

YTrace: End-to-end Performance Diagnosis in Large Cloud and Content Providers

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ABSTRACT

Content providers build serving stacks to deliver content to users. An important goal of a content provider is to ensure *good user experience*, since user experience has an impact on revenue. In this paper, we describe a system at Yahoo called YTrace that diagnoses bad user experience in near real time. We present the different components of YTrace for end-to-end multi-layer diagnosis (instrumentation, methods and backend system), and the system architecture for delivering diagnosis in near real time across all user sessions at Yahoo. YTrace diagnoses problems across service and network layers in the end-to-end path spanning user host, Internet, CDN and the datacenters, and has three diagnosis goals: detection, localization and root cause analysis (including cascading problems) of performance problems in user sessions with the cloud. The key component of the methods in YTrace is capturing and discovering causality, which we design based on a mix of instrumentation API, domain knowledge and blackbox methods. We show three case studies from production that span a large-scale distributed storage system, a datacenter-wide network, and an end-to-end video serving stack at Yahoo. We end by listing a number of open directions for performance diagnosis in cloud and content providers.

1. INTRODUCTION

Large content providers such as Yahoo, Google, Netflix and Facebook serve users from large-scale serving stacks in geographically distributed datacenters on the Internet. They can be modeled as cloud infrastructure that consists of multiple datacenters and a Content Distribution Network (CDN) (Figure 1). Users interact with the content provider by making RPCs (also called *user sessions*) to the CDN and the datacenters. The *user experience* of a user session with the provider depends on several factors from the serving stack, to the datacenter network and the Internet, to the content. *Bad* user experiences result in loss of users and revenue [1].

Content providers build for good user experience by building high-performance serving stacks and network

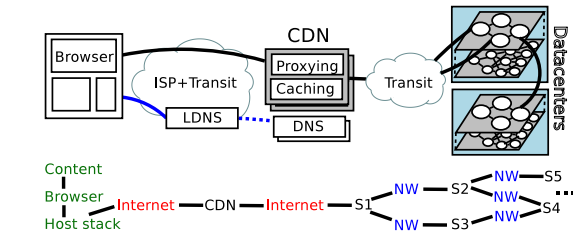


Figure 1: Model of a large content provider showing the end-to-end path for a user session. Lower figure shows canonical execution graph to determine instrumentation; “S” and “NW” represent services and network respectively.

infrastructure. Serving stacks are compositions of services, and services are usually large distributed systems comprising of hundreds to thousands of hosts – on top of the datacenter network and inter-datacenter wide area paths. Serving stacks include latency-tolerant distributed execution techniques such as parallelism and redundancy [11]. For example, a user request for a personalized web page could be served by “assembling” parts of the page, each generated by a service¹. In order to do this, services (specifically, hosts in a service) make RPCs to each other over the underlying network paths.

Due to the composition scale and heterogeneity of a serving stack, it is prone to performance problems that span multiple layers – from the infrastructure layer such as network and servers, to the higher layers such as the OS, containers and service processes within a server, to the distributed systems layer – and localized among nodes in the end-to-end path (Figure 1). Detecting and troubleshooting bad user experience is a complex and tedious problem at scale, since it often involves multiple services and layers, and hence, coordination between multiple teams across service tiers and underlying layers. It is hence equally important to build systems that continuously monitor and diagnose bad user experiences. Such systems help troubleshoot to quickly fix performance problems, and know where to allocate resources in the medium-term. Further, near real time *di-*

¹Such designs are also called service-oriented and microservices architectures.

agnosis as a service is a useful primitive to optimize existing systems against performance problems. Content providers have designed and deployed several systems in practice [9, 19, 20, 30, 32, 34, 38, 41]; however, these systems do not diagnose performance problems end-to-end and across layers.

We present YTrace, a system that we are building at Yahoo to diagnose end-to-end performance problems that impact user experience. YTrace has three components: instrumentation to collect data, diagnosis methods that run on the data, and an efficient backend to index the data and execute diagnosis queries (Figure 2). In this paper, we focus on the first two components and touch upon the third. We consider dynamic web content that is tailored for users – perhaps the most common on the Internet. Our definition of user experience depends on the content type: for web content, we estimate user experience as the page load time – the latency between the user’s content request and the Javascript On-Load event; and for video streams, we consider duration of rebuffering events. Our work can easily be extended to diagnose performance problems with other content types and definitions of user experience.

When building an end-to-end diagnosis system, there are key requirements for large content providers:

- Tie to user experience: Instrumentation and diagnoses should directly relate to user experience of real users.
- The diagnosis output should be general enough to help troubleshoot *almost all* performance problems, including cascading failures.
- Multi-layer: The diagnosis should span as many layers in the serving stack as possible. At a minimum, it should include all services, the host machines and the underlying network layer.
- Instrumentation should have low overhead, so it does not affect the user experience.
- Accuracy: Diagnosis should have low false positive and false negative rates for the use cases. It should be able to diagnose tail latency.

The key ideas behind YTrace rely on identifying concurrent event execution, both at the service level and in the network. Knowing the context of concurrency enables YTrace to compute the most important information for diagnoses – the critical path in the execution. In order to find concurrency, YTrace records and mines causal relationships between events in a user session at the service and network layers. It aggregates diagnoses across user sessions and renders an interactive dashboard geared towards troubleshooting.

2. PROBLEM STATEMENT

There are three broad classes of use cases of YTrace: troubleshooting, resource provisioning and service adap-

tation. Troubleshooting aims to fix performance problems that users face after the problems occur. It requires the system to deliver near real time, actionable, insights into performance problems. Resource provisioning is a relatively longer-term task that involves querying the system for aggregate views of diagnosis to find where to add resources². Service adaptation uses YTrace as a near real time diagnosis-as-a-service to build serving stacks that optimize for user experience. For example, the traffic engineering service at a CDN may route users to CDN nodes based on diagnoses of Internet paths; the rate adaption module in a video player may make strategic rate choices if it had diagnoses. Since this involves pre-defined queries, the system may materialize such queries to minimize query times³.

Based on discussions with teams across Yahoo, we formulate a problem statement whose solution provides actionable input for the three use cases. YTrace has three goals for every user session:

Detection: Is a user session seeing a performance problem?

Localization: Where are the performance problems in the end-to-end path (and across all layers)?

Root cause analysis: Why are the performance problems occurring?

In addition to per-session diagnoses, the YTrace backend supports (and materializes views of) aggregate queries over multiple user sessions, such as clusters of users (e.g., ISP and geography), and over a service in the datacenter in a time window. Aggregate queries with such predicates enable statistically significant analyses while conditioning on confounding variables.

3. INSTRUMENTATION

The first step towards performance diagnosis of a user session is instrumentation of components that participate in the session. The instrumentation should not add significant latency to the session. The key is to determine *necessary and sufficient* instrumentation for diagnosis. We implement optimized libraries for instrumentation so that the instrumentation overhead is very low relative to end-to-end latency.

One way to determine instrumentation is by considering the canonical end-to-end user session graph, whose nodes are components (which impact user experience) that participate in user sessions and whose edges represent point-to-point communication between nodes; it

²Resource provisioning also requires answers to “what-if” questions. This is outside the scope of our current work.

³Large query delays can be detrimental to performance, e.g., in load balancing [24].

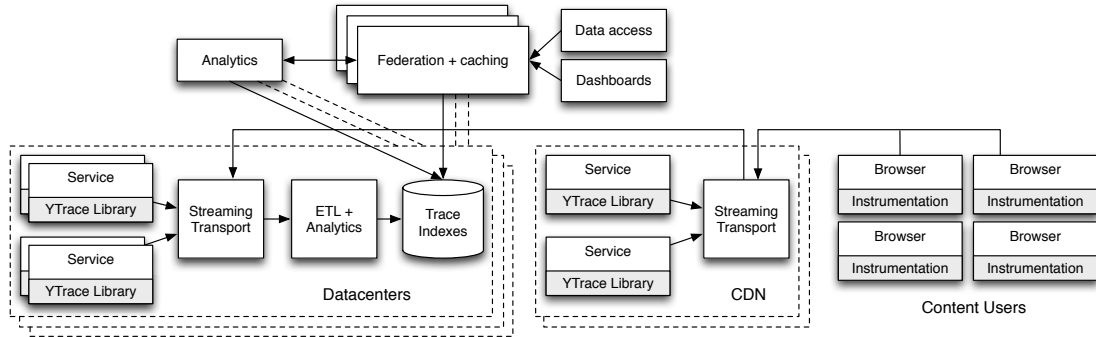


Figure 2: YTrace architecture and components.

should cover all components and layers that are necessary for diagnosis. Figure 1 shows the graph for large content providers that spans: the user end-host, the CDN, the serving stack spanning one or more datacenters, and the underlying network infrastructure.

In order to diagnose performance problems with each node in the canonical graph, the necessary and sufficient instrumentation will include performance data from every node in the graph (necessary condition) and will not include redundant instrumentation between edges (sufficient). The necessary and sufficient instrumentation for root cause analysis at a node depends on the attributes YTrace needs to be able to fingerprint and match problem signatures (§4).

YTrace includes two forms of instrumentation: (1) synchronous instrumentation that is in-band with the user session, and (2) asynchronous instrumentation from components that cannot be modified for instrumentation (such as network devices). We implement synchronous instrumentation in the form of *distributed tracing*, which allows YTrace to tie performance of any component into the user experience. YTrace uses causal relationships in instrumentation data to diagnose performance problems.

3.1 Synchronous Instrumentation

User-side instrumentation. User end-host instrumentation enables YTrace to diagnose performance problems with events at the end-host (includes browser, any containers, and the content itself). In general, content providers cannot alter the browser (e.g., by introducing plugins), which leaves them with a limited set of user-side performance measurements.

The work of content in a browser can be modeled as a sequence of events spanning fetching resources (either via local cache or network), execution and rendering. The W3C Navigation Timing (NavTiming) recommendation [2] describes such an event model for origin content (the page HTML) and exposes it via a Javascript API to the web page.⁴

⁴A similar event API for the other resources that the page re-

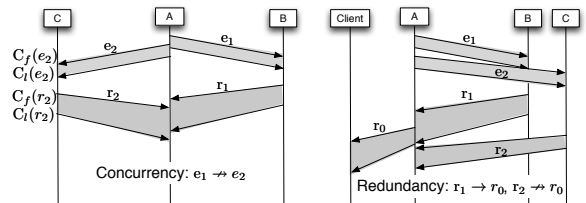


Figure 3: Inferring causality in RPC patterns.

We use the NavTiming event model for user-side instrumentation for web content in YTrace. This enables us to break down the user experience (page load time) into timing of events for origin content. There is a causal relationship between all NavTiming events: for example, DNS lookup (if any) causes TCP connect to the CDN. In particular, all events measured by NavTiming and Resource Timing have well-defined causal relationships. Having causal relationships helps us understand the events that resulted in bad user experience, since they are necessary to construct the latency critical path of the session.

In the case of video streaming (which is a linearizable sequence of RPCs per-segment to the CDN), YTrace uses an event model that includes timing of per-segment events at the video player. These events span segment RPCs, and decoding and rendering of those segments to the screen.

Distributed tracing. YTrace synchronously traces user sessions (i.e., RPCs from user agent) through all execution nodes in the serving stack, including the CDN services and the user host (see user-side instrumentation above). Distributed tracing is a common monitoring primitive in large-scale serving stacks [9, 32], and involves two steps: assigning a globally unique ID to a user session, and propagating this ID through all nodes in the serving stack. The ID propagation is typically

quires is supported by the W3C Resource Timing recommendation [3].

implemented by adding the ID to all RPCs during session execution – for example, in the form of a serialized header. YTrace records the timing of events related to each RPC during session execution using node-local clocks.

When implementing distributed tracing, there are a few design constraints that arise from large-scale environments. Such environments are highly heterogeneous, not only in the platforms used, but also in runtime complexity such as RPC execution patterns (see Figure 3), serialization formats and protocols. We find two forms of RPC-level concurrency in distributed execution: parallelism and redundancy – both in the context of RPC “fanout” implementations. Parallelism includes parallel RPCs; the opposite of which is serialized RPC execution. Redundancy is a case where a service doing the fanout only waits for a few responses before sending back a response to the caller; this is typically used in search engine stacks.

Perhaps the most important requirement in distributed tracing implementations is to *capture causality* among *all* events in the end-to-end execution. Ideally, causality among events should be described by the services themselves (during tracing), and not inferred offline using tracing data (an approach adopted by prior work [5, 9]). The reason for this is dynamic behavior in web services: for example, the concurrent/serialized and redundant RPC execution patterns shown in Figure 3 can be triggered as functions of session attributes, performance history and runtime environment. Such dynamics makes offline inference of causal relationships between RPC edges hard (without additional data that may not be within the scope of a tracing system).

YTrace captures causality between RPC “edges” (requests and responses), since causality in RPC execution patterns such as concurrency and redundancy exists between RPC edges. This RPC model is a key difference between YTrace and prior tracing systems such as Dapper (and Zipkin), which capture causality at the granularity of RPCs. YTrace captures causality in two forms: during tracing using service-level APIs designed to capture causality, and offline using (well-defined) happens-before relationships [21].

Services call the YTrace tracing API at each RPC edge. The API returns an immutable session context (passed as a handle) for each incoming RPC, until that RPC is fully served. The API times each RPC edge, and any annotations⁵ across the session. It consumes and returns all headers that are/should be serialized in RPCs.

```
void *handle = create(/*String*/ in_header);
```

⁵The annotations are optional service-specific timestamped key-value pairs, such as lock events. They are used by developers to understand service-specific performance, such as impact of lock contention on end-to-end performance.

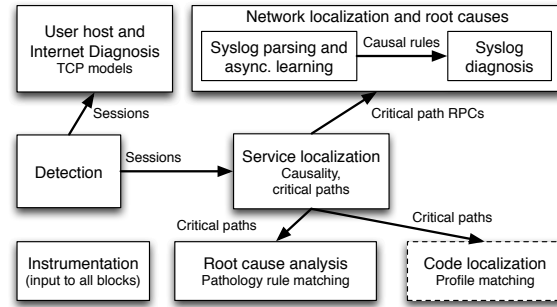


Figure 4: YTrace diagnosis flow.

```
String out_header = sendtonext(handle);
recvfromnext(handle, /*String*/ in_header);
String out_header = sendtoprev(handle);
annotate(handle, /*String*/key, /*String*/val);
close(handle);
```

The API captures causality in two ways. First, the session context (handle) allows YTrace to capture parent-child relationships between RPC edges. Second, the headers that the API generates include an RPC ID and parent RPC ID (that are unique to the session), and these IDs record causality between the request and response(s) (if any) of an RPC. The parent-child RPC IDs also record global ordering of RPCs in the session.

We implement the YTrace tracing API as a userspace library that services call during execution. The library provides a 99th percentile runtime SLA of $3\mu s$ per RPC. The low runtime overhead of the library is due to two reasons. First, the APIs are stateless, since the session state (handle) in a service is immutable. The state, instead, is passed over the network in the serialized headers; an example of such state is the child-parent RPC IDs in the session. This design choice trades-off expensive state maintenance in the API with a few additional bytes on the network; and also avoids any need for synchronization at session-level in a service. Second, all logging in YTrace is asynchronous.

The API captures a significant set of causal relationships in sessions, but it does not capture causality (or lack of it) in RPC execution patterns such as parallelism and redundancy in the execution graph [9, 11]; see Figure 3 – we found that doing so makes the API complex (which slows down adoption). YTrace uses happens-before relationships to infer this causality (see §4).

CDN instrumentation. The wide area Internet path can be a significant source of performance problems that impact user experience. In order to diagnose these problems and their impact on user experience, we need to instrument the Internet path in isolation. Typical approaches explored in literature include active probing (which is asynchronous) or model-based methods that

infer path performance user-side and/or CDN-side measurements of the trace. Both approaches have limitations: the former adds network traffic and may not be causally related to the session (since it is asynchronous), while the latter methods are prone to user host problems (which are not uncommon).

In order to diagnose and isolate Internet performance problems, we take periodic snapshots of measurements that the TCP stack in the CDN kernel maintains, for the TCP connection used by user host RPCs. Specifically, we snapshot `tcp_info` structures from the Linux kernel. The structure contains end-to-end statistics of the TCP connection that affect serving performance, such as packet retransmissions, reordering, RTT, sender and receiver windows, etc.; it hence measures the Internet path as the flow sampled it. YTrace uses the TCP connection statistics to localize throughput bottlenecks to sender (content generation), receiver and path-based limitations; and to diagnose download bottlenecks with user hosts. Note that we do not include diagnosis of CDN traffic engineering-related performance problems; in other words, YTrace’s diagnosis is conditioned on the traffic engineering decision for a user session (see discussion, §8).

Process profiling. We are adopting Continuous Profiling [6, 30] in Yahoo services for a small fraction of user sessions. At a high level, Continuous Profiling collects performance counters exposed by modern CPUs. Performance counters allow us to understand host-level bottlenecks and localize bad user experience down to code using the associated program counters (in conjunction with the process binaries).

At the end of each session, YTrace records a directed trace graph that includes: (i) the end-to-end execution graph with compute, serialization and RPC timings at each node and event causality, (ii) user-side event timings and event causality, and (iii) TCP-layer measurements of user-side Internet at the CDN.

3.2 Asynchronous Instrumentation

Despite service stack-level concurrency, the underlying network is a shared resource and typically under-provisioned (e.g., fat-tree datacenter topologies). The network can introduce performance problems in RPCs during session execution, which can impact user experience. YTrace collects asynchronous instrumentation from components in the end-to-end serving stack that cannot be modified to do tracing. Such components are typically in the underlying network layer, such as the datacenter network devices.

YTrace collects *syslogs* from all datacenter network devices. Syslogs include detailed and fine-grained state information of each device and the root cause. In conjunction with syslogs, YTrace uses network topology

to localize user session performance problems to network devices. It collects network topology snapshots of: (i) the wide area Internet paths from the CDN to *client clusters* and to the datacenters using traceroutes, and (ii) each datacenter network using device configurations.

4. DIAGNOSIS

YTrace uses synchronous and asynchronous instrumentation to diagnose performance problems that impact user experience. In this section, we sketch the diagnosis methods. See Figure 4 for a flow overview.

Detection. The first step towards performance diagnosis is to detect performance problems. Since our focus is on user experience, we frame the detection problem around it: Is the page load time⁶ *large* for the user session? YTrace answers this question by *estimating a baseline* (normal behavior) for the page load time based on history, and finding if the session has a statistically significant deviation from the baseline. The page load time is measured at the user-side. Note that detection algorithms have to be aware of confounding variables such as the web page (session) attributes, the user attributes and time of day; YTrace conditions the detection based on domain knowledge of pre-defined confounding variables. YTrace also supports detection based on other definitions of user experience, or not based on user experience. For example, video quality of experience, abnormal service latencies or unusual execution graphs for a session. YTrace currently estimates a simple baseline as the historic inter-quartile range, since we are interested in understanding performance behind both low and high user experience metrics.

4.1 Content Diagnosis

For sessions that were detected as having performance problems, YTrace uses the user-side instrumentation to determine whether there were performance problems that were localized to the user agent (browser). To do this, it checks whether the latency of user-side events from the Navigation Timing API [2] (e.g., DOM processing and rendering) are significant relative to the OnLoad time for the page. Note that NavTiming events are causally related and the critical path of user-side events includes all events.

In general, resources on the page are fetched (and executed) concurrently with the origin page – and the concurrency depends on the origin content, ordering of resource arrivals and execution latency (parsing, DOM construction, etc.). This dependency between resources leads to blocking periods; however, such analysis requires browser modifications [36]. YTrace currently treats

⁶We can ask similar detection questions about user experience metrics for other content types, e.g., rebuffering in video.

all content (origin and resources) performance as independent (note that origin content is typically the dynamic, non-cacheable content in personalized pages). We are investigating dependency and blocking time measurement that avoids browser changes.

4.2 Service Diagnosis

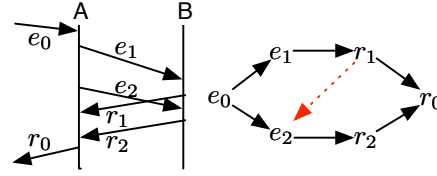
Service localization refers to the question of which services in the session execution graph *caused* a performance problem for sessions that were detected as having performance problems. YTrace localizes service-level problems by estimating the critical path(s) – in terms of service latencies – in the session execution graph. In order to compute the critical path, YTrace needs context of concurrency in the execution graph, which is determined by causality between RPC edges.

YTrace tracks causality as follows. The synchronous instrumentation system tracks two forms of RPC causality during tracing: parent-child RPC relationships, and request-response causality. In order to keep the tracing API simple to use and reduce usage errors, we do not track (at the API-level) causality *between* sibling RPC edges at a single node. Causality between sibling RPC edges may (or may not) exist, depending on the RPC execution patterns used (see Figure 3). Since such patterns are typically dynamic, based on session and environment attributes, we cannot use blackbox methods that mine causal relationships from offline session trace data [5, 9].

The parallelism and redundancy RPC patterns lend well to happens-before relationships (directly follows from their definition). Consider outgoing RPC edges $e_1 \dots e_n$ at a service node A (Figure 3); and let the responses to the outgoing edges be the edges $r_1 \dots r_n$ (incident on A). Denote the first byte and last byte timestamps (A 's wall clock) of an edge e by $C_f(e)$ and $C_l(e)$. Timestamps are taken from user space. Note that e_i causes r_i for all i , denoted as $e_i \rightarrow r_i \forall i$. Causality in *non-parallelism*: $r_i \rightarrow e_j: C_f(r_i) < C_f(e_j)$; $r_i \not\rightarrow e_j$ otherwise.

Redundancy: If edge r_0 is A 's reply to calling node, $r_i \rightarrow r_0 \forall r_i: C_f(r_i) < C_l(r_0)$; $r_i \not\rightarrow r_0$ otherwise.

YTrace uses edge causality to estimate the critical path in the execution graph, defined as the *causal* round trip path in the graph with the largest total (service and network) latency. Latency at a service with an incoming edge e_0 and a causal outgoing edge e_1 is the computation time: $l_{01}^s = C_f(e_1) - C_l(e_0)$. The network latency is the RPC edge (de)serialization time at the caller node. Note that the critical path in the same execution graph can change based on RPC causality: for example, if service A makes two RPCs e_1 and e_2 to B , the critical path may include one or both of e_1 and e_2 depending on $e_1 - e_2$ causality:



YTrace estimates the contribution of a service as the sum of computation latencies for all incoming-causal outgoing edge pairs l_{ij} . It reports the service-level localization output as the top service contributors, and their fraction of end-to-end (user-side) latency, amongst services in the critical path.

4.3 Network Diagnosis

YTrace uses syslogs from network devices to diagnose datacenter network problems. It uses TCP stack measurements at the CDN to isolate problems on the user-to-CDN Internet path (note that we cannot instrument the Internet path). We first look at datacenter network problem diagnosis.

Datacenter network diagnosis. The critical path found during service localization represents the subset of execution that contributed to user latency, and it includes time spent by RPCs in the network. The network can degrade the performance of RPCs by inducing latency, packet losses and reordering, which increase the RPC time and reduce throughput (especially for RPCs with large payloads). Our goal in network diagnosis is to localize and find root causes of datacenter network problems. We are interested in localizing cascading problems and finding root causes that propagate across the network stack; for example, a hardware problem in a switch that cascades into problems in the connected router as both L2 and routing plane problems.

YTrace uses syslogs and the datacenter network topology to diagnose cascading problems. Each datacenter network device emits a stream of syslog messages, which are semi-structured text that include a timestamp, severity level and semantics of the problem (network interface, problem type and attributes, etc.). Our goal is to represent a problem as a structured graph that describes the causal activity (the cascade) in the problem. It uses domain knowledge to preprocess syslogs: mapping them to structured “templates” (including equivalence classes of problem types), and extracting device attributes (if any). We leverage some of the prior work on template extraction [29]. The domain knowledge is a one-time input to YTrace and does not need changes unless the syslog templates change (e.g., due to vendor or major OS changes, which are infrequent).

The first step towards diagnosing session performance due to network problems is to find RPCs in the session critical path that impacted user experience. YTrace

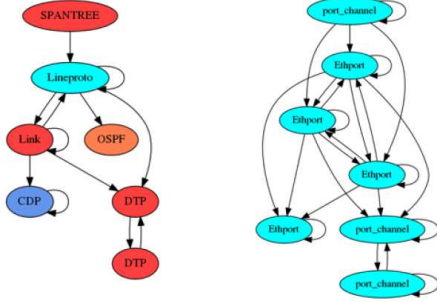


Figure 5: Example network problem graphs from our datacenter.

computes a candidate list of RPCs per-session as follows. Consider two services A and B , and an RPC e from A . The local clock at node A is C_f^A (we consider timestamps at the start of each RPC request/response to avoid self-loading effects). For diagnosis, we are interested in the variable component of the one-way delay – typically queueing delays. YTrace estimates queueing delay during the RPC as $d_{AB}(e) = C_f^B(e) - C_f^A(e) - \min_{\Delta}(d_{AB})$, where the min is taken over the recent Δ time window⁷; the min is an estimate of the constant components of the one-way delay. YTrace detects an RPC as having a performance problem if the queueing delay is significant relative to the end-to-end latency. It then computes a set of network devices that the RPC could have traversed.

The typical way to localize network-level performance problems is boolean network tomography [12] on end-to-end observations of RPC queueing delays. Tomography takes as input observations of paths – good and bad – that *overlap* with a problem path. It aims to isolate the part of the network that led to the bad observations. Tomography is not directly applicable in datacenter networks, since such networks use multi-path routing – hence, the path an RPC takes is not deterministic. This makes the problem combinatorial and expensive to solve. Syslogs provide a single network-wide solution that addresses both localization and root cause analysis.

YTrace’s network diagnosis module has two components: real time problem graph mining that ingests all syslogs from a datacenter, and asynchronous low-volume learning that periodically generates *causal rules* as input for the real time component.

More formally, a problem graph is a directed graph of syslog templates, where an edge $T_i \rightarrow T_j$ implies that template T_i caused template T_j . A problem graph could exist within a single device or span multiple devices. A causal rule connects two templates by a causal relationship: $T_i \rightarrow T_j$; depending on whether T_i and

⁷The time window should be large to include queue dissipation (μs in datacenter networks) but smaller than clock drift timescales (mins.).

T_j happen within a single device or different devices, a causal rule could be either intra-device or inter-device. For example, Figure 5 shows two instances of problems from a Yahoo datacenter (colors encode layer in protocol stack). The left graph shows a multi-layer problem that spans aggregate and top-of-rack tiers in the fat-tree network, and multiple layers in the protocol stack. It encodes a cascading problem: a module failure causes a link down event, which triggers a spanning tree protocol status change, and causing an interface status change on a peering device. The right graph shows a problem within a top-of-rack devices that is an Ethernet (L2) flapping issue.

YTrace’s diagnosis module mines problem graphs as follows. It divides the syslog timeline across the datacenter into small time windows. Within each time window, it maps syslog lines into templates and uses the corpus of causal rules to iteratively construct problem graphs, starting from intra-device edges and then adding inter-device edges. At any point of time, we typically have 100-200 causal rules. Hence, the runtime overhead of mining problem graphs in a small time window of syslog messages across the datacenter is relatively low (it can run on a single machine).

The problem of mining causal relationships between syslog templates is relatively harder, since it is the problem of finding needles in a haystack of syslogs. In such cases, happens-before relationships result in significant false positive rates. We adopt statistical causality mining techniques to discover causal rules – in particular, we use Quasi Experimental Design (QED). First, we find (in a larger time window) template pairs that have a statistically significant correlation in their timeseries. For each template pair T_i, T_j that is correlated, QED finds causality by testing the hypothesis that an element of the *treated* set is much more likely than an element of the *untreated* set. The treated set consists of instances when T_i and T_j exists together at any time; while the untreated set has instances when T_i exists but not T_j . If the treated set is more likely, QED assigns a causal relationship $T_i \rightarrow T_j$.

For each RPC in a session that is detected as having a performance problem, YTrace summarizes the set of problem graphs on devices that the RPC could have traversed. At this point, the network diagnosis in YTrace is meant to show *possible* problems in the network that impact an RPC, since these problems may not manifest as performance problems in all RPCs. We are working on methods to establish causal relationship between a network problem and RPC performance. A limitation of syslog-based diagnosis is that it will only mine problems that syslogs can describe. We believe that our syslog-mining methodology can be applied on logs from any multi-layer distributed service. We refer the reader to

our prior work [22] for details of the network diagnosis methods.

Internet path diagnosis. YTrace synchronously instruments the user-to-CDN (and user-to-datacenter) path. In the context of Internet path performance, it captures userspace RPC timing at the user host, and RPC timing at the CDN and TCP stack measurements of the RPC at the CDN node. In practice, we observed that a common source of performance problems is the user host. Hence, the measurements taken from the browser (or any container on top) include a mix of problems in the user host and the Internet path (even after we measure and account for CDN-side latencies). We use measurements from the TCP stack in the CDN host kernel as estimators of the Internet path performance (as sampled by TCP). The TCP measurements include path RTT, RTT variation, segment retransmissions, congestion windows and reordering. YTrace uses the TCP measurements to estimate the impact of the Internet path on RPCs from user host, and isolate Internet problems from the user host performance. We are looking into using tomography on the TCP measurements to localize bottlenecks on the Internet (in conjunction with topology measurements).

4.4 Ongoing Work

Process localization. A part of our localization goal is to simplify performance debugging by localizing user session performance problems to source code. One approach requires YTrace to track performance counters for processes within each service and associate the counters with code; and it has to be low-overhead. The performance counters provide a context for fingerprinting runtime behavior of code (for node-local root cause analysis), and include program counters that help associate with code. This is early-stage work.

Root cause analysis. Root cause analysis in operational practice typically relies on fingerprinting performance problems based on domain knowledge and experience. While YTrace includes root cause analysis of network problems using syslogs, an open question is how to incorporate service and network operator inputs (domain knowledge) to do service-level root cause analysis. The key to this is to provide a suitable model of performance problems that operators can input, using the following grammar:

```
SYMPTOM symptom
PATHOLOGY pathology DEF ( symptom | NOT ←
    symptom )
symptom := symptom1 AND symptom2
symptom := symptom1 OR symptom2
symptom := ( symptom )
PROCEDURE symptom funcname
```

We model a performance problem as a boolean-valued expression on one or more boolean-valued *symptoms*.

A symptom is a function of instrumentation. For each detected problem, we evaluate matching problem expressions to identify the root cause(s). The root cause analysis is based on prior work on network root cause analysis [17].

5. YTRACE BACKEND

A key aspect of YTrace is a high-performance analytics backend that enables near real time and accurate diagnoses. Figure 2 shows an overview of the backend. The backend ingests YTrace instrumentation data (a timeseries of events) and runs statistical analyses and diagnosis on the event stream. The events and analyses are written to a persistent store that drives an interactive visualization system.

Data transport. The first step after instrumentation is to transport the data to the indexing and analysis systems. YTrace uses a publish-subscribe messaging system to transport instrumentation events.

Since the YTrace libraries and the transport system implement asynchronous write semantics, instrumentation events can incur delivery delays or be delivered out of order, be lost, or sometimes be duplicated. This is particularly the case for all tracing events in a session, where it is not always feasible to determine if all data for a session has arrived for analyses. Moreover, due to event asynchrony, there may be statistical biases in certain analytics leading to false diagnosis. In our implementation, we trigger analysis of an event after a delay δ ; δ is pre-computed as the minimum duration after which any event is delivered with a high likelihood.

In order to find biases, the YTrace backend measures event volume as a function of service and datacenter; and uses it to estimate the expected volume at the current time. If there is a bias, it does not trigger analysis for that statistic. Inferring and avoiding bias is a part of our ongoing work.

Indexing. The indexing system provides a high-throughput write, low-latency read interface for structured data. Data in YTrace is a timeseries of graphs from the network (topology) and application layers (session traces). Since events for a session are transferred asynchronously, it is important that the writes are idempotent and session updates do not require any reads. The ETL process materializes a number of indices for sessions for common queries. We currently use an Apache HBase cluster as our persistent store. Domain-specific queries such as the network paths connecting two server hosts or Internet path to a client host are processed by an API tier. Such queries are useful for diagnosis such as tomography.

Making it real time. In order to make the diagnosis near-real time, we would need to: (1) minimize the la-

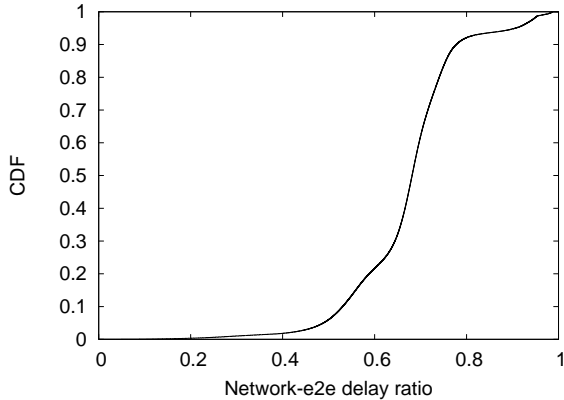


Figure 6: Effect of network delays on about 2m user operations with the Sherpa data store from two Yahoo datacenters.

tency between end of a session and when the events in the session are analyzed, and (2) build a high-throughput analytics backend. A significant factor that contributes to the latency above is data movement from multiple datacenters into a central indexing system in a single datacenter. Note that on the contrary, a central indexing system improves the analytics throughput; however, the latency induced by wide area data movement degrades performance more significantly since wide area links have limited bandwidth and are shared resources.

To reduce wide area data movement, we are working on a federated database that is partitioned across all datacenters. Each datacenter includes a local indexing system, and the data partitioning is based on the datacenter-locality of events in user sessions. Events inside a datacenter are transported within the datacenter; hence, the events for a session that is served by two datacenters will reside in two indexing systems. In the ideal case, the processing for a query would be done at the relevant indexing systems, and the aggregated output(s) returned to the federation layer – the aggregations are relatively low-volume. This is, however, not true of some queries such as joins, which may require inter-datacenter data movement.

We are also adding support for approximate queries to speed up query processing and reduce wide area data movement. The database has to be aware of data biases, both from transport and partitioning, in order to minimize statistical bias in query output. Our work builds on prior work in wide area and approximate query processing (e.g., the recent work on WANalytics [35] and BlinkDB [4]).

6. CASE STUDIES

In this section, we show some experiences and results using YTrace in production.

6.1 Distributed Storage

We consider a hosted large-scale, low-latency, distributed key-value storage system, Sherpa [10], that is used as a common storage backend in serving stacks at Yahoo in Figure 6. Sherpa aims for an SLO of 2ms for key reads. We look at a multi-layer analysis of latencies in Sherpa.

Operations with Sherpa traverse router nodes and are served by Storage Unit (SU) nodes – all connected by the datacenter network. We use YTrace data to look at the impact of round-trip network latencies⁸ on latency of two million Sherpa operations in two datacenters. The figure shows that the network contributes to a significant fraction of operation latency. The tail of the distribution (top-10%) includes operations that saw variable delays in the network (e.g., due to congestion or non-shortest path routing).

Using a simple model of network delay for a key read payload, we can show that the minimum delay for a read RPC to traverse the router and SU nodes and back is 0.5 to 0.9ms (depending on the number of round-trips TCP takes). Under per-hop queueing or non-shortest path routing conditions (a router-SU path normally traverses 1-2 ToR and/or one AGG device), the delay can be 0.7-1.3ms. Hence, in order to optimize for operation latency and maintain SLOs, the storage system could be designed to minimize the number of network hops traversed by RPCs.

6.2 Datacenter Network

We look at datacenter-wide problems from a single Yahoo datacenter using YTrace’s network diagnosis output. The datacenter consists of a large fat-tree network topology with thousands of network devices. The topology is made of multiple “tiers”: traversing bottom-up, Top-of-Rack (ToR) devices that connect servers (running services), multiple aggregation (AGG) tiers and a core tier that connects the datacenter to the Internet. RPCs between services within the datacenter typically traverse the ToR and AGG tiers; hence, any problems in the two tiers will impact a significant fraction of RPCs in the datacenter.

Figure 5 shows two examples of problem graphs from ToR and AGG tiers in the datacenter network; see §4.3 for details. Figure 7 shows the distribution of different problem classes across the three network tiers. Over 93% of the problems occur in the ToR switches (which dominate in number and are relatively low-cost devices). A large fraction of ToR and AGG problems occur in the lower layers (PHY and L2), and sometimes in higher layers such as the routing plane. On the other hand, middleboxes (that can be topologically placed anywhere in

⁸Latency computations in this study use a single clock. Network latency is: (router-SU RPC exchange at router) - (processing delay at SU).

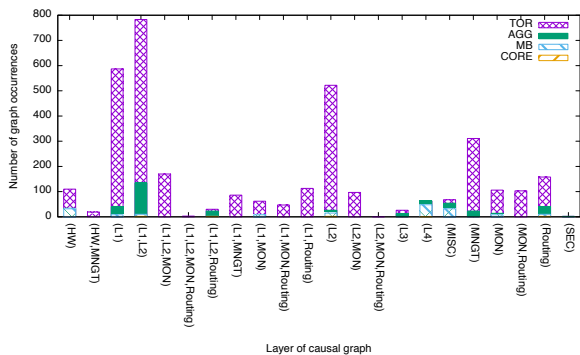


Figure 7: Number of problem graphs for each network tier.

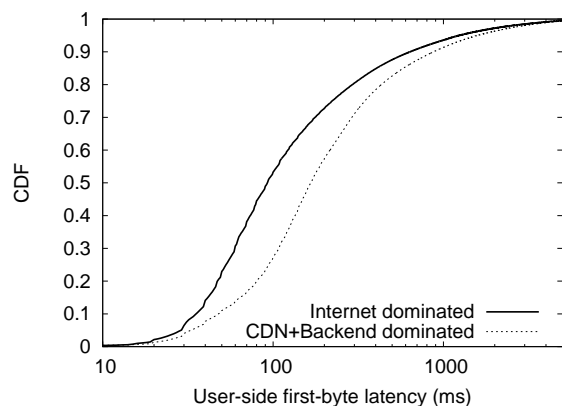


Figure 8: User-side RPC first-byte latency broken down by the dominant bottleneck (Internet or CDN).

the network) show problems mostly in the higher layers (L3 and L4). The duration of the problem graphs can last between a few seconds to hundreds of seconds – which makes the likelihood of RPCs being affected high. We refer the reader to our prior work [22] for more results and details of network diagnosis methods.

6.3 Video Stack

Video serving stacks can be modeled as three tier architectures, spanning the video player (user-side), the CDN and a backend store. A video playback is a sequence of RPCs by the player to the CDN; the CDN makes an RPC to the backend store if it does not have the response cached. We trace RPCs from the video player through the CDN, while synchronously instrumenting the TCP stack in the CDN kernel periodically over the course of the RPC. We use the TCP measurements as the source of truth for the Internet path performance, since the delays induced by the kernel space are relatively very low. We collect data for all user sessions over a course of two weeks for this case study.

We first look at the impact of backend and Internet performance on the user experience. We quantify the user experience as the first-byte delay for each RPC.

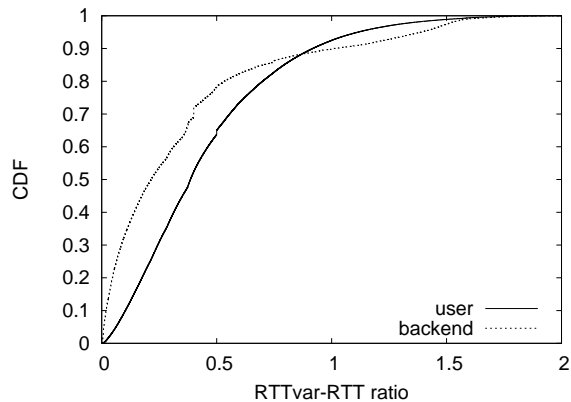


Figure 9: Network RTT variation of user and datacenter paths in 350m user sessions with the Yahoo CDN.

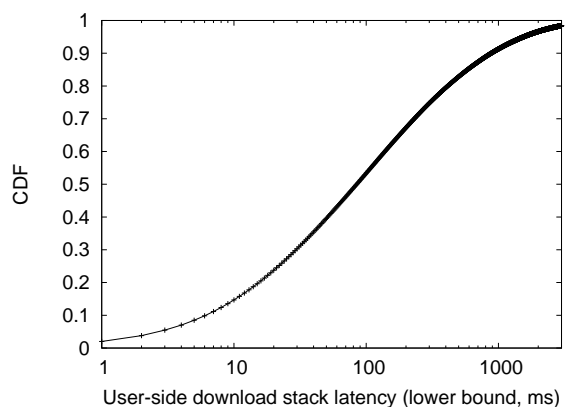


Figure 10: User-side stack latency estimates (lower bound).

Figure 8 shows the distribution of user-side latencies after dividing the set of RPCs into two parts: RPCs that are bottlenecked by the Internet path and RPCs that are bottlenecked by the CDN or backend. About 95% of the RPCs are bottlenecked by the Internet path as we would expect. In the remaining 5% RPCs that are bottlenecked by the CDN/backend, the cache miss rate is 40% as compared to 2% overall. Further, the user experience degradation due to RPCs bottlenecked by the CDN/backend is tens of milliseconds higher than RPCs bottlenecked by the Internet. This shows that in order to troubleshoot or fix tail latencies, we should focus on the CDN/backend.

When there is a cache miss, the CDN makes an RPC to the backend. We look at RTT of TCP connections at the Yahoo CDN – for RPCs from the user host and to the backend in Figure 9. The RTT is the delay between a TCP data segment and the corresponding TCP acknowledgement at the CDN node’s TCP stack. For 350m user sessions, we analyze the *variation* in RTT of each TCP connection, defined as the ratio of RTTvar and smoothed RTT in the kernel. We see that the RTT variation is significantly higher for user connections than

datacenter connections; however, the tail RTT variation is dominated by the datacenter connections. This also makes the case for troubleshooting tail latency problems by looking at the CDN/backend.

Finally, we show that it is possible to estimate content download latencies in the user host by tracing instrumentation alone (i.e., timing at user and CDN hosts, and TCP kernel variables). The first-byte delay at the user host for video segment RPCs to the CDN (δ_{fb}) includes an RTT (δ_{rtt}) on the Internet, CDN and backend (if any) latencies (δ_{cdn} and δ_{be}), and the download stack latency at the user host (δ_{ds}). Considering the TCP Retransmission Timeout (δ_{rto}) as a conservative estimate for δ_{rtt} , we can estimate a lower bound for δ_{ds} : $\delta_{ds} \geq \delta_{fb} - \delta_{cdn} - \delta_{be} - \delta_{rto}$. Figure 10 shows the distribution of the lower bound of download stack latencies across video sessions (truncated to positive real numbers). We see that the user host contributes tens to hundreds of milliseconds of latency when delivering data to the video player application running on the browser. Although user-side download stack delays are not under the control of a content provider, providers can avoid the effect of such problems by ordering RPCs to mask the problem. We refer the reader to our prior work [15] for more results on the video stack.

7. RELATED WORK

Diagnosis systems are typically designed for diagnosing a subset of the end-to-end path or a specific layer of the stack. YTrace is an attempt to build an end-to-end multi-layer diagnosis system at web-scale, since performance troubleshooting activities typically rely on such insights. In doing so, it builds on some prior systems. We capture representative work in this section.

Distributed tracing systems. Distributed tracing is a common instrumentation primitive in content providers. Capturing, recording or mining causality between events in a distributed trace is necessary to make sense of session performance. Systems in prior work differ in the amount of instrumentation and trace analysis complexity – in fact, there is a tradeoff between instrumentation overhead and analysis complexity to do the same amount of diagnosis.

Systems implement causality synchronous with execution [13, 32] or mine using historic traces [9]. For example, Dapper (and its derivative, Zipkin) capture causality between *spans*, which are combinations of requests and associated responses. While span-level causality is useful, it is not expressive enough to model RPC executions such as parallelism and redundancy. History-based causality mining helps minimize instrumentation overhead in production; it relies, however, on resources for offline mining of causal relationships. It works well in homogeneous environments, where there is a common

RPC library and RPC execution patterns are predictable, but may not be feasible in heterogeneous and dynamic runtime environments due to runtime transitions to non-causality within a session. Magpie [8] lies on the instrumentation side of the spectrum – it captures detailed instrumentation, such as OS events and packet traces, to infer causality without needing offline analysis. While this yields detailed diagnoses, it may not be feasible in production. Project 5 [5], Mystery Machine [9] and Pinpoint [] lie on the analysis side of the spectrum – they require offline resources to mine causality. X-Trace is an experimental system that requires session tracing support from network devices; having such support helps do multi-layer causal discovery synchronously with the session (a limitation of YTrace), but network support may not be feasible in practice.

Network diagnosis. There has been significant research on network diagnosis methods. Sun et al. capture TCP variables at the CDN to localize performance bottlenecks [34]; they require OS kernel changes in the critical path, since they require TCP instrumentation outside of the `tcp_info` structure. WhyHigh [20] and LatLong [41] further discover client clusters with performance problems and diagnose user-to-CDN path problems at an aggregate level (instead of per-session). Yu et al. [38] and Ghasemi et al. [14] diagnose datacenter network performance using detailed instrumentation (e.g., socket logs and packet traces). At large serving rates, such logging may be infeasible. Network tomography techniques [12] localize bad performance to network interfaces; they assume that the path between two hosts is known – uncommon in datacenter networks. Monitor-Rank [19] uses similar tomography-based localization.

Log mining. Service and network log mining are common diagnosis methods. Distalyzer compares anomalous logs with known baseline logs [25] for diagnosis. Spectroscope compares two trace logs to understand differences between them [31]. Xu et al. mine log features [37]. Syslogs have been used to study network-specific failures in datacenters [16, 27, 28], but not for root cause analysis. Prior work has not explored causal discovery for log analysis – this becomes particularly necessary when looking for a small number of cascading problems in large log volumes.

Code and content localization. Binary profiling [6, 7, 30] and code mining methods [40] have been used to diagnose performance problems in single hosts down to code. These systems do not track code-level problems with user experience. More recently, Pivot Tracing [23] allows users to insert breakpoints in running code and log them while tracing (synchronously) – mainly tailored towards debugging within a distributed system (as opposed to a content provider). Content diagnosis methods used browser modifications [36] and middleboxes

[18]. We are exploring the feasibility of these methods in YTrace.

8. DISCUSSION AND CONCLUSION

In this paper, we presented the design of YTrace, a system for end-to-end multi-layer performance diagnosis in large content providers. We formulated a problem statement that covers diagnosis use cases, and presented instrumentation and methods for diagnosis. Our discussion opens several research questions that we cover next.

If an RPC is observed to have high latency in the datacenter, YTrace currently lists correlated network problems from devices that the RPC potentially traversed (based on syslogs). The longer the problem, the more likely that RPCs that traversed the devices will be impacted. Such correlations are useful towards troubleshooting (esp. when looking at aggregated data). Going from correlation to causation – in other words, whether a network problem *caused* performance problems with RPCs – is an open question. It requires apriori knowledge of devices the RPC traversed, e.g., using Netflow (since datacenter networks use multi-path routing), and inferring causal relationships between problems in those devices and RPC performance. One approach is to look for symptoms in RPCs instrumentation that are caused by each network pathology.

YTrace diagnoses distributed root causes such as cascades in the datacenter network, but does not diagnose distributed root causes across services. Such problems create runtime dependencies between services that impact performance (despite RPC parallelism and redundancy). A common service-level cascading problem is backlog that builds up across services (typically calling services). Distinguishing these from backlogs that arise due to problems within the host requires appropriate instrumentation and diagnosis methods. We are looking into adopting causality-based joint mining of service logs and network syslogs to diagnose distributed root causes.

We assumed that Traffic Engineering (TE) at the CDN is a given: YTrace’s diagnosis is conditioned on the TE for a user session. Diagnosing performance-*sub-optimal* TE for a session (i.e., whether a user was directed to a CDN node that caused bad user experience) requires knowledge of Internet path performance from the user to all CDN nodes at that time; accurately doing it is an open research direction. A related system, LatLong, diagnoses *average* latency [41].

Content providers may not have a complete view of the user end-host stack performance (hardware, OS environment, browser, etc.) as the content is parsed, executed and rendered. Analysis similar to WProf [36] that does not require browser modifications would help diagnose bottlenecks that reside in the user end-host, and

could be exposed to the content provider similar to Navigation Timing [2].

In order to reduce overhead due to instrumentation, YTrace supports sampling a fraction of user sessions. Sampling leads to challenges in analyzing tail latency – it requires inversion of the sampled distribution of execution graphs to estimate high quantiles. For example, prior work on latency looked at estimating confidence intervals for latency quantiles [33].

In order to localize performance problems to networks and inter-domain links on the Internet, we are looking into adopting tomography methods that work on TCP measurement data. Tomography methods assume that the Internet path for a user IP address is known. In practice, provider networks may use multipath routing. Without additional active probing or data (e.g., Netflow) at the time of the RPC flow [26], it is challenging to find the sequence of Internet hops that a given RPC took.

Finally, Internet and transit providers can deploy traffic management mechanisms that do not follow conventional wisdom and can impact performance. For example, traffic shaping leads to changes in link capacity, which can impact long-running flows. YTrace currently diagnoses such mechanisms as a part of the user-CDN Internet path; diagnosing such root causes, however, is an open problem. Recent work on tomography shows that the methods can be used (under sufficient sample size) to find content discrimination [39], under assumptions of static routing.

Web-scale performance diagnosis requires re-thinking from ground up: the instrumentation design, algorithms and systems design to enable near real time diagnoses. There is an inherent tradeoff between complexity of and how detailed diagnosis could be, versus the amount of per-session instrumentation volume we can collect in production at scale. Traditional methods such as tomography and blackbox RPC causality learning are hard to apply in large-scale heterogeneous cloud environments. YTrace is an attempt to accomplish performance diagnosis at scale.

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