the one hand, if such Y exists, the available-time of Y will always be later than that of X. This is because X is a non-stream object and Y cannot be downloaded until X

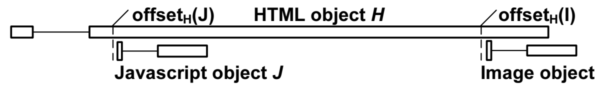


Figure 3: Stream parent example.

is available, which implies X cannot be the parent of Z. On the other hand, if Y does not exist, we can imagine a scenario where X is delayed until all the other ancestors of Z are available. This is possible because none of the other ancestors of Z depend on X. This implies X may indeed be the parent of Z. Based on this observation, Algorithm `ExtractNonStreamParent` takes the set of objects and the set of descendants of each object (inferred from the previous step) as input and computes the parent set of each object.

```
ExtractNonStreamParent(Object, Descendant)
For X in Object
    For Z in Descendant(X)
        IsParent = True
        For Y in Descendant(X)
            If (Z in Descendant(Y))
                IsParent = False
                Break
            EndIf
        EndFor
        If (IsParent) add X to Parent(Z)
    EndFor
EndFor
```

Extracting stream parents and dependency offsets: The method described above may not be useful for discovering the stream parent of an object. We illustrate this with an example in Figure 3. A large HTML object H contains a Javascript J and an image I. J and I are embedded in the beginning and the end of H respectively ($offset_H(J) < offset_H(I)$). Because the URI of I is defined in J, I cannot be downloaded until J is executed. This causes I to depend on both H and J while J only depends on H. According to the previous method, H cannot be the parent of I since J is the descendant of H and the ancestor of I. Nonetheless, when the download of H is slow, J may have been downloaded and executed before $offset_H(I)$ becomes available. In this case, H becomes the last parent of I.

Given a stream object H and its descendant I, we use the following method to determine whether H is the parent of I. We first reload the whole page and control the download of H at an extremely low rate λ. If H is the parent of I, all the other ancestors of I should have been available by the time $offset_H(I)$ is available. We can then estimate $offset_H(I)$ with $offset_H(I)'$, where the latter is the offset of H that has been downloaded when the request of I starts to be sent out. $offset_H(I)'$ can be directly inferred from network traces and is usually a bit larger than $offset_H(I)$. This is because it may take

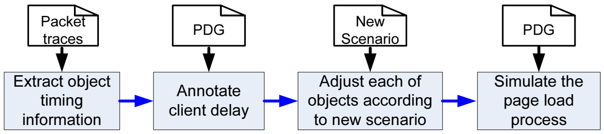


Figure 4: Performance prediction procedure.

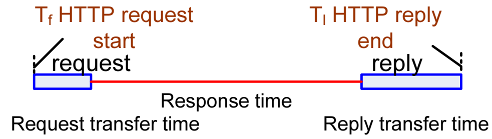


Figure 5: Decomposition of an HTTP activity.

some extra time to request I after $offset_H(I)$ is available. Since H is downloaded at an extremely low rate, these two offsets should be very close.

Given $offset_H(I)'$, we perform an additional parental test to determine whether H is the parent of I. We reload the whole page again. This time, we control the download of H at the same low rate λ as well as delay the download of all the known non-stream parents of I by τ. Let $offset_H(I)''$ be the offset of H that has been downloaded when the request of I is sent out in this run. If $offset_H(I)'' - offset_H(I)' \ll \tau \times \lambda$, this indicates the delay of I's known parents has little effect on when I is requested. Therefore, H should be the last parent of I.

The choice of λ reflects the trade-off between measurement accuracy and efficiency. A smaller λ allows us to estimate $offset_H(I)$ more accurately but leads to longer running times. The parameter τ directly affects the accuracy of parental tests. If τ is too small, the results may be susceptible to noise in experiment, increasing the chance of missing true parents. If τ is too large, we may mistakenly infer a parental relationship because $offset_H(I)'' - offset_H(I)'$ is bounded by $size_H - offset_H(I)$ where $size_H$ is the page size of H. In our current system, we use $\lambda = size_H/200$ bytes/sec and $\tau = 2$ seconds. This means the HTML object H will take 200 seconds to transfer. We will study the accuracy of dependency extraction in § 6.

Discussion: We currently infer the timing information from the packet trace of a page load (§4.1). One alternate approach is to extract dependencies through some combination of static and dynamic program analysis. In fact, it is quite straightforward to parse an HTML object to extract its dependencies. However, extracting the dependencies of Javascript objects requires extensive browser instrumentations. Since the PDG of a page may vary depending on how the page is rendered by a browser, we will have to instrument each type and each version of the major browsers. In comparison, our trace-based approach can more easily work with different browsers.

4 Performance Prediction

In this section, we describe our methodology for predicting performance under hypothetical scenarios. Given the PLT of a webpage in a baseline scenario, we aim to predict the new PLT when there are changes in the *delay factors* (including client delay, server delay, RTT, and DNS lookup time) of any objects in the page. The basic idea is to develop a model that can simulate the page load process of a browser under any hypothetical scenarios. In practice, the page load process can be very complex, since it also relates to browser behavior and parameters, web objects dependencies, versions of TCP and HTTP protocols, and network conditions. The key challenge is to keep the model simple and yet accurate. This requires us to provide the right level of abstraction in the model which captures the most fundamental characteristics of webpages and browsers.

Figure 4 illustrates the overall flow of performance prediction in WebProphet. We first infer the timing information of each object from the packet trace of a page load in a baseline scenario. Based on the PDG of the page, we further annotate each object with additional timing information related to client delay. We then adjust the object timing information to reflect the changes from the baseline scenario to the new one. Finally, we simulate the page load process with the new object timing information to estimate the new PLT. We will explain the first three steps in §4.1 and leave the details of the last step in §4.2.

4.1 Acquiring object timing information

Inferring basic object timing information: We infer web objects and their timing information from the packet trace of a page load collected on the client side. This makes our approach easily deployable since it does not require any instrumentation in browsers or applications. We identify three types of *activities* in the trace:

- DNS: the time used for looking up a domain name.
- TCP connection: the time used for establishing a TCP connection.
- HTTP: the time of loading a web object. As illustrated in Figure 5, an HTTP activity can be further decomposed into three parts: (i) Request transfer time: the time to transfer the first byte to the last byte of an HTTP request; (ii) Response time: the time from when the last byte of the HTTP request is sent out to when the first byte of the HTTP reply is received. This includes one RTT plus server delay; (iii) Reply transfer time: the

time to transfer the first byte to the last byte of an HTTP reply.

In addition, we infer the RTT for each TCP connection. The RTT of a TCP connection should be quite stable since the entire page load process usually lasts for only a few seconds. We also infer the number of round-trips involved in transferring an HTTP request or reply. Such information allows us to predict HTTP transfer times when RTT changes. We will provide the details of packet trace analysis in §5.3.

Adding client delay information: When the last parent of an object X becomes available, the browser will not issue a request for X immediately. This is because the browser needs time to do some additional processing, *e.g.*, parsing HTML page or executing Javascript. For object X, we use the *client delay* to denote the time from when its last parent is available to when the browser starts to request it. When the browser loads a sophisticated webpage or the client machine is slow, client delay may have significant impact on PLT. We infer the client delay of each object by combining basic object timing information with the PDG of the page. Note that when the browser starts to request an object, the first activity can be DNS, TCP connection, or HTTP depending on the current state and behavior of the browser.

Many browsers limit the maximum number of TCP connections to a host, *e.g.*, six in IE 8 and Firefox 3. This can cause the request for an object to wait for available connections even when it is ready to be sent. Therefore, the client delay we observe in a trace may be longer than the actual browser processing time. To overcome this problem, when collecting the packet trace in a baseline scenario, we set the TCP connection limit of the browser to a large number, for instance, 30. This helps to eliminate the effects of connection waiting time. Nonetheless, we will still predict the PLT in a new scenario under the default TCP connection limit of the browser (§4.2).

Adjusting object timing information according to new scenario: So far, we have obtained the object timing information under the baseline scenario. We need to adjust the timing information for each object according to the new scenario. Let $server_\delta$ be the server delay difference between the new and the baseline scenario. We simply add $server_\delta$ to the response time of each object to reflect the server delay change in the new scenario. We use similar methods to adjust DNS activity and client delay for each object. RTT change (rtt_δ) needs some special handling. Suppose the HTTP request and response transfers involve m and n round-trips for object X. We will add $(m + n + 1) \times rtt_\delta$ to the HTTP activity of X and rtt_δ to the TCP connection activity if a new TCP connection is required for loading X. Our assumption is that the number of round-trips involved in loading an object is the same in the baseline and new scenarios. Our results in §7 confirm the validity of this assumption in PlanetLab experiments. This assumption could be violated if bandwidth becomes the bottleneck, *e.g.*, in DSL link. Further research is needed to deal with such scenarios.

Discussion on object & DNS cache: Besides the four delay factors mentioned above, the PLT of a page in a new scenario will also be affected by the object and DNS cache. To handle cached objects and DNS names in a new scenario, we collect page load traces with the same set of cached objects and DNS names in a baseline scenario. We will explain how to control object and DNS cache in §5.1. Suppose Ψ is the PDG of a page when no object is cached. When an object x is cached, Ψ will transform into a new PDG Ψ' where x is removed and each of its children x_c is directly connected with each of its parents x_p. Accordingly, the client delay of (x_c, x_p) in Ψ' will include the cache lookup time of x and the client delay of (x, x_p) and (x_c, x) in Ψ. Hence, there is no need to explicitly consider the timing information of x in Ψ'.

Our current approach can only predict the PLT under the same caching state. Given a page with n objects, we will need to measure 2^n baseline scenarios to handle all the possible caching states. To reduce the measurement overheads, we could explicitly model the timing information of a cached object x in three cases: i) TTL has not expired: x is directly looked up from cache; ii) TTL has expired but x has not changed: x is revalidated and then looked up from cache; iii) TTL has expired and x has changed: x is revalidated and downloaded from the server. To predict the PLT under any caching state, we simply need to extend our model to include the cache lookup time and the number of round trips involved in the revalidation of each object. We can use a small constant to represent the former and perform controlled experiments to measure the latter. The details are out of the scope of this paper.

4.2 Simulating page load process

We now describe our methodology for predicting PLT based on object timing information. The key challenge here is object downloads are not independent from each other. The download of an object may be blocked because its dependent objects are unavailable or because there are no TCP connections ready for use. To tackle these problems, we simulate the page load process by taking into account the constraints of browser and PDG.

Browser behavior: We studied a few popular browsers including IE, Firefox and Chrome. They share a few important features. Presently, they all use HTTP/1.1 either with HTTP pipelining disabled by default or without pipelining support at all. This is because HTTP pipelin-

Case	I	II	III	IV	V
First web object of a domain	Y	Y	N	N	N
Cached DNS name	N	Y	-	-	-
Available TCP connections	-	-	Y	N	N
Max # of parallel connections	-	-	-	N	Y
Involved activities in Figure 6	a	b	c	b	d

Table 1: Five possible cases for loading an object.

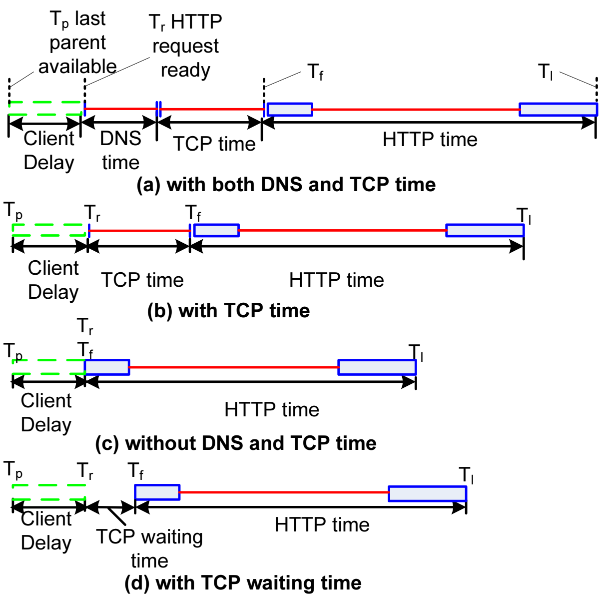


Figure 6: Four cases of activities for loading an object.

ing has not been widely supported by proxies and may have head-of-line blocking with the presence of dynamic contents [1], *e.g.*, one slow response in the pipeline will block other subsequent responses. Given the fact, we do not consider the effect of pipelining in this paper. More sophisticated techniques might be needed to model pipelining if it becomes widely-used in the future. Without pipelining, HTTP request-reply pairs do not overlap with each other within the same TCP connection.

In HTTP/1.1, a browser uses persistent TCP connections which can be reused for multiple HTTP requests and replies. The browser attempts to keep the number of parallel connections small. It opens a new connection only when it needs to send a request but all the existing connections are occupied by other requests or replies. A browser is configured with an internal parameter to limit the maximum number of parallel connections with a particular host. Note that the limit is applied to a host instead of to an IP address. If multiple hosts map to the same IP address, the number of parallel connections with that IP address can exceed the limit.

Loading an object may trigger multiple activities including looking up a DNS name, establishing a new TCP connection, waiting for an existing TCP connection, and/or issuing an HTTP request. Table 1 lists the five possible cases and the conditions of each of these cases. A "-" in the table means the corresponding condition does not matter. The activities involved in each case are illustrated in Figure 6. For instance, in Case V, a browser needs to load an object from a domain with which it already has TCP connections. Because all the existing TCP connections are occupied and the number of parallel connections has reached the maximum limit, the browser has to wait for the availability of an existing connection to issue the new HTTP request (Figure 6(d)).

```
PredictPLT(ObjectTimingInfo, PDG)
Insert root objects into CandidateQ
While (CandidateQ not empty)
  1) Get earliest candidate C from CandidateQ
  2) Load C according to conditions in Table 1
  3) Find new candidates whose parents
     are available
  4) Adjust timings of new candidates
  5) Insert new candidates into CandidateQ
Endwhile
```

Simulating page load: Given a webpage, Algorithm `PredictPLT` takes the timing information of each object and the PDG as input and simulates the page load process. The PLT is estimated as the time when all the objects are loaded. For each object X, the algorithm keeps track of four time variables: i) T_p: when X's last parent is available; ii) T_r: when the HTTP request for X is ready to be sent; iii) T_f: when the first byte of the HTTP request is sent; and iv) T_l: when the last byte of the HTTP reply is received. Figure 6 illustrates the position of these time variables in four different scenarios. In addition, the algorithm maintains a priority queue $CandidateQ$ which contains the objects that can be requested. The objects in $CandidateQ$ are sorted based on T_r.

5 Implementation

As illustrated in Figure 2, the implementation of WebProphet comprises three major components. In this section, we will describe each of them in more detail. The whole system is implemented with roughly 11,000 lines of code in Python, Perl, Javascript and Bro's policy language [18].

5.1 Measurement engine

The measurement engine includes a set of *web agents* which are currently deployed at multiple PlanetLab sites. These web agents allow us to measure the PLT of a webpage under diverse client, server, and network conditions. A centralized *controller* is used to maintain the continual operation of the agents and perform upgrade when a new version of agent software becomes available. The controller can upload script snippets to an agent to control the interaction between the agent and a webpage. It also retrieves and stores the packet traces from the agents logged by `tcpdump`. The controller is written in Perl and Python with 1,300 lines of code.

The web agent needs to meet a few requirements. First, it should be able to interact with a webpage automatically. As mentioned in §2, WebProphet requires a potentially large number of page load traces in a baseline scenario to predict the statistical properties (*e.g.*, median or 95th-percentile) of the PLT distribution in a new scenario. Second, it should behave like a full-featured web browser in order to simulate user interaction with sophisticated web 2.0 applications, *e.g.*, Google Maps. This is especially important for correctly measuring the user-perceived PLT of these complex applications. Third, it should provide support for setting object and DNS cache, which will affect the PLT (§4.1). We need to control the web agent to cache the same set of objects and DNS names in the baseline and new scenarios. Fourth, it should be able to adjust the parallel TCP connection limit, *e.g.*, to a large number, to eliminate the impact of connection waiting time (§4.1).

Existing web measurement tools cannot meet our requirements. Simple web clients (*e.g.*, wget, curl, and lynx) do not execute the Javascripts in the pages. Web form automation tools [3, 5, 7] and KITE [4] (an automated web measurement tool developed by Keynote) do not provide control for object/DNS cache or TCP connection limit. This prompts us to develop our own web agent, which uses Jssh plug-in to take full control of the Firefox 3 browser. Through the XPCOM [8] interfaces of Firefox, we use Javascript to call the internal APIs of Firefox. These internal APIs supports object and DNS cache control, TCP connection limit adjustment, and user input simulation. The user inputs from mouse and keyboard can be simulated as DOM [6] events.

We developed a set of script snippets to automate the interactions with multiple complex web services, such as Google/Yahoo Search, Google/Yahoo Maps, Gmail, Hotmail, Flickr, *etc.* The script snippet for each web service comprises only about 10 to 150 lines of code, depending on the complexity of the service. We believe it is quite easy to create new script snippets for other services too. The web agent, excluding the service-specific script snippets, is implemented in Javascript and Python with 1,100 lines of code. The whole automation part of the web agent has no measurable effects on PLT since it incurs very little overhead.

5.2 Dependency extractor

To extract the PDG of a web page, we setup a web agent to go through a web proxy running on the same host. The web proxy is modified from a simple proxy written in Python. We extended the proxy with the support of delaying the download of any specified object, which is required for discovering the descendants of the object (§3.2). We also added the functionality of controlling the download speed of a stream object, which is required for discovering stream parent and dependency offset (§3.2).

Given a webpage, we first obtain the list of its embedded objects by loading it once. The proxy will cache all the objects observed in the first round for future use. This reduces the measurement overhead imposed on the origin servers. We then subsequently control the download of one object during each page reload and record the timing information of object download. Finally, we extract the PDG according to the procedure described in §3.2. The dependency extractor and web proxy include 2,800 lines of code in Python.

5.3 Performance predictor

The performance predictor comprises a *trace analyzer* and a *page simulator*. The trace analyzer extracts basic object timing information (described in §4.1) from packet traces in pcap format. It leverages Bro [18], a network intrusion detection system, to parse DNS, TCP, and HTTP protocol information. We write programs using Bro's policy language to recover timing information, *e.g.*, DNS lookup time, TCP handshake time, and HTTP transfer and response times.

We estimate the RTT of a TCP connection using the time between the SYN and SYN/ACK packets. This is because many web services have relatively short TCP connections (*e.g.*, a few seconds) and the RTT is usually quite stable in such time scale. We could use other existing techniques [12, 24] to estimate RTT for web services that involve long TCP connections. We infer the number of round trips involved in an HTTP transfer based on the TCP self-clocking behavior [24] — the packets in the same TCP send window are very close to each other while the packets in two adjacent send windows are at least one RTT apart. We compute the server delay by subtracting one RTT from the time interval between two adjacent send windows. Using this method, we find Google and Yahoo Search process user query in a streamlined fashion. The server will return partial results to users while additional results are being generated. This causes some extra delay to the reply packets in multiple different round trips. Our method can handle such cases well, leading to high prediction accuracy reported in §7.

The page simulator combines the basic object timing information and the PDG to infer the client delay of each object. It then adjusts the timing of each object according to the specifications in the new scenario. Finally, it simulates the page load process (§4.2) and outputs the predicted PLT. The trace analyzer and page simulator include 6,200 lines of code written in Python and Bro's policy language.

6 Results of Dependency Extraction

We now characterize and validate the PDGs of Google/Yahoo Search and Maps extracted by WebProphet. Google/Yahoo Search are two of the most popular web services and their PDGs are relatively easy to validate. In contrast, the PDGs of Google/Yahoo Maps are much more complex. In fact, Yahoo Maps has the most complicated PDG in terms of the number of objects and dependencies among all the web services we studied (including Amazon.com, Flickr, and Google Docs).

In this paper, we only present the results on the cases where there is no cached object. This is common for accessing webpages in which most contents are dynamic. For instance, Yahoo performance team found 40 to 60% of Yahoo users have an empty cache when visiting Yahoo [22]. Our approach also works when some objects are cached and we omit those results here due to lack of space.

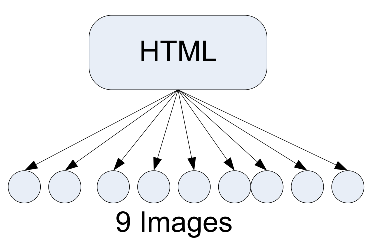


Figure 7: The PDG of Google Search.

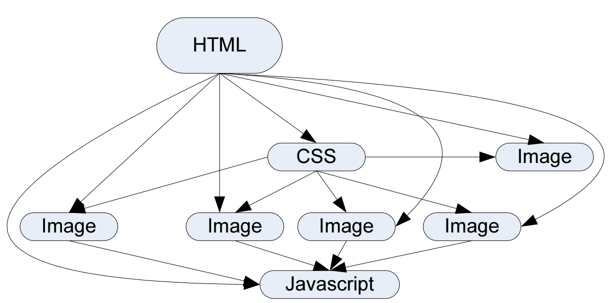


Figure 8: The PDG of Yahoo Search.

Google/Yahoo Search PDG: Figure 8 illustrates the inferred PDGs of Google/Yahoo Search for the search keyword "mapouka". The Google Search page has one HTML and several images while the Yahoo Search page has one HTML, one CSS, and a few Javascripts and images. The Google Search page is simpler than that of Yahoo. The former has not only a fewer number but also fewer levels of dependencies. This could be one of the factors that cause the PLT of Google Search to be smaller (§7). The PDGs for different keywords have similar structure. Some keywords may lead to an extra Javascript object or a different number of images in the PDG of Google Search. Because the Search pages are not very complicated, we are able to verify that the PDGs produced by WebProphet are the same as those extracted through manual code analysis.

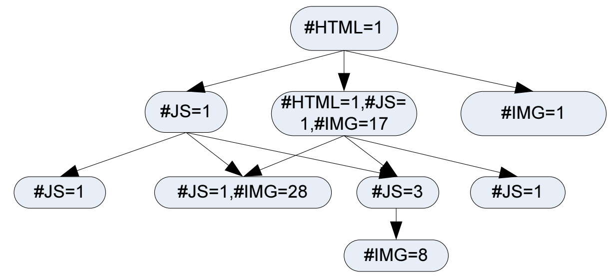


Figure 9: The simplified PDG of Google Maps.

Google/Yahoo Maps PDG: We study the PDG of the driving direction pages of Google/Yahoo Maps. We use a pair of addresses of the Whole Foods stores in Arkansas, USA. The full PDGs of Google/Yahoo Maps are too complex to read, *e.g.*, Yahoo Maps has a total number of 110 objects and 172 dependencies. Instead of showing the full PDGs, we simplify them by merging the objects that share the same sets of parents and children into a single node. The two simplified PDGs are shown in Figure 9 and 10. Each node carries a label which describes the number of objects of certain type. For instance, label "#HTML=1,#JS=1,#IMG=17" means this node corresponds to 1 HTML, 1 Javascript, and 17 image objects in the full PDG.

Apparently, the PDGs of Maps are significantly more sophisticated than those of Search. They include more Javascripts for user interactions and more images for map tiles. The PDG of Yahoo Maps is even more complex than that of Google Maps, as the former comprises a larger number and more levels of dependencies. The PDGs for different address inputs are quite similar. The main differences are in the map tile images.

The Javascripts of Google/Yahoo Maps are not only large (536KB and 670KB respectively) but also obfuscated. It is difficult for us to validate the extracted PDGs via manual code analysis. Instead, we verify their correctness in an indirect manner. First, we use our dependency extractor to obtain the "approximate" PDGs of Google/Yahoo Maps. Then we construct our own web-

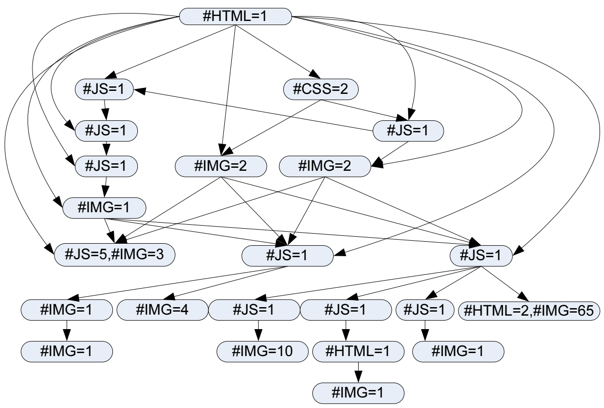


Figure 10: The simplified PDG of Yahoo Maps.

pages which exactly match the "approximate" PDGs in the number of objects, the types of objects, and the dependencies between objects. After that, we attempt to infer the PDGs of the constructed pages as if we know nothing about the "approximate" PDGs. We find the inferred PDGs exactly match the "approximate" PDGs. Although this does not prove that we have extracted the real PDGs of Google/Yahoo Maps, it at least suggests that we can correctly handle webpages as complex as Google/Yahoo Maps. Moreover, in §7, we will show that WebProphet can accurately predict the PLT of Google/Yahoo Maps under various hypothetical scenarios using the "approximate" PDGs.

7 Prediction Accuracy

In this section, we evaluate the PLT prediction accuracy of WebProphet for Google/Yahoo Search and Maps. We first conduct controlled experiments by manipulating the DNS delay, RTT, and server delay for all the objects or a subset of the objects in a webpage. We then conduct real-world experiments in which every delay factor of every object changes simultaneously. We find that ignoring object dependencies may lead to significant errors in the PLT prediction for complex webpages. Finally, we show that identifying stream parent and dependency offset is particularly important for accurate PLT prediction for simple webpages.

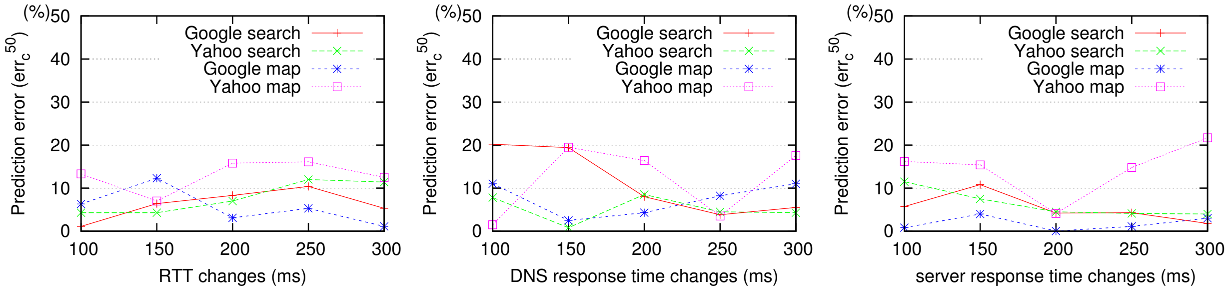
Suppose t_b and t_n are the PLT in the baseline and new scenarios and t_p is the PLT predicted by WebProphet. We could have used $err_r = \frac{abs(t_p - t_n)}{t_n}$, the relative error between t_p and t_n, to evaluate the prediction accuracy. However, we find err_r may not be the right metric because it tends to be small when $abs(t_b - t_n) << t_n$. Therefore, we choose $err_c = abs(1 - \frac{t_p - t_b}{t_n - t_b})$ as our evaluation metric. It represents the relative error of predicted PLT change compared to the actual PLT change between the baseline and new scenarios. For instance, suppose $t_b = 5$, $t_n = 4$, and $t_p = 4.2$ seconds. The prediction error will be 5% measured in err_r *vs.* 20% measured in err_c. As mentioned in §2, the PLT of a webpage may not be a constant under a given scenario. In this paper, we focus on err_c^{50} and err_c^{95} which are computed based on the median and 95th-percentile in the baseline, new, and predicted PLT distributions. These two metrics help to quantify whether WebProphet can make accurate prediction both for the normal case and for the extreme case.

In the following experiments, we consider the scenarios where a web service provider is interested in predicting the PLT reductions as a result of certain optimizations to the service. To evaluate the prediction accuracy in each of the experiments, we collect two set of page load traces in the baseline scenario. The first set, collected with normal TCP connection limit, is for producing the baseline PLT distribution. The second set, collected with a large TCP connection limit, is for inferring the object timing information in the baseline scenario (§4.1). Thereafter, this object timing information is used to generate the predicted PLT distribution in the new scenario. We also collect one set of traces in the new scenario, from which we can extract the actual new PLT distribution for validation purpose. Each of the three sets contains 500 page load traces, which provides enough samples for computing err_c^{95} and err_c^{50}. We only present the results based on one random keyword for the Search services and one random pair of addresses for the Maps services. The results of using other keywords or pairs of addresses are similar.

Before presenting the results, we discuss two problems that may cause the predicted PLT to deviate from the actual PLT. First, there could be slight differences between the times when the three set of traces are collected. These time differences may lead to differences in the client, server, and network conditions under which the traces are collected. The resulting "prediction error" is actually due to the limitations of our validation methodology rather than due to the limitations of our approach. Second, as mentioned in §2, we currently do not explicitly consider packet loss in our model. Any loss behavior differences between the baseline and new scenarios may also lead to prediction error. As shown in the following results, WebProphet can attain high prediction accuracy in spite of these two problems.

7.1 Controlled experiments

In the controlled experiments, we evaluate the accuracy of our performance prediction under various RTTs, DNS lookup times, and server response times. Figure 11 depicts the setup of our experiments located at Northwestern University. We run a web agent to collect the packet



(a) RTT (b) DNS lookup time (c) Server response time

Figure 12: The prediction errors under different injected delays of RTT, DNS lookup time, and server response time.

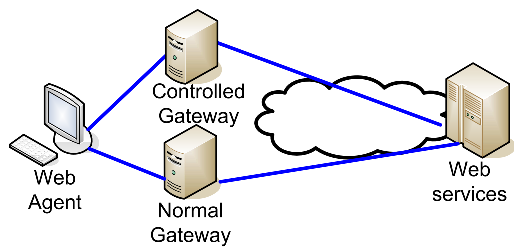


Figure 11: Setup of controlled experiments.

traces of page loads. The controlled gateway is used to inject extra delays during page loads. The normal gateway does not manipulate any traffic. We configure the routing table on the web agent to forward the traffic to the controlled gateway or to the normal gateway to create the baseline and new scenarios respectively. Since we currently do not have a precise way to inject client delays, we simply keep the web agent lightly-loaded all the time. This ensures client delays are roughly the same in all the controlled experiments. In the next section, we will show that WebProphet can achieve high prediction accuracy even when client delays change.

We use `netem` to inject extra RTT and DNS lookup times on the controlled gateway. `netem` is a network emulator in Linux which can add queuing delay to each traversing packet. To inflate RTT, we simply forward web traffic to the controlled gateway while forwarding the DNS traffic to the normal gateway. We may inflate DNS lookup time in a similar way. Unfortunately, `netem` cannot be used to inject extra server response time because it can only add queuing delay to every packet. Instead, we develop our own tool based on `libpcap` and `libdnet` to inflate server response time. Our tool can identify and delay the packets that correspond to the HTTP requests from the agent to the web server for certain amount of time. In effect, this extra delay will be considered as part of the server response time (§4.1). Note that this may trigger TCP timeout on the web agent. Our tool will intercept and drop all the related retransmitted packets.

Service	t_b^{50}	t_n^{50}	t_p^{50}	err_c^{50}	err_c^{95}	Indep err_c^{50}
Gsearch	0.74	0.21	0.23	3.8%	15.9%	1.2%
Ysearch	1.04	0.26	0.24	3.2%	2.2%	13.0%
Gmap	4.10	2.12	2.01	5.5%	11.0%	49.7%
Ymap	6.19	3.99	4.03	1.7%	1.2%	85.5%

Table 2: Changing RTT and DNS lookup time together.

Manipulating one delay factor at a time: In the first group of experiments, we evaluate the prediction accuracy when we change one delay factor for all the objects across a certain range. We inject five different delay values (100, 150, 200, 250, and 300 ms) to create the baseline scenarios. These values reflect the real delay differences observed from different PlanetLab sites (*e.g.*, those in Asia *vs.* those in the US) to our server at Northwestern University. We use the scenario without any injected delay as the new scenario that we aim to predict. Figure 12 (a)-(c) illustrate the err_c^{50} for the four web services as we change RTT, DNS delay, and server delay. Among the total of 60 experiments, 50% of them have $err_c^{50} \leq 6.1\%$, 90% $err_c^{50} \leq 16.2\%$. The maximum err_c^{50} is 21.7%.

Manipulating RTT and DNS delay together: Next, we evaluate the accuracy of performance prediction when multiple delay factors change simultaneously. We inflate both RTT and DNS delay by 100 ms for all the objects to create the baseline scenario. We still use the scenario without injected delay as the new scenario. Table 2 shows the prediction error for the four applications. t_b^{50}, t_n^{50} and t_p^{50} are the median PLT of the baseline, new, and predicted scenarios. WebProphet can accurately predict not only the median PLT but also the 95th-percentile PLT. The maximum err_c^{50} and err_c^{95} are only 5.5% and 15.9% respectively.

Manipulating only a subset of objects: So far, we have changed the delay factors for all the objects simultaneously. In fact, WebProphet can make accurate predic-

DC	err_c^{50}	err_c^{95}
Akamai	16.0%	11.8%
YDC_1	6.5%	9.7%
YDC_2	14.8%	6.0%

Table 3: Inflating the RTT to different DCs.

tion when we change the delay factors for any subset of objects. When visiting Yahoo Maps from Northwestern University, the web agent will download objects from Akamai CDN and two Yahoo data centers (YDC_1 and YDC_2). In the following experiments, we create three baseline scenarios by injecting 100 ms extra RTT to the objects from Akamai CDN, YDC_1, or YDC_2 respectively. We still use the scenario without injected delay as the new scenario. Our setup is to simulate the case in which the owners of Yahoo Maps want to predict the new PLT if they could reduce the RTT from users to one of their DCs or Akamai CDN. The results in Table 3 show that the prediction errors are reasonably small in all the three experiments.

7.2 Real-world experiments

In the controlled experiments, we changed the delay factors by the same amount for a set of objects. In this section, we conduct experiments on PlanetLab to demonstrate the effectiveness of WebProphet even when each delay factor of each object changes by a different amount simultaneously. The PlanetLab nodes in the US normally experience smaller PLT when accessing Google/Yahoo Search and Maps than those in Asia and Europe. For each of the four web services, we pick one international node as the baseline scenario. We use a node at Northwestern University as the new scenario. This is to simulate the case where the service owners want to predict the new PLT if they could optimize their services for international users in certain way. To predict the new PLT, we replace the timing information of each object in the baseline scenario with the timing information of the same object in the new scenario and then run the page load simulation.

Table 4 shows the locations of the baseline scenario and the prediction errors. Both err_c^{50} and err_c^{95} are within 10.7% for all the four services. We find the prediction errors in the PlanetLab experiments are generally smaller than those in the controlled experiments. Since we directly use the object timing information in the new scenario for PLT prediction in the PlanetLab experiments, the prediction results are no longer affected by the trace collection time differences between the baseline and new scenarios. This suggests our model does capture sufficient level of detail for accurate PLT prediction.

Service	Baseline	New	err_c^{50}	err_c^{95}	No-stream err_c^{50}
Gsearch	Singapore	US	2.0%	10.7%	21.2%
Ysearch	Japan	US	6.1%	0.3%	258.7%
Gmap	Sweden	US	1.2%	1.8%	1.2%
Ymap	Poland	US	0.7%	1.3%	0.1%

Table 4: The results in the real-world experiments.

7.3 Importance of modeling object dependencies

One alternate approach for performance prediction is to measure the PLT under a range of values for each delay factor of each object and then make predictions by extrapolating from these measured PLTs through some form of regression. This may not be feasible for complex webpages with many embedded objects. For instance, even if we measure the PLT only under two different values for each delay factor of each object in Yahoo Maps, we will end up measuring the PLT in 2^{440} scenarios, when considering all the possible combinations of four factors each for 110 objects. Without detailed domain knowledge, it is difficult to decide how many distinct scenarios indeed need to be measured for accurate prediction.

One way to reduce the number of measured scenarios required for prediction is by assuming independence among every delay factor of every object. Let x_i ($i = 1...n$) be the delay factors of all the objects that impact the PLT of a webpage. Under this assumption:

$$f(d_{x1}, d_{x2}, ..., d_{xn}) = \sum_{1}^{n} f_i(d_{xi})$$

Here, d_{xi} denotes the change of delay factor x_i. $f_i(d_{xi})$ is a function that describes the PLT change when only x_i changes. $f(d_{x1}, d_{x2}, ..., d_{xn})$ is a function that describes the PLT change when all the x_i's change simultaneously. In essence, this equation says the PLT change caused by each x_i is independent from the PLT changes caused by other delay factors. If this assumption holds, the number of measured scenarios required for prediction will become linear to the number of delay factors, significantly reducing the measurement overheads. Recently, Chen *et al.* developed a latency prediction tool based on similar assumption [10].

In the following, we study to what extent such independence assumption affects the prediction accuracy. We use the same baseline scenario as that of Table 2 in §7.1, in which both RTT and DNS delay are inflated by 100 ms for all the objects. We still use the scenario without injected delay as the new scenario. For each web service, we divide the objects in the page into three groups (G_1, G_2, and G_3) and subsequently measure the PLT change δ_i when we only change the delay factors for one group G_i at a time. We then predict the PLT change between the baseline and new scenarios by taking the sum of δ_i's. As shown in column "Indep err_c^{50}" of Table 2, the prediction errors are significantly higher than those of WebProphet for Google/Yahoo Maps. In particular for Yahoo Maps, err_c^{50} is as high as 85.5%. The prediction errors are smaller for Google Search because its webpage has very simple dependencies. Since each δ_i is directly measured instead of being predicted by any model, the prediction error should be close to zero when the delay factors are indeed independent. The results of the experiment highlight the importance of capturing object dependencies for accurate PLT prediction.

7.4 Importance of identifying stream parent

One of the key steps in our PDG extraction is to identify stream parents and dependency offsets (§3.2). We now evaluate the importance of identifying stream parents in prediction accuracy. We use the same baseline and new scenarios as those in the PlanetLab experiments in §7.2. The only difference is that we ignore all the dependencies on stream parents in the PDGs when we make predictions. As shown in column "No-Stream err_c^{50}" in Table 4, the prediction errors without stream parents are much higher than those with stream parents for the Search services. Nonetheless, the prediction errors are roughly the same for the Maps services. This is because the HTML objects account for a significant portion of the Search pages. In contrast, most of the objects in the Maps pages are non-stream ones, *e.g.*, Javascripts and images.

8 Usage Scenarios

As illustrated in the previous sections, the PLT of a complex webpage may depend on the delay factors of many objects. The owner of the page often faces the challenge of finding a cost-effective way to improve service performance from a huge number of possible optimization strategies. Since WebProphet can make fast and accurate prediction under the changes of any delay factor and/or object, it provides the service owner an easy way to narrow down the strategies that could bring the most benefit.

Because Yahoo Maps has the most complex webpage and the largest median PLT (measured from Northwestern University) among all the four services, we use it as an example to demonstrate the power of WebProphet. Though we cannot directly validate the effect of these changes, the experiments described in §7 provide a basis for trust in the predictions. Suppose the owners of Yahoo Maps are considering three methods to optimize the median PLT: i) OPT_{rtt}: reducing the RTT of certain static objects by moving them from Yahoo data centers to the Akamai CDN; ii) OPT_{server}: reducing the server response time by half for certain dynamic objects; and iii) OPT_{client}: reducing the client execution time by half for certain objects. Since the Yahoo Maps page contains about 110 objects including roughly 74 static objects and 36 dynamic ones, it could be too costly to optimize for all of them. Hence, we seek to identify a small set of *candidate objects* whose optimization would lead to significant PLT reduction.

In this paper, we use a simple greedy-based algorithm to search for those candidate objects. In the future, we could also leverage other more sophisticated search algorithms (such as simulated annealing) to obtain better results. Our search algorithm considers one of the optimization methods (OPT_{rtt}, OPT_{server}, or OPT_{client}) at a time. It starts with a list of all the objects and the original object timing information extracted from the page load trace that corresponds to the median of the baseline PLT distribution. At each step, it greedily picks the candidate object whose optimization will lead to the largest PLT reduction among all the remaining objects. It then removes the new candidate object from the list and updates its timing information according to the optimization method. This process terminates when the PLT reduction resulting from the optimization of a new candidate object becomes negligibly small.

After evaluating 2,176 hypothetical scenarios, we identify 5 candidate objects for OPT_{server} and OPT_{rtt} respectively. We also identify 14 candidate objects for OPT_{client}. The predicted PLT reductions by applying OPT_{rtt}, OPT_{client}, and OPT_{server} are 14.8%, 26.6%, and 1.6% respectively. Apparently, OPT_{server} does not seem to be promising, since it can only reduce PLT slightly. The PLT can be further reduced by 40.1% by combining OPT_{rtt} and OPT_{client} together. Therefore, by simply optimizing the client execution time of 14 objects and moving 5 static objects to Akamai CDN, we predict that the median PLT of Yahoo Maps can be cut from 3.99 to 2.39 seconds.

9 Systems Evaluation

We now evaluate the systems overhead of dependency extraction and performance prediction. The dependency extraction process includes two steps: 1) subsequently control the download of each object during a page load; and 2) extract the PDG from the recorded timing information of object download (§3.2). Step 2 is relatively simple. The running time is dominated by step 1 because we need to reload a page many times and artificially delay the download of one object during each page load. Given a page with n objects and m stream objects, we need to reload the page n times to discover all the descendants and at most $m \times n$ times to discover all the stream parents and dependency offsets (§3.2). All the webpages we have studied so far have only a few stream (HTML) objects. Thus, the running time is roughly linear to the total number of objects in the page. Even for Yahoo Maps which has the most complex PDG, the running time is only two hours. Note that since each controlled page load is independent, we can easily run dependency extraction on multiple machines in parallel to speed up the process.

To predict the PLT of a page, we first need to parse page load traces to extract object timing information and then to simulate page load process under new scenarios (§4). We evaluate the performance predictor on a commodity server with two 2.5 GHz Xeon processors and 16 GB memory running Linux 2.6.18. We use Yahoo Maps as an example because its page incurs the largest prediction time among the four services. The trace parsing time depends on the size of the traces. For Yahoo Maps, it takes 317 seconds to parse 500 page load traces of one scenario with a total size of 455 MB. The page load simulation time depends on the complexity of the PDG. For Yahoo Maps, it takes about 9 ms to run one page load simulation under our current implementation in Python. This translates to a total of 20 seconds simulation time to evaluate all of the 2,176 hypothetical scenarios in §8. We could further optimize the running time by rewriting the simulation code in C/C++.

10 Related Work

There is a large body of prior work on web performance measurement and modeling. For instance, Smith *et al.* leveraged TCP/IP headers in packet traces to characterize the nature of web traffic and the structure of webpages [21]. Nahum *et al.* built an emulator to study the impact of network delay and packet loss on web server performance [17]. Olshefski *et al.* developed techniques for inferring client response time from server-side logs. These works either treat a webpage as a single object or treat each web object independently while ignoring the dependencies between different objects.

Web performance measurement tools, such as Firebug and IBM Page Detailer [2], can provide detailed object timing information of a page load. Nonetheless, they can neither extract object dependencies nor perform PLT predictions.

CPRT [19] used client-side Javascript code to measure user-perceived response times. AjaxScope [15] provided more detailed Javascript code instrumentations to debug client-side errors. Due to the limited information exposed by the browser and OS to the Javascript layer, these approaches cannot reason about the impact of network-layer conditions, such as DNS delay or RTT, on web service performance.

Several existing systems, *e.g.*, Orion [11], eXpose [13], NetMedic [14], and Sherlock [9], employed various techniques to automatically infer causalities between hosts, processes, and network flows. They leveraged these causalities to diagnose performance problems in network applications. In contrast, WebProphet focuses on extracting dependencies between web objects and predicting the performance of web applications.

Wischik used a manually constructed dependency graph of Gmail to study the effects of TCP parameter settings on web performance [25]. In this paper, we formally define the object dependencies of a webpage including ancestors, stream and non-stream parents, and dependency offsets. We further develop an automated system to extract the PDG of a webpage.

11 Conclusion

We built WebProphet, a system that automates performance prediction for web services. The key idea of WebProphet is the use of PDG to encapsulate web object dependencies for accurate and scalable predictions. WebProphet leverages a novel technique based on timing perturbation to extract object dependencies of complex webpages. It implements a simple and yet effective model to simulate the page load process of a web browser, which enables accurate PLT prediction under changes to any web objects. It can also predict the statistical properties of a PLT distribution under a hypothetical scenario. Applying WebProphet to the Search and Maps services of Google and Yahoo, we successfully extract their PDGs and keep the PLT prediction error rates under 16% in most cases. Our results show WebProphet provides a solid foundation for web service providers to quickly find cost-effective optimization strategies for real applications.

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