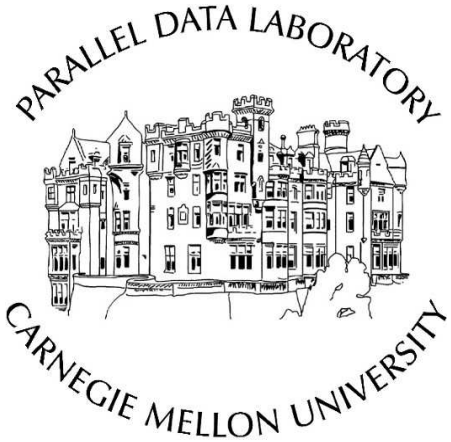

Visualizing request-flow comparison to aid performance diagnosis in distributed systems

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CMU-PDL-13-104 (Supersedes CMU-PDL-12-102)
April 2013

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Abstract

Distributed systems are complex to develop and administer, and performance problem diagnosis is particularly challenging. When performance degrades, the problem might be in any of the system's many components or could be a result of poor interactions among them. Recent research efforts have created tools that automatically localize the problem to a small number of potential culprits, but effective visualizations are needed to help developers understand and explore their results. This paper compares side-by-side, diff, and animation-based approaches for visualizing the results of one proven automated localization technique called request-flow comparison. Via a 26-person user study, which included real distributed systems developers, we identify the unique benefits that each approach provides for different usage modes and problem types.

Acknowledgements: We thank the members and companies of the PDL Consortium (including Actifio, APC, EMC, Emulex, Facebook, Fusion-io, Google, Hewlett-Packard Labs, Hitachi, Intel, Microsoft Research, NEC Laboratories, NetApp, Oracle, Panasas, Riverbed, Samsung, Seagate, STEC, Symantec, VMware, and Western Digital) for their interest, insights, feedback, and support. This research was sponsored in part by a Google research award, NSF grant #CNS-1117567, and by Intel via the Intel Science and Technology Center for Cloud Computing (ISTC-CC). Ilari Shafer was supported in part by an NSF Graduate Research Fellowship and a National Defense Science and Engineering Graduate Fellowship. Michelle L. Mazurek is supported in part by a Facebook Fellowship.

Keywords: distributed systems, performance diagnosis, request-flow comparison, user study, visualization

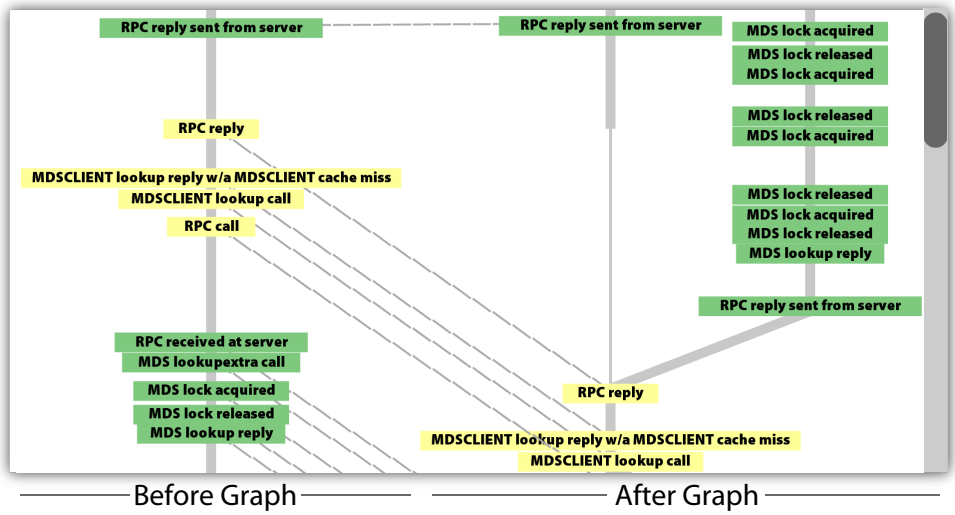


Figure 1: Comparing request-flow graphs: This side-by-side visualization, one of three interfaces we evaluate, illustrates the output of a diagnosis technique that compares graphs. It shows these two graphs juxtaposed horizontally, with dashed lines between matching nodes in both. The rightmost series of nodes in the screenshot do not exist in the graph on the left, causing the yellow nodes to shift downward in the graph on the right.

1 Introduction

A distributed system is a set of software components running on multiple networked computers that collectively provide some service or result. Examples now pervade all walks of life, as society uses distributed services to communicate (e.g., Google's Gmail), shop (e.g., Amazon), provide entertainment (e.g., YouTube), and so forth. Though such distributed systems often have simple interfaces and usually respond quickly, great complexity is involved in developing them and maintaining their performance levels over time. Unexpected performance degradations arise frequently, and substantial human effort is involved in addressing them.

When a performance degradation arises, the crucial first step in addressing it is figuring out what is causing it. The *root cause* might be any of the system's software components, unexpected interactions between them, or slowdowns in the network connecting them. Exploring the possibilities and identifying the most likely root causes has traditionally been an ad-hoc manual process, informed primarily by raw performance data collected from individual components. As distributed systems have grown in scale and complexity, such ad-hoc processes have grown less and less tenable.

To help, recent research has proposed many tools for automatically localizing the many possible sources of a new problem to just a few potential culprits (e.g., [19, 25, 30]). These tools do not identify the root cause directly, but rather help developers build intuition about the problem and focus their diagnosis efforts. Though complete automation would be ideal, the complexity of modern systems and the problems that arise in them ensure this human-in-the-loop model will be dominant for the foreseeable future. As such, many researchers recognize the need for localization tools to present their results as clearly as possible [22, 26]. But apart from a few select instances [20, 22], far too little research has been conducted on what types of presentations are most useful for distributed systems developers.

As a step toward addressing this need, this paper presents a 26-person user study that compares three promising approaches for visualizing the results of one powerful, proven automated localization technique called *request-flow comparison* [30]. Our user study uses real problems observed in Ursa Minor [1], a real distributed system. It includes 13 professionals (i.e., developers of Ursa Minor and software engineers from Google) and 13 graduate

students taking distributed systems classes. As expected, no single approach is best for every diagnosis task, and we make no attempt to identify a single best one in this paper. Rather, our goal is to identify which approaches work best for different usage modes and for diagnosing different types of problems.

Request-flow comparison contrasts how a distributed system services requests (e.g., "read this e-mail message" or "find books by this author") during two periods of operation: one where performance was fine ("before") and the new one in which performance has degraded ("after"). Each request serviced has a corresponding workflow within the system, representing the order and timing of components involved; for example, a request to read e-mail might start at a frontend web server that parses the request, then be forwarded to the e-mail directory server for the specific user, then be forwarded to the storage server that holds the desired message, and then return to the web server so it can respond to the requester. Figure 2 shows a similar example for a distributed storage system. Each request flow can be represented as a directed acyclic graph, and comparing before and after graphs can provide significant insight into performance degradations. Many organizations are interested in algorithms and visualizations for comparing request flows, including Google [33], Microsoft, and Twitter [35].

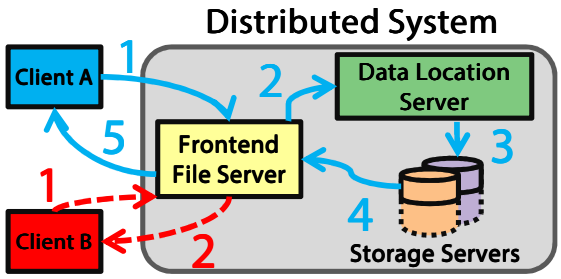


Figure 2: Example distributed storage system. To read a file, clients connect to this distributed system. A frontend file server handles their requests, but may need to access other components like the data location server and storage servers. This figure shows two of many possible paths through the system.

The initial version of request-flow comparison used an inadequate Graphviz-based interface that required graphs to be manually and painstakingly compared with each other. The approaches we compare in this paper were chosen based on the recommendations of developers who previously used this initial version to diagnose real problems in Ursa Minor and certain Google services [30]. They occupy three corners in the space of approaches to visualizing differences, as identified by a taxonomy of comparison approaches [14]. The side-by-side approach is is nearly a "juxtaposition," which presents independent layouts. Diff is an "explicit encoding," which highlights the differences between the two graphs. Animation is closest to a "superposition" design that guides attention to changes that "blink."

Despite the large body of work on comparing graphs [3,4,10], we found no existing implementations of side-by-side, diff, and animation that are suitable for request-flow comparison's domain-specific needs. For example, differences must be found in directed acyclic graph structure and edge weights. Also, correspondences between nodes of before-and-after graphs are not known a priori and must be identified algorithmically. Therefore, we built our own interfaces.

Our user study results show that side-by-side is the best approach for helping developers obtain an overall understanding of a problem. Animation is best for helping diagnose problems that are caused by a change in the amount of concurrent activity (e.g., extra concurrent activity that is excessively slow) or by a slower thread of activity replacing a faster thread. Diff is best for helping diagnose problems caused by non-structural differences.

2 Request-flow comparison

Request-flow comparison [30] is a technique for automatically localizing the root causes of performance degradations in distributed systems, such as Ursa Minor (identical to the system shown in Figure 2) and

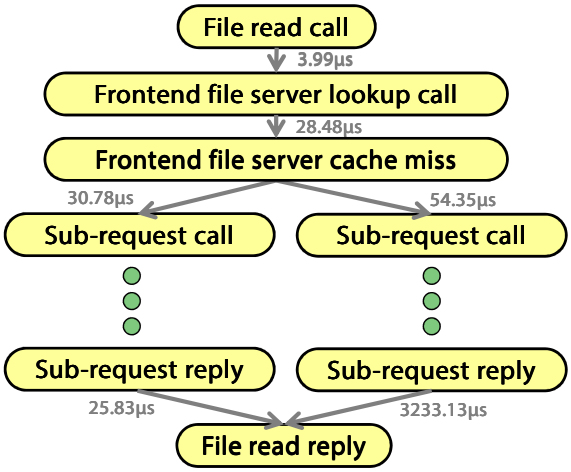


Figure 3: Example request-flow graph. This graph shows the flow of a read request through the distributed storage system shown in Figure 2. Node names represent important events observed on the various components while completing the required work. Edges show latencies between these events. Fan-outs represent the start of parallel activity, and synchronization points are indicated by fan-ins. Due to space constraints, only the events observed on the frontend file server are shown.

Bigtable [7]. It uses the insight that such degradations often manifest as changes in the workflow of individual requests as they are serviced by the system. Exposing these changes and showing how they differ from previous behavior localizes the problem's source and significantly guides developer effort.

Request-flow comparison works by contrasting request-flow graphs observed during two periods: one of good performance and one of poor performance. Nodes of these directed acyclic graphs show important events or activities observed on different components during request processing, and edges show latency between these events (see Figure 3). Request-flow comparison groups the flows observed during both periods (often numbered in the hundreds of thousands) into clusters of identically structured ones, then identifies those from the poor-performance period that most contribute to the performance degradation. As output, it presents pairs of *before-and-after* graphs of these culprits, showing how they were processed before the performance change versus after the change. Identifying differences between these pairs of graphs localizes the source of the problem and provides developers with starting points for their diagnosis efforts. To preserve context, entire request-flow graphs are presented.

This technique identifies two important types of differences. *Edge latency changes* are differences in the time required to execute successive events and represent unforeseen slowdowns in request processing. Request-flow comparison attempts to identify these changes automatically, using hypothesis tests to identify edges with latency distributions that have a statistically significant difference in the before and after periods. Similar tests are used in several automated diagnosis tools [19, 25, 30]. Since hypothesis tests will not identify all edges worth investigating, developers must still examine the graphs manually to find additional such divergences. *Structural changes* are differences in the number and causal ordering of system events. They represent slowdowns due to extra (or less) concurrent activity or additional (or different) activity within a single sequential thread (i.e., intra-thread event changes). Developers must contrast the two graphs manually to identify such divergences. Further details about request-flow comparison can be found in Sambasivan et al. [30].

3 Related work

Recent research has explored a number of approaches, including some akin to side-by-side, diff, and animation, to help users identify differences in graphs, but no single one has emerged as the clear winner [3, 4, 29]. The choice depends on the domain, the types of graphs being compared, and the differences of interest, thus motivating the need for the study presented in this paper.

Archambault et al. [4] suggest that animation may be more effective for helping users understand the evolution of nodes and edges in a graph, whereas small multiples (akin to our side-by-side approach) may be more useful for tasks that require reading node or edge labels. In contrast, Farrugia et al. [10] find that static approaches outperform animation for identifying how connections evolve in social networks. Both evolution-related and label-related comparisons are necessary to understand differences in request-flow graphs. Robertson et al. [29] compare animation's effectiveness to that of small multiples and one other static approach for identifying trends in the evolution of Gapminder Trendalyzer [12] plots (3-dimensional data plotted on 2-D axes). They find that animation is more effective and engaging for presenting trends, while static approaches are more effective for helping users identify them. For unweighted, undirected graphs, Archambault et al. [3] find that a "difference map" (akin to our diff view) is significantly preferred, but does not improve task completion time. Melville et al. develop a set of general graph-comparison questions and find that for small graphs represented as adjacency matrices, a superimposed (akin to diff) view is superior to a juxtaposed (side-by-side) view [23].

In addition to user studies comparing different approaches, many tools have been built to identify graph differences. Many use domain-specific algorithms or are built to analyze specific graph structures. For example, TreeJuxtaposer [24] uses domain knowledge to identify node correspondences between trees that show evolutionary relationships among different species. TreeVersity [15] uses a diff-based technique to identify differences in node attributes and structure for trees with unweighted edges and known correspondences. G-PARE [32] presents overlays to compare predictions made by machine-learning algorithms on graph-based data. Visual Pivot [28] helps identify relationships between two trees by using a layout that co-locates a selected common node. Donatien [16] uses a layering model to allow interactive matching and comparison of graphs of document collections (i.e., results from two search engines for the same query). Beck and Diehl [5] use a matrix representation to compare software architectures based on code dependencies.

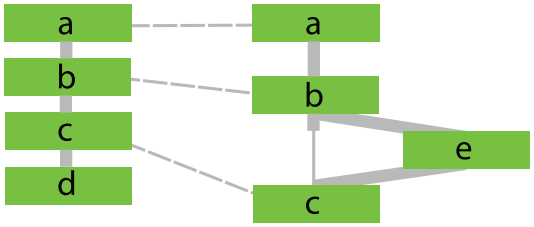
In contrast, in this study, we attempt to identify good graph comparison techniques for helping developers identify performance-affecting differences in distributed system activities. These are intuitively represented as directed, acyclic, weighted graphs, often with fan-ins and fan-outs, and for which node correspondences are not known. These graphs may differ in structure (e.g., node names and their connections) and edge weight. We also believe our intended audience—those familiar with distributed systems development—will exhibit unique preferences distinct from the general population.

In the systems community, there has been relatively little research conducted on visual methods for diagnosis. Indeed, a recent survey of important directions for log analysis concludes that because humans will remain in the diagnosis loop for the foreseeable feature, visualization research is an important next step [26]. One project in this vein is NetClinic, which considers root-cause diagnosis of network faults [20]. The authors find that visualization in conjunction with automated analysis [19] is helpful for diagnosis. As in this study, the tool uses automated processes to direct users' attention, and the authors observe that automation failures inhibit users' understanding. In another system targeted at network diagnosis, Mansmann et al. observe that automated tools alone are limited in utility without effective presentation of results [22].

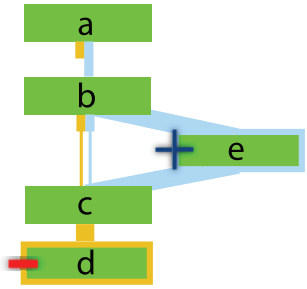
4 Interface design

Figure 4 shows our implementations of side-by-side, diff, and animation. All of them were guided by an initial pilot study, which is not described in this paper. These interfaces are implemented in JavaScript, and use modified libraries from the JavaScript InfoVis Toolkit [6]. This section further describes them.

Side-by-side: Our side-by-side interface (illustrated with a simplified diagram at right and in Figure 4a,d) computes independent layered layouts for the before and after graphs and displays them beside each other. Nodes in the before graph are linked to corresponding nodes in the after graph by dashed lines. This interface is analogous to a parallel coordinates visualization [18], with coordinates given by the locations of the nodes in the before and after graphs. Using this interface, latency changes can be identified by examining the relative slope of adjacent dashed lines: parallel lines indicate no change in latency, while increasing skew is indicative of longer response time. Structural changes can be identified by the presence of nodes in the before or after graph with no corresponding node in the other graph.

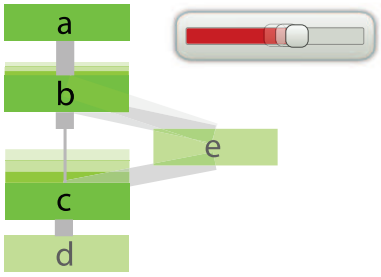


Diff: Our diff interface (at right and in Figure 4b,e) shows a single static image in an explicit encoding of the differences between the before and after graphs, which are associated with the colors orange and blue respectively. The layout contains all nodes from both the before and after graphs. Nodes that exist only in the before graph are outlined in orange and annotated with a minus sign; those that exist only in the after graph are outlined in blue and annotated with a plus sign. This structural approach is akin to the output of a contextual diff tool [21] emphasizing insertions and deletions.



We use the same orange and blue scheme to show latency changes, with edges that exist in only one graph shown in the appropriate color. Edges existing in both graphs produce a per-edge latency diff: orange and blue lines are inset together with different lengths. The ratio of the lengths is computed from the ratio of the edge latencies in before and after graphs, and the next node is attached at the end of the longer line.

Animation: Our animation interface (at right and in Figure 4c,f) switches automatically between the before and after graphs. To provide a smooth transition, it interpolates the positions of nodes between the two graphs. Nodes that exist in only one graph appear only on the appropriate terminal of the animation. They become steadily more transparent as the animation advances, and vanish completely by the other terminal. Independent layouts are calculated for each graph, but non-corresponding nodes are not allowed to occupy the same position. Users can start and stop the animation, as well as manually switch between terminal or intermediate points, via the provided slider.



4.1 Correspondence determination

All of the interfaces described above require determining *correspondences* between the before and after graphs, which are not known a priori. We must determine which nodes in the before graph map to which matching

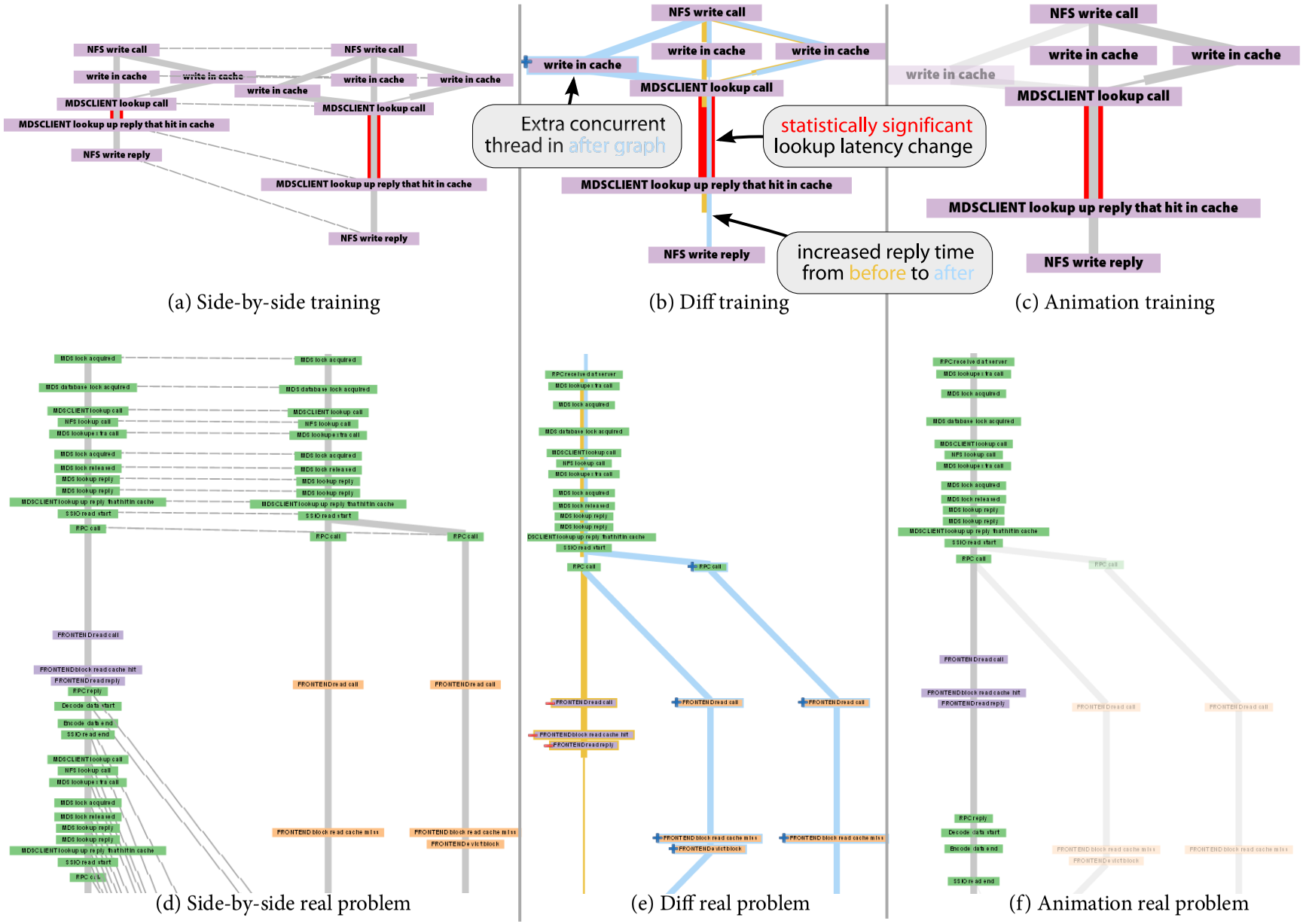


Figure 4: Three interfaces. This diagram illustrates the three approaches to visualizing differences in request-flow graphs that we compare in this study Figures a, b, and c show the interfaces applied to a mocked-up problem that was used to train participants (slightly modified for clarity on paper). Figures d, e, and f show the interfaces applied to a portion of one of the real-world problems that was presented to participants.

nodes in the after graph, and by extension which nodes in each graph have no match in the other. This problem is not feasible using graph structure and node names alone, because many different nodes can be labeled with the same name (e.g., due to software loops). Fortunately, the converse is guaranteed to be true—if a node in the before graph matches a node in the after graph, their node names will be the same. We exploit this property to obtain approximate correspondences.

Our approximation technique runs in $O(N^2)$ time in the number of nodes. First, we use a lexically-ordered depth-first traversal to transform both graphs into strings. Next, we keep track of the insertions, deletions, and mutations made by a string-edit distance transformation of one string into another. Finally, we map these edits back onto the appropriate interface. Items that were not inserted, deleted, or modified are ones that correspond in both graphs. Despite the limitations of this approach, we have found it to work well in practice. Gao et al. survey a variety of related algorithms [11]; because the problem is hard (in the formal sense), these algorithms are limited in applicability, approximate, or both.

4.2 Common features

All three of our interfaces incorporate some common features, tailored specifically for request-flow graphs. All graphs are drawn with a layered layout based on the technique by Sugiyama et al [34]; layouts that modify this underlying approach enjoy widespread use [9].

To navigate the interface, users can pan the graph view by clicking and dragging or by using a vertical scroll bar. In large graphs, this allows for movement in the neighborhood of the current view or rapid traversal across the entire graph. By using the wheel on a mouse, users can zoom in and out, up to a limit. We employ rubber-banding for both the traversal and zoom features to prevent the interface from moving off the screen or becoming smaller than the viewing window.

For all of the interfaces, edge lengths are drawn using a sigmoid-based scaling function that allows both large and small edge latencies to be visible on the same graph. Statistically significant edge latency changes are highlighted with a bold red outline. When graphs contain join points, or locations where multiple parallel paths converge at the same node, one path may have to wait for another to complete. Our interfaces illustrate the the distinction between *actual* latency and waiting time by using thinner lines for the latter (see the "write in cache" to "MDSCLIENT lookup call" edge in Figures 4a-c for an example).

Each interface also has an annotation mechanism that allows users to add marks and comments to a graph comparison. These annotations are saved as an additional layer on the interface and can be restored for later examination.

4.3 Interface Example

To better illustrate how these interfaces show differences, the example of diff shown in Figure 4b is annotated with the three key differences it is meant to reveal. First, the after graph contains an extra thread of concurrent activity (outlined in blue and marked with a plus sign). Second, there is a statistically significant change in metadata lookup latency (highlighted in red). Third, there is a large latency change between the lookup of metadata and the request's reply. These observations localize the problem to those system components involved in the changes and thus provide starting points for developers' diagnosis efforts.

5 User study overview & methodology

We compared the three approaches via a between-subjects user study, in which we asked participants to complete five assignments using our interfaces. Each assignment asked participants to find key performance-affecting differences for a before/after request-flow graph pair obtained from Ursa Minor [1]. Four of the five assignments used graphs derived from real problems observed in the system. These problems are described in more detail in Sambasivan et al. [30].

5.1 Participants

Our tool's target users are the developers of the distributed system being diagnosed. As our example tasks come from Ursa Minor, we recruited the seven Ursa Minor developers to whom we had access as expert participants. In addition, we recruited six professional distributed-system developers from Google. We refer to the Ursa Minor and Google developers collectively as *professionals*.

Many of our professional participants are intimately familiar with more traditional diagnosis techniques, perhaps biasing their responses to our user-study questions somewhat. To obtain a wider perspective, we also recruited additional participants by advertising in undergraduate and graduate classes on distributed systems and posting fliers on and around our campus. Potential participants were required to demonstrate (via a pre-screening questionnaire) knowledge of key undergraduate-level distributed systems concepts. Of the 33 volunteers who completed the questionnaire, 29 were deemed eligible; we selected the first 13 to respond as participants. Because all of the selected participants were graduate students in computer science, electrical and computer engineering, or information networking, we refer to them as *student* participants.

During the user study, each participant was assigned, round-robin, to evaluate one of the three approaches. Table 1 lists the participants, their demographic information, and the interface they were assigned. We paid each participant $20 for the approximately 1.5-hour study.

5.2 Creating before/after graphs

Each assignment required participants to identify salient differences in a before/after graph pair. To limit the length of the study, we modified the real-problem graph pairs slightly to remove a few differences that were repeated many times. The only synthetic before/after pair was modified from a real request-flow graph observed in the system. Table 2 describes the various assignments and their properties.

To make the before/after graphs easier for participants to understand, we changed node labels, which describe events observed during request processing, to more human-readable versions. For example, we changed the label "e10__t3__NFS_CACHE_READ_HIT" to "Read that hit in the NFS server's cache." The original labels were written by Ursa Minor developers and only have meaning to them. Finally, we omitted numbers indicating edge lengths from the graphs to ensure participants used visual properties of our interfaces to find important differences.

5.3 User study procedure

The study consisted of four parts: training, guided questions, emulation of real diagnoses, and interface comparison. Participants were encouraged to think aloud throughout the study.

ID	Gender	Age	Interface
PS01	M	26	S
PS02	M	33	S
PS03	M	38	S
PS04	M	44	S
PS05	M	30	S
PD06	M	37	D
PD07	M	44	D
PD08	M	37	D
PD09	M	28	D
PA10	M	33	A
PA11	M	26	A
PA12	M	40	A
PA13	M	34	A

(a) Professionals

ID	Gender	Age	Interface
SS01	F	23	S
SS02	M	21	S
SS03	M	28	S
SS04	M	29	S
SD05	M	35	D
SD06	M	22	D
SD07	M	23	D
SD08	M	23	D
SD09	M	25	D
SA10	F	26	A
SA11	M	23	A
SA12	M	22	A
SA13	M	23	A

(b) Students

Table 1: Participant demographics. Our 26 participants included 13 professional distributed systems developers and 13 graduate students familiar with distributed systems. The ID encodes the participant group (P=professional, S=student) and the assigned interface (S=side-by-side, D=diff, A=animation). Average ages were 35 (professionals) and 25 (students).

5.3.1 Training

In the training phase, participants were shown an Ursa Minor diagram similar to the one in Figure 2. They were only required to understand that the system consists of four components that can communicate over the network. We also provided a sample request-flow graph and described the meaning of nodes and edges. Finally, we trained each participant on her assigned interface by showing her a sample/before after graph (identical to those shown in Figures 4(a-c)) and guiding her through tasks she would have to complete in latter parts of the study. Participants were given ample time to ask questions and were told we would be unable to answer further questions after the training portion.

5.3.2 Finding differences via guided questions

In this phase of the study, we guided participants through the process of identifying differences, asking them to complete five focused tasks for each of three assignments. Rows 1–3 of Table 2 describe the graphs used for this part of the study.

Task 1: *Find any edges with statistically significant latency changes*. This task required participants to find all of the graph edges highlighted in red (i.e., those automatically identified by the request-flow-comparison tool as having statistically significant changes in latency distribution).

Task 2: *Find any other edges with latency changes worth investigating*. The request-flow-comparison tool will not identify all edges worth investigating. For example, edges with large changes in average latency that also exhibit high variance will not be identified. This task required participants to find edges with notable latency changes not highlighted in red.

Phase	Assignment and type	Differences	Before/after graph sizes (nodes)
G	1/Real	4 statistically sig. 5 other edge latency	122/122
	2/Real	1 structural	3/16
	3/Synth.	4 statistically sig. 2 other edge latency 3 structural	94/128
E	4/Real	4 structural	52/77
	5/Real	2 structural	82/226

Table 2: Before/after graph-pair assignments. Assignments 1–3 were used in the guided questions phase (G); 4 and 5 were used to emulate real diagnoses (E). Four of the five assignments were the output of request-flow comparison for real problems seen in Ursa Minor.

Task 3: *Find any groups of structural changes*. Participants were asked to identify added or deleted nodes. To reduce effort, we asked them to identify these changes in contiguous groups, rather than noting each changed node individually.

Task 4: *Describe in a sentence or two what the changes you identified in the previous tasks represent*. This task examines whether the interface enables participants to quickly develop an intuition about the problem in question. For example, many of the edge latency changes presented in assignment 1 indicate a slowdown in network communication between machines. Identifying these themes is a crucial step toward understanding the root cause of the problem.

Task 5: *Of the changes you identified in the previous tasks, identify which one most impacts request response time*. The difference that most affects response time is likely the one that should be investigated first when attempting to find the root cause. This task evaluates whether the interface allows participants to quickly identify this key change.

5.3.3 Emulating real diagnoses

In the next phase, participants completed two additional assignments. These assignments were intended to emulate how the interfaces might be used in the wild, when diagnosing a new problem for the first time. For each assignment, the participant was asked to complete tasks 4 and 5 only (as described above). We selected these two tasks because they most closely align with the questions a developer would ask when diagnosing an unknown problem.

After this part of the study, participants were asked to agree or disagree with two statements using a five-point Likert scale: "I am confident my answers are correct" and "This interface was useful for solving these problems." We also asked them to comment on which features of the interface they liked or disliked, and to suggest improvements.

5.3.4 Interface comparison

Finally, to get a more direct sense of what aspects of each approach were useful, we showed participants an alternate interface. To avoid fatiguing participants and training effects, we did not ask them to complete the

assignments and tasks again; instead we asked them to briefly consider (using assignments 1 and 3 as examples) whether the tasks would be easier or harder to complete with the second interface, and to explain which features of both approaches they liked or disliked. Because our pilot study suggested animation was most difficult to use, we focused this part of the study on comparing side-by-side and diff.

5.4 Scoring criteria

We evaluated participants' responses by comparing them to an "answer key" created by an Ursa Minor developer who had previously used the request-flow-comparison tool to diagnose the real problems used in this study. Tasks 1–3, which asked for multiple answers, were scored using precision/recall. *Precision* measures the fraction of a participant's answers that were also in the key. *Recall* measures the fraction of all answers in the key identified by the participant. Note that it is possible to have high precision and low recall—for example, by identifying only one change out of ten possible ones. For task 3, participants who marked any part of a correct group were given credit.

Tasks 4 and 5 were graded as correct or incorrect. For both, we accepted multiple possible answers. For example, for task 4 ("identify what changes represent"), we accepted an answer as correct if it was close to one of several possibilities, corresponding to different levels of background knowledge. In one assignment, several students identified the changes as representing extra cache misses in the after graph, which we accepted. Some participants with more experience explicitly identified that the after graph showed a read-modify write, a well-known bane of distributed storage system performance.

We also captured completion times for the five quantitative tasks. For completion times as well as precision/recall, we use the Kruskal-Wallis test to establish differences among all three interfaces, then pairwise Wilcoxon Rank Sum tests (chosen a priori) to separately compare the animation interface to each of side-by-side and diff. We recorded and analyzed participants' comments from each phase as a means to better understand the strengths and weaknesses of each approach.

5.5 Limitations

Our methodology has several limitations. Most importantly, it is difficult to fully evaluate visualization approaches for helping developers diagnose problems without asking them to go through the entire process of debugging a real, complex problem. However, such problems are often unwieldy and can take hours or days to diagnose. As a compromise, we designed our tasks to test whether our interfaces enable participants to understand the gist of the problem and identify starting points for diagnosis.

Deficiencies in our interface implementations may skew participants' notions of which approaches work best for various scenarios. We explicitly identify such cases in our evaluation and suggest ways for improving our interfaces so as to avoid them in the future.

We stopped recruiting participants for our study when their qualitative comments converged, leading us to believe we had enough information to identify the useful aspects of each interface. However, our small sample size may limit the generalizability of our quantitative results.

Many of our participants were not familiar with statistical significance and, as such, were confused by the wording of some of our tasks (especially tasks 1 and 2). We discuss this in more detail in the Future Work section.

Our participants skewed young and male. To some extent this reflects the population of distributed-systems developers and students, but it may limit the generalizability of our results somewhat.

6 User study results

No single approach was best for all users and types of graph differences. For example, side-by-side was preferred by novices, and diff was preferred by advanced users and experts. Similarly, where side-by-side and diff proved most useful for most types of graph differences, animation proved better than side-by-side and diff for two very common types. When one of our participants (PD06) was asked to pick his preferred interface, he said, "If I had to choose between one and the other without being able to flip, I would be sad." When asked to contrast side-by-side with diff, SS01 said, "This is more clear, but also more confusing." Section 6.1 compares the approaches based on participants' quantitative performance on the user study tasks. Sections 6.2 to 6.4 describe our observations and participants' comments about the various interfaces and, based on this data, distill the approaches best suited for specific graph difference types and usage modes.

6.1 Quantitative results

Figure 5 shows completion times for each of the three interfaces. Results for individual tasks, aggregated over all assignments, are shown (note that assignments, as shown in Table 2, may contain one or multiple types of differences). Participants who used animation took longer to complete all tasks compared to those who used side-by-side or diff, corroborating the results of several previous studies [4, 10, 29]. Median completion times for side-by-side and diff are similar for most tasks. The observed differences between animation and the other interfaces are statistically significant for task 1 ("identify statistically significant changes")[1] and task 4 ("what changes represent").[2] The observed trends are similar when students and professionals are considered separately, except that the differences between animation and the other interfaces are less pronounced for the latter.

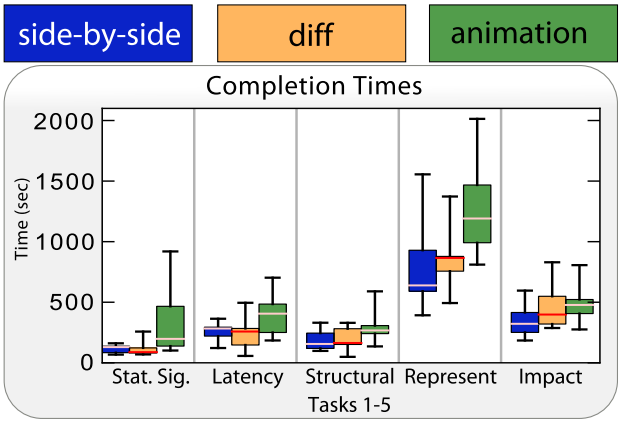
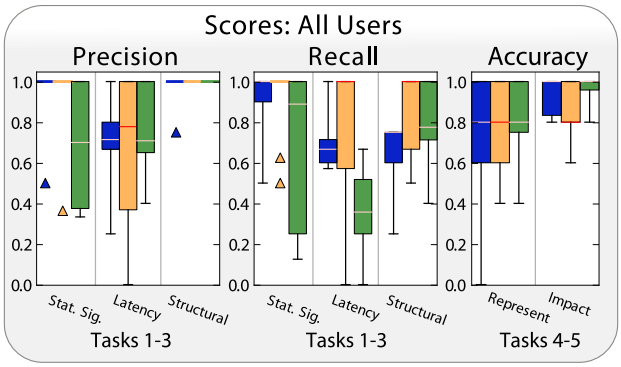


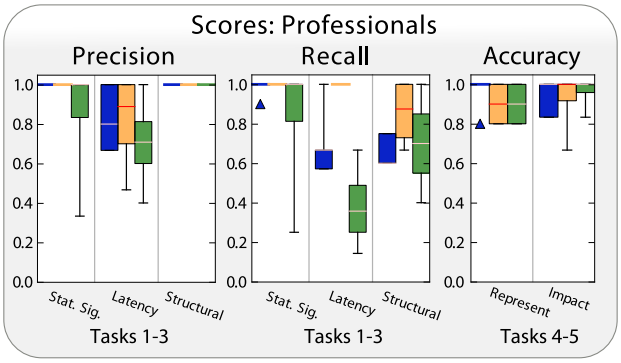
Figure 5: Completion times for all participants. The boxplots show completion times for individual tasks, aggregated across all assignments.

Figure 6a shows the precision, recall, and accuracy results for each of the three interfaces. Our results are not statistically significant, but do contain artifacts worth describing. Overall, both side-by-side and diff fared well, and their median scores for most tasks are similar for precision, recall, and accuracy. Notable exceptions include recall for task 2 ("find other latency changes") and recall for task 3 ("identify structural changes"), for which diff performed better. Overall, both diff and animation exhibit much higher variation in scores than side-by-side. Though animation's median scores are better than or comparable to the other interfaces for tasks 3, 4, and 5, its scores are worse for precision for task 1 and recall for task 2.

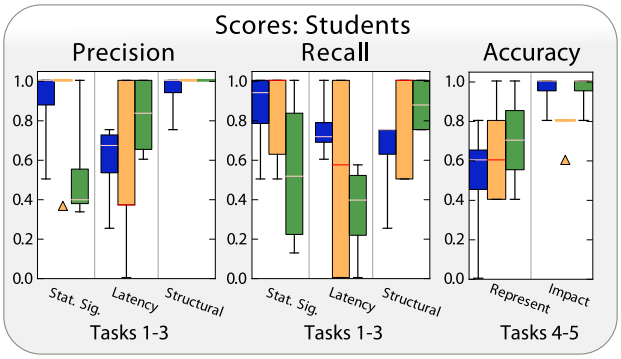
[1] p-value=0.03 (side-by-side vs. anim), p-value=0.02 (diff vs. anim)
[2] p-value=0.003 (side-by-side vs. anim), p-value=0.03 (diff vs. anim)



(a) Precision, recall, and accuracy scores for all participants



(b) Precision, recall, and accuracy scores for professionals



(c) Precision, recall, and accuracy scores for students

Figure 6: Precision/recall scores. The boxplots show precision, recall, and accuracy scores for individual tasks, aggregated across all assignments.

Figures 6b and 6c show the results broken down by participant type. No single interface yielded consistently higher median scores for either group. Though professionals performed equally well with diff and side-by-side for many tasks, their scores with diff are higher for tasks 2 and 3 and higher with side-by-side for task 4. Students' median scores were higher with side-by-side for task 2 and task 5 and higher for recall with diff for task 1 and task 3. Also, students' diff scores exhibit significantly more variation than side-by-side, perhaps because not all of them were familiar with text-based diff tools, which are often used by professionals for source code-revision control. For professionals, animation's median scores are almost never higher than side-by-side. Students had an easier time with animation. For them, animation's median scores are higher than diff and side-by-side for task 2 (precision), task 4, and task 5. Animation's median score is higher than side-by-side for task 3 (recall).

Figure 7 shows likert-scale responses to the questions "I am confident my answers are correct" and "This interface was useful for answering these questions." Diff and side-by-side were tied in the number of participants that strongly agreed or agreed that they were confident in their answers (5 of 9, or 56%). However, where one side-by-side user strongly agreed, no diff users did so. Only one animation user (of eight; 12.5%) was confident in his answers, so it is curious that animation was selected as the most useful interface. We postulate this is because participants found animation more engaging and interactive than the other interfaces, an effect also noted by other studies [10, 29].

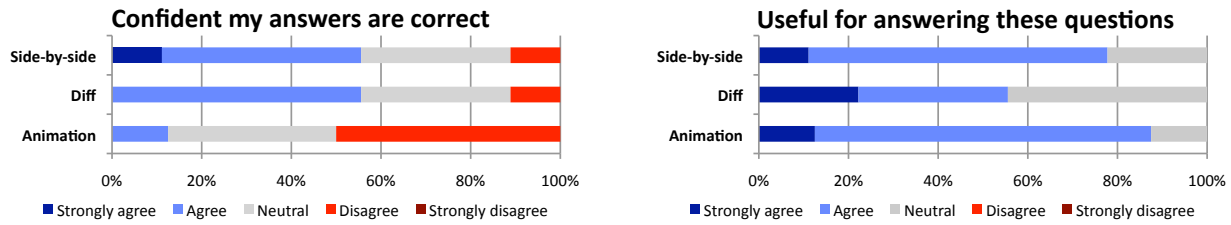


Figure 7: Likert responses, by condition. Each participant was asked to respond to the statements "I am confident my answers are correct" and "The interface was useful for answering these questions."

6.2 Side-by-side

Participants liked the side-by-side interface because it was the most straightforward of the three interfaces. It showed the true response times (i.e., overall latencies) of both graphs, enabling participants to quickly get a sense of how much performance had changed. Correspondence lines clearly showed matching nodes in each graph. Also, this interface allowed independent analyses of both graphs, which our professional participants said was important. Comparing diff to side-by-side, PD08 said "it's [side-by-side] a lot easier to tell what the overall latency is for each operation. . . . [the nodes are] all put together without any gaps in the middle." SD09 said, "With [side-by-side], I can more easily see this is happening here before and after. Without the dashed lines, you can't see which event in the previous trace corresponds to the after trace." These sentiments were echoed by many other participants (e.g., SD06, SD07, PD07).

Our side-by-side interface suffers from two key drawbacks. First, it is difficult to identify differences when before/after graphs differ significantly because corresponding ones become further apart. PS01 complained that "the points that should be lining up are getting farther and farther away, so it's getting more difficult to compare the two." PD06 complained that it was more difficult to match up large changes since the matching counterpart could be off the screen. Similar complaints were voiced by other participants (e.g., PS02, SS02, PS04). Adding the ability to pin one graph relative to another to our side-by-side implementation would limit vertical distance between differences. However, horizontal distance, which increases with the number of concurrent threads in each request, would remain.

Second, when nodes are very close to another, correspondence lines became too cluttered and difficult to use. This led to complaints from several participants (e.g., PS03, SS01, SS03, PA13). To cope, SS03 and PS05 gave up trying to identify corresponding nodes between the graphs and instead identified structural differences by determining if the number of correspondence lines on the screen matched the number of nodes visible in both the before and after graph. Modifying our side-by-side interface to draw correspondence lines only at the start of a contiguous run of corresponding nodes would help reduce clutter, but would complicate edge latency comparisons.

Based on participants' comments above and our observations, Table 3 shows the use cases for which we believe side-by-side is the best of the three approaches. As shown in Table 3, side-by-side's simple approach works best for aiding comprehension. However, due to potential for horizontal skew and clutter, it is not the best approach for identifying any type of difference.

6.3 Diff

Participants' comments about our diff interface were polarized. Professionals and more advanced students preferred diff's compactness, whereas others were less decisive. For example, PS03 claimed diff's compact

representation made it easier for him to draw deductions. Indeed, unlike side-by-side, diff always shows differences right next to each other, making it easier to find differences when before and after graphs have diverged significantly. Also, by placing differences right next to each other, diff allows for easier identification of smaller structural and edge latency changes. In contrast, SS04 said, "[Side-by-side] may be more helpful than [diff], because this is not so obvious, especially for structural changes."

Though participants rarely made explicit comments about finding diff difficult to use, we found that diff encouraged incorrect mental models in student participants. For example, SD08 and SD09 confused structural differences within a single thread of activity with a change in the amount of concurrency. It is easy to see why participants might confuse the two, as both are represented by fan-outs in the graph.

We postulate that participants' comments about diff vary greatly because its compact representation requires more knowledge about software development and distributed systems than that required by the more straightforward side-by-side interface. Additionally, many of our professionals are familiar with diff tools for text, which would help them understand our graph-based diff technique more easily.

Since it places differences close together, Table 3 lists diff as the best approach for showing edge latency changes. However, because it encourages poor mental models for many structural differences, it is not the best approach for showing concurrency changes and intra-thread event changes.

6.4 Animation

Our participants often struggled when using our animation interface. With this interface, all differences between the two graphs appear and disappear at the same time. This combined movement confused participants when multiple types of changes were present in the same thread of activity, an effect also noticed by Ghani et al. [13]. In such cases, edge latency changes would cause existing nodes to move down and, as they were doing so, trample over nodes that were fading in or out due to structural changes. PA11 complained, "Portions of graphs where calls are not being made in the after trace are fading away while other nodes move on top of it and then above it …it is confusing." These sentiments were echoed by many other participants (e.g., SA11, PA12, SA10, PA13).

The combined movement of nodes and edges also prevented participants from establishing static reference

	Comprehension		**Difference identification**			
	Shows overall latency change	Supports independent analyses	Concurrency change	Intra-thread event change	Edge latency change	Intra-thread mixed
Side	✓	✓				
Diff		×			✓	
Anim		✓	✓	✓		×

Table 3: Most useful approaches for aiding overall comprehension and helping identify the various types of graph differences contained in the user study assignments. These results are based on our qualitative observations and participants' comments. A ✓ indicates the best approach for a particular category, whereas a × indicates an approach poorly suited to a particular category. Side-by-side is best for aiding overall comprehension because of its straightforward presentation. Diff is best for showing edge latency changes because it places such changes right next to one another. Animation is best for showing structural differences due to extra concurrency and event changes within a single thread due to the blinking effect it creates. Due to their various drawbacks, no single approach is best for showing mixed differences within a single thread of activity.

points for gauging the impact of a given difference. SA10 told us: "I want to…pick one node and switch it between before and after. [But the same node] in before/after is in a different location completely." SA12 said he did not like our animation interface because of the lack of consistent reference points. "If I want to measure the size of an edge, if it was in the same position as before…then it'd be easy to see change in position or length." Staged animation, in which individual differences are animated in one at a time, could reduce the trampling effect mentioned above and allow users to establish reference points [17]. However, significant research is needed to understand how to effectively stage animations for graphs that exhibit both structural and edge length changes. Many graph animation visualizations do not use staging and only recent work has begun to explore where such basic approaches fail [13].

Another negative aspect of animation (staged or not) is that it suggests false intermediate states. As a result, SA13 interpreted our interface's animation sequence as a timeline of changes and listed this as a feature he really liked. PA13 told us we should present a toggle instead of a slider so as to clarify that there are only two states.

Despite the above drawbacks, animation excels at showing structural differences—i.e., a change in concurrency or change in intra-thread activity—in graphs without nearby edge latency changes. Such changes do not create the trampling effect stated above. Instead, when animated, distinct portions of the graph appear and disappear, allowing users to identify changes easily. For one such assignment, both PA11 and PA12 told us the structural difference was very clear with animation. Other studies have also noted that animation's effectiveness increases with separation of changed items and simultaneous appearance/disappearance (e.g., [4, 13]).

Due to the blinking effect it creates, Table 3 lists animation as the best approach for showing differences due to concurrency changes and intra-thread event changes. The potential for trampling means it is the worst of the three for showing both latency and structural differences within a single thread of activity.

7 Future Work

Comparing these three interfaces has yielded insights about which approaches are useful for different circumstances. Performing this study also produced a number of directions for improving each of our interfaces. Here we highlight a few that participants found important and that are complex enough to warrant further research.

Addressing skew, horizontal layout, and trampling: Many users struggled with the increasing skew in the side-by-side layout, as well as the inability to quickly trace a correspondence from one graph to another (e.g., PS02, SA10, and PS05). The animation interface, which produces a trampling effect as all changes are animated together, also made it difficult to focus on individual differences. A future interface might anchor the comparison in multiple or user-selectable locations to mitigate this problem. However, there are subtleties involved in choosing and using anchor points.

One option, as requested by most of our participants (e.g., PA12 and PD08), is to anchor the comparison at a user-selectable location. Another is to re-center the graph as users scroll through it. However, both techniques distort the notion that time flows downward, and neither would reduce horizontal distance or clutter. Approaches that restructure the comparison to minimize the horizontal distance between corresponding nodes are an interesting opportunity.

For the animation technique, anchoring in multiple locations could be achieved by staging changes. Questions of ordering immediately arise: structural changes might be presented before, after, or between latency changes. The choice is non-obvious. For example, it is not clear whether to animate structural and latency changes

together when the structural change *causes* the latency change or even how to algorithmically determine such cases (see Figure 1 for an example).

Semantic zooming and context: Even when they were navigable, graphs with hundreds of nodes posed an obstacle to understanding the output at a high level. While the straightforward approach to zooming we implemented for this study allows the entire graph to be seen, it does not provide intuition into the meaning of the graph when zoomed out. Therefore, users needed to scroll through graphs while zoomed in, a complaint for multiple users (e.g., SD05, SA10).

Further work is needed to investigate options for a higher-level view of the graph that could be shown instead. Some options for semantic zooming based on such a view include coalescing portions of the comparison that are the same in both graphs, or grouping sequences of similar operations (mentioned by several participants, including SD09, PS02, and PD09). Determining which portions to coalesce and defining "similar" operations are nontrivial problems, and solutions may require user guidance or automated techniques to learn meaningful groupings.

Exploiting annotation: Annotation was used in this study to record answers, but has the potential to be a valuable tool for collaborative debugging. Developing and debugging a large system involves multiple components built and maintained by different parties, many without knowledge of the internal workings of components that might contain a problem. Users could make annotations for other developers or for documentation. In fact, several professional participants from Google listed our annotation mechanism as a strength of the interfaces (e.g., PA13, PS04, and PD08). PS04 said "[I] really like the way you added the annotation.…So other people who are later looking at it can get the benefit of your analysis." Supporting cooperative diagnosis work with an annotation interface, such as that used in Rietveld [27] for code reviews, is an interesting avenue of future work.

Matching automation to users' expectations: Like several other diagnosis techniques, request-flow comparison uses statistical significance as the bar for automatically identifying differences, because it bounds wasted developer effort by limiting the expected number of false positives. However, many of our participants did not have a strong background in statistics and so mistook "statistically significant" to mean "large changes in latency." They did not know that variance affects whether an edge latency change is deemed statistically significant. This generated confusion and accounted for lower than expected scores for some tasks. For example, some participants (usually students) failed to differentiate between task 1 and task 2, and a few students and professionals refused to mark a change as having the most impact unless it was highlighted in red (as statistically significant). Trying to account for why one particularly large latency change was not highlighted, SA10 said, "I don't know what you mean by statistically significant. Maybe it's significant to me." These concerns were echoed by almost all of our participants, and demonstrate that automation must match users' mental models. Statistics and machine learning techniques can provide powerful automation tools, but to take full advantage of this power—which becomes increasingly important as distributed systems become more complex—developers must have the right expectations about how they work. Both better techniques and more advanced training may be needed to achieve this goal.

Extending to other domains: While we applied the three interfaces to request-flow graphs, similar graphs are also compared in other areas of systems diagnosis (e.g., call graph comparison [8]). We believe the design guidelines we identified for future diagnosis visualizations can help guide approaches to understanding the output of these diagnosis tools. Beyond diagnosis, the need to compare directed acyclic graphs to find differences is common across many domains. Examples include comparing business-process graphs [2] and comparing general workflows [31]. We expect that many of the insights about the relative strengths of side-by-side, diff, and animation could inform work in these areas.

8 Summary

For tools that automate aspects of problem diagnosis to be useful, they must present their results in a manner developers find clear and intuitive. This paper investigates improved visualizations for request-flow comparison, one particular automated problem localization technique. We contrast three approaches for presenting its results through a 26-participant user study, and find that each approach has unique strengths for different usage modes, graph difference types, and users. Moving forward, we expect that these strengths, and the research directions inspired by their weaknesses, will inform the presentation of request flows and related graphs.

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