How to diagnose nanosecond network latencies in rich end-host stacks

Roni Haecki[1], Radhika Niranjan Mysore[2], Lalith Suresh[2], Gerd Zellweger[2],
Bo Gan[2], Timothy Merrifield[2], Sujata Banerjee[2], Timothy Roscoe[1]
[1]*ETH Zurich,* [2]*VMware*

Abstract

Low-latency network stacks have brought down network latencies within end-hosts to the *microsecond-regime*. However, end-host profilers have such high overheads that they are useful only to confirm a hypothesis, not to diagnose a problem in the first place. Indeed, every one of twenty low-latency network projects we surveyed rolled their own analysis tools instead of using an existing profiler.

This paper shows how to build a latency diagnosis tool with full-stack coverage and low overhead that can identify, not just confirm, sources of latency in end hosts. The unique measurement methodology reconstructs network-message lifetimes within end hosts with nanosecond precision, by reconciling CPU and NIC hardware profiling traces across multiple time domains (network and CPU). It uncovers unexpected latency sources in both kernel and user-space stacks.

We demonstrate these capabilities by using our implementation, NSight, to systematically identify and remove performance overheads in `memcached`, reducing 99.9th percentile latency by a factor of 40 from 2.2 ms to 41 µs.

1 Introduction

Operating systems and network stacks are routinely blamed for increasing network latencies. Clearly, we need diagnostic tools to identify sources of latency in end-host stacks. Thankfully, there is no paucity of end-host profilers [1, 3, 4, 6, 13, 16, 22, 25, 29, 31, 37, 38, 49–51, 73, 77]. We examined 21 networking projects whose goal was to achieve low latency [2, 5, 8, 11, 20, 23, 26, 27, 33–36, 41, 46, 48, 55, 57, 58, 60, 65, 69]. Surprisingly, not one of these projects have used these profilers! Instead, all of them design their own handcrafted latency measurement system. This indicates that in spite of the excellent and vast body of prior work, there is no diagnostic tool for *network latencies* introduced at the end host, especially in the microsecond regime. In this paper we present NSight to address this important gap.

Our investigations identify three reasons that existing end-host profilers fail at network latency diagnosis. First, existing profilers fail to capture latency deviations added by the *NIC*, from the point when messages enter (or exit) the NIC to the point that they are received by (or exit) the driver. Many system designs identify these latency deviations to be important [8, 24, 26, 34, 35, 48, 55, 58, 60, 62].

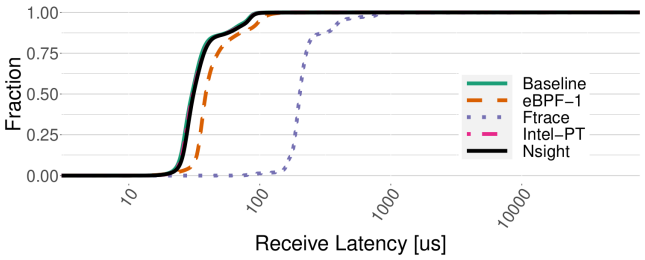


Figure 1: CDF of `memcached` request receive-latencies with and without profiling. eBPF-1 stands for eBPF probing a single function; Ftrace, Intel-PT and NSight, profile all system functions in the end-host stack. eBPF-1 and Ftrace add variable latencies to functions being profiled that are hard to differentiate from true latency deviations.

Second, their high overheads severely disturb the latency distribution, overwhelming the root causes being pursued. Figure 1 shows how two widely-used profilers, eBPF and Ftrace, add to `memcached` request-receive latencies, measured from the point requests are received at the NIC to the point they are received by `memcached` (socket `recv`). eBPF adds 18-40% overhead while measuring the latency of a single function, while Ftrace adds 298-841% profiling all functions of the end-host software stack. Also shown is the minimal impact of NSight and in the same range as Intel-PT, which is an example of a hardware CPU profiler that NSight builds on.

Third, existing profilers are too heavyweight to apply to the entire stack. A developer diagnosing network latencies must already have a guess of where to look before such a profiler is useful. Blogs [15, 28, 32, 43, 45] tell exactly this story: Users determine the parts of the stack that *might* add latency deviations and then use profiling tools to measure latencies in these parts. The unfortunate result is that the latency sources from unexamined parts of the stack are not caught. In addition, important interactions between different parts of the stack go unnoticed [46, 68]. For example, profiling the NIC separately from the network software stack hides the impact of NIC deviations on scheduling decisions. When there are large latency deviations at the NIC, a CPU waiting for network messages can idle and go into a lower power state. This increases scheduling latency, and in turn, overall network latency (§7.4 has an example).

Our contribution. We correct these shortcomings by demonstrating the feasibility of a low-overhead, holistic tool called NSight for diagnosing network latency deviations introduced at end hosts. The guiding principle is that *entire lifetimes of network messages within end hosts* must be examined to determine the precise causes of latency deviations. These lifetimes are defined by *all system activity*, not limited to network processing, that impacts messages from the time they enter end hosts to when they exit it. To be useful in the microsecond regime, NSight must reconstruct these lifetimes with nanosecond precision. NSight does so by reconciling timelines of two fine-grained data sources, CPU hardware profiling and NIC hardware timestamps.

This reconstruction is challenging for two reasons. First, the two data sources record time using different hardware clocks. Hardware CPU profiling uses a monotonically increasing clock for capturing precise *intra*-end-host latencies, while NIC and software CPU clocks are often synchronized using PTP [61] to aid *inter*-end-host latency measurements. To align the timestamps in these sources correctly, NSight tracks the conversion between the two time domains during profiling.

Second, CPU hardware profiling does not track the passage of network messages in multi-core systems across kernel cores (which process the message) and application cores. To track this path, NSight captures timestamps and core numbers at the boundary where kernel hands off the message to the application. This boundary is also the point where message processing can move across cores.

Once the lifetimes of messages are constructed, they can be compared to identify anomalous processing that led to their latency deviations. Unfortunately, due to the deep nesting of end-host call stacks, latency deviations in functions introduce deviations in their *parent* functions making them look anomalous too! To reduce ambiguity in attributing root causes to anomalies, NSight traverses the call stacks until it finds functions with latency deviations that cannot be attributed to nested calls.

NSight demonstrates that these techniques are sufficient to overcome the listed challenges, while incurring overheads comparable to hardware profiling (see Figure 1). Due to its low overhead, NSight can be used to diagnose even sub-microsecond increases in network latency at the end host. We describe our use of NSight to profile both the Linux kernel and Mellanox's VMA [48], a user-space network stack. On these stacks we describe how we profile unmodified applications `memcached` and `redis`. We dive deeply into a detailed case study of `memcached`, the application of choice in several low-latency end-host stack papers [11, 35, 36, 39, 55, 58, 60, 70, 71], to prove the diagnosis capability of NSight. In the case study NSight systematically narrows down the bottlenecks of the Linux stack, as we mitigate 99.9th percentile `memcached` tail latency by over 40x - from 2.2 ms to 51 µs. When one of the mitigations increases latencies below the median by as much as 11 µs, NSight helps identify the reasons for this increase.

2 Background and related work

The vast body of profiling and diagnostic tools fall broadly into two groups: fault diagnosis tools ([10, 64, 74]) and performance diagnosis tools ([21, 75, 76]). Some diagnose problems *within* end-hosts ([1, 3, 4]). Others help in distributed settings ([19, 21, 68]). NSight is a performance diagnosis tool for end-hosts. Its focus is on *latency* diagnosis. We focus on software- and hardware- based tools built for latency diagnosis below.

Software-based end-host tools. Software-based diagnostic tools are built on top of profiling data sources such as probes (Uprobes [17], Kprobes [30]), kernel tracepoints, performance counters, and software tracing. The data source determines the overheads and insights that can be drawn from the tool.

Tools that depend on probes (LTTng [13], eBPF [1]) and kernel tracepoints (dtrace [51]) allow users to instrument functions of interest. Users of these tools must already know where to look, making them less suited for latency diagnosis than tools that depend on software tracing (Ftrace [3]). Tools based on performance counters (`perf stat` [4]) do not capture outlier latency events (due to aggregation) making them unsuited for tail latency diagnosis in particular.

Unlike NSight, all of these tools miss NIC delays altogether and have much higher overheads than hardware profilers.

Hardware-based end-host tools. CPU profilers ([12, 40, 53]) record software function `call` and `return` times, their core number and process names at processor speeds. The timestamps help measure software latencies with nanosecond precision and low overhead. NSight, like `perf` and `VTune` [25], uses CPU profilers to track software function latencies.

Most NICs support hardware timestamping [14] for network packets. The timestamps can be retrieved per-message using standard Linux socket calls, to determine network latencies across and within end-hosts. NSight uses NIC timestamps to track entry and exit of network messages during profiling.

Unlike NSight, these tools cannot identify the sources of network latencies in end-hosts by themselves or when combined with one another. Instead they require the user to make a conjecture that the tools can help confirm (See §2.1 and §4).

Distributed tools. Even though NSight is designed for network latency diagnosis *within* end-hosts rather than in distributed settings, some similarities and differences are worth noting. Like NSight, many diagnostic tools for distributed systems [7, 9, 18, 19, 44, 54, 68, 72] reconstruct the path of messages but in distributed settings. They do not capture network latency sources at end-hosts but capture other latency sources like packet drops, routing issues and workload spikes.

Inband network telemetry (INT) [56] is a mechanism to probe specific points in network dataplanes. In software, these probes are expensive [67] and do not cover many points in end-host stacks, like the OS stack, that we do with NSight. Therefore they can only confirm causes of latency, not identify them. On the other hand, INT works with all programmable network hardware while NSight is relevant only for end-hosts.

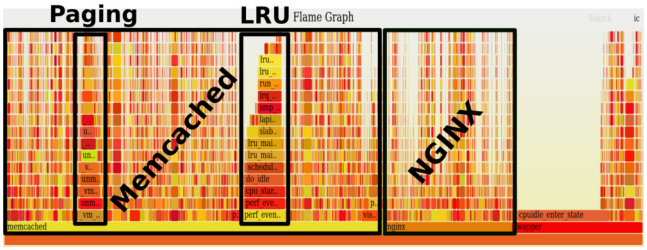


Figure 2: A flame graph is not very useful for diagnosing latency problems because it only highlights common events in system activity. It leaves the identification of events that are deviations from the norm to the user.

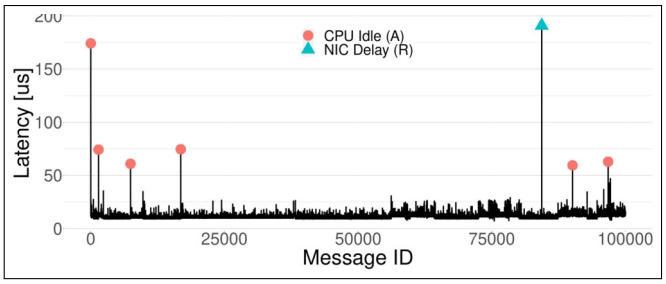


Figure 3: Balloon plots summarize message latencies(Y-axis) with the top causes for latency deviations (legend) mapped to corresponding messages using similar balloons.The balloons are in Message ID order (X-axis) to identify bunching together of balloons that indicates a single underlying cause. If they are spaced apart, there are likely multiple independent reasons that need to be addressed separately.

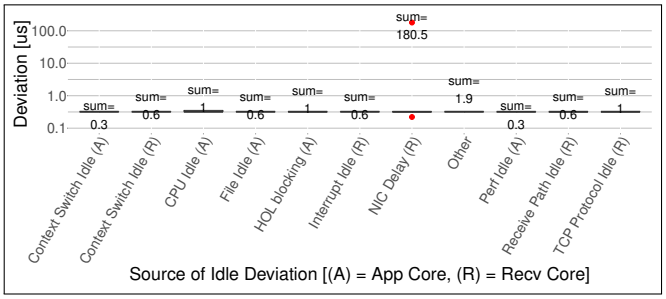


Figure 4: A zoomed-in box plot of causes for CPU idling that impacted the slowest message. This presentation is valuable for identifying why the cores were idling (X-axis), and the latency deviation due to those causes (Y-axis). Both the application (*A*) and receive cores (*R*) idle, for reasons ranging from waiting during a context switch or file access, with NIC interrupt coalescing, *NIC delay (R)*, causing the largest wait.

2.1 Diagnosing network delays at end-hosts

We now describe common network latency debugging practices at end-hosts using existing tools (blogs [15, 28, 32, 43, 45]). The process usually begins with tools that summarize system activity, like `perf` [4], `SystemTap` [59], unless developers already have deep knowledge of the application of interest [32]. These tools help identify the parts of the stack that are most active and *might* impact network latency.

For example, we can generate flame graphs like Figure 2 with `perf`. The flame graph shows two applications, `memcached` and `NGINX` both running on the same machine. It is natural to ask whether they interfere to cause network delays [20, 27, 55]. To verify, developers can isolate applications, or turn on software tracing, like `Ftrace`, and visualize network send/receive paths using tools like `KernelShark` [66].

Figure 2 also shows `memcached` LRU cache maintenance and paging activity to be high. Even though unrelated, these *can* delay network activity if scheduled during network processing. To verify, developers can use tools like eBPF or Ftrace to track periods of such activity and correlate them with periods of high network latencies. To verify delays *on* network processing paths, these tools can generate latency distribution graphs for the functions of interest [45].

These steps alone might be insufficient [15]. System activity summaries like Figure 2 do not show problems like NIC delays, scheduling bottlenecks, or head-of-line blocking that can slow down network processing. Finding these problems requires tracking specific system/NIC performance counters [4, 52] or handcrafted measurements [35, 39].

3 Using NSight for diagnosis

We now describe a typical debugging experience with NSight. Let us suppose users are running `memcached` on Linux and see large tail latencies despite light query loads. To use NSight to quickly diagnose the cause of poor performance, the user first turns on NSight profiling for a second. Once NSight analyzes the profiling data, the user inspects the initial result, Figure 3. This *balloon plot* shows the latencies of all `memcached` requests profiled and the top causes of the slowest (tail) requests. The user notices that the tail requests are largely slowed down by idling CPU cores, *CPU Idle (A)*, where `A` stands for application-core on which `memcached` runs. The slowest request is also slowed down by core idling due to NIC interrupt coalescing delay, *NIC Delay (R)*, where `R` stands for the core on which the kernel receives the request.

From this result, the user can drill down into the presented causes for tail latencies. For instance, the user cross-checks why the cores were idling when processing the slowest request. Figure 4 shows that, among various causes, the largest latency deviation was due to NIC interrupt coalescing.

The user could also manually verify this diagnosis using Figure 5, a detailed timeline of all system-activity that impacted the slowest message. Eyeballing the presentation, the user confirms that there is a gap in system activity *before* the message is processed but long *after* the message is received at the NIC, showing that interrupt coalescing delays slowed down the tail request by as much as 180 µs.

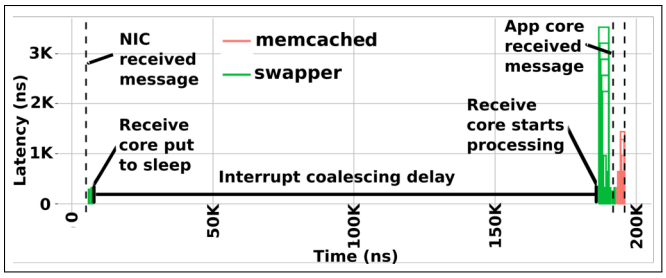


Figure 5: NSight's presentation of processing timeline of the slowest message. The presentation tracks *system activity* from the time the message was received at the NIC (leftmost dashed vertical line) to the time it was received at the application (rightmost dashed vertical line). The reader can ignore the Y-axis for now; a full explanation of this presentation is available in Figure 8. Gaps in system activity indicate CPU idling.

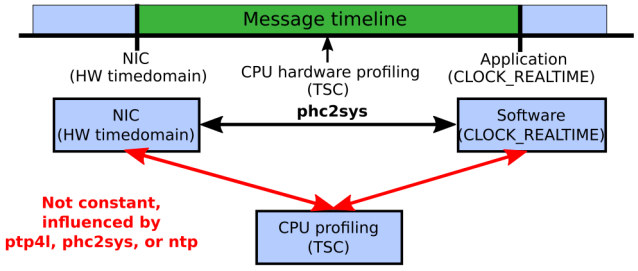


Figure 6: Constructing message lifetimes from timestamps taken on NIC and CPU, whose clocks are independent, is hard because the timestamps do not line up into a single timeline. We overcome this challenge by monitoring the relationship between CPU profiling clock and NIC/Software clocks (shown in red arrows) *during* profiling with low *latency*-overhead.

4 Challenges and key ideas

Why is latency diagnosis hard? To derive the precise causes of message slowdowns within end-hosts, we must profile *network-message lifetimes*, like Figure 5. These lifetimes capture *all system activity (G1)* that slowdown message processing, whether it is network stack activity or something unrelated, from the point a network message enters (or exits) the end-host to the point it is received (or sent) by the application. To work with low-latency stacks, we must capture these lifetimes *automatically (G2)*, with *nanosecond-precision (G3)* and *low overhead (G4)*. We must then analyze these message lifetimes to identify system activity that slows messages down and their precise impact, as shown in Figure 3.

4.1 Profiling network-message lifetimes

Unfortunately, the task of capturing network-message lifetimes is difficult, because there is not *one* system component that processes network messages. Rather, in most modern OSes [42, 47, 55], network messages are processed across the NIC and one or multiple CPU cores. Capturing message lifetimes that span these devices is challenging for two reasons.

Challenge 1 (C1): NIC, CPU profiling, and software timestamps come from independently *changing* clocks. Figure 6 illustrates this problem. To construct message lifetimes NIC, CPU profiling, and software clocks must align at all times, but they do not. NIC and CPU profiling clocks drift independently of each other. This is not a problem for CPU profiling, because it uses the hardware clock to report nanosecond-granularity function latencies *within* an end-host.

NIC timestamps are used to measure *both* inter-host and intra-host message latencies. To aid latency measurement across multiple time-domains, socket libraries convert NIC timestamps to software timestamps *during profiling*, with the help of conversion parameters calculated by software synchronization mechanisms like `phc2sys` on Linux.

Software clocks across end-hosts are usually synchronized using protocols like `ptp`. These synchronization mechanisms constantly readjust software clocks and change their relationship with the CPU profiling clock, under the hood. These changes pose a problem for constructing message lifetimes.

Key idea 1, Time reconciliation: The ideal solution to this problem would be to modify time synchronization protocols to expose clock changes to profilers like `perf`. Profilers could then present all measurements based on the software clock to simplify system-wide latency measurements.

We do not want to refactor the entire software stack, so we use a simpler but more expensive workaround. *After* time synchronization protocols change the software clock, the kernel recalculates the conversion between CPU profiling clock and software clock. By exposing these conversion parameters to user-space using virtual dynamic shared object (vDSO) mechanisms, we can poll them from a user-thread for the duration of profiling. The goal is to capture *every* change to the software clock to have the most accurate mapping between the clocks at all points in time. A log of the conversion parameters helps reconcile CPU profile timestamps to software-clock domain *post* profiling. This method burns an entire core for the user-thread, but it adds no latency overhead *during* profiling because the user thread is isolated from the rest of the system.

Challenge 2 (C2): There is no support to track network-message lifetimes *within* host software stacks. Software profiling tools can only track network messages *within* the network stack, missing other system activity that slows down message processing. This is because CPU architecture and operating systems treat network messages like regular data structures, as objects in memory. Consequently, network messages have no relevance outside of network stack functions.

On the other hand, CPU profiling tracks all system activity but not the message lifetimes within which such system activity occurs. Figure 7 illustrates this problem. The two rectangular boxes labeled Core **X** and Core **Y** show the timeline of system activity captured by CPU profiling at these two

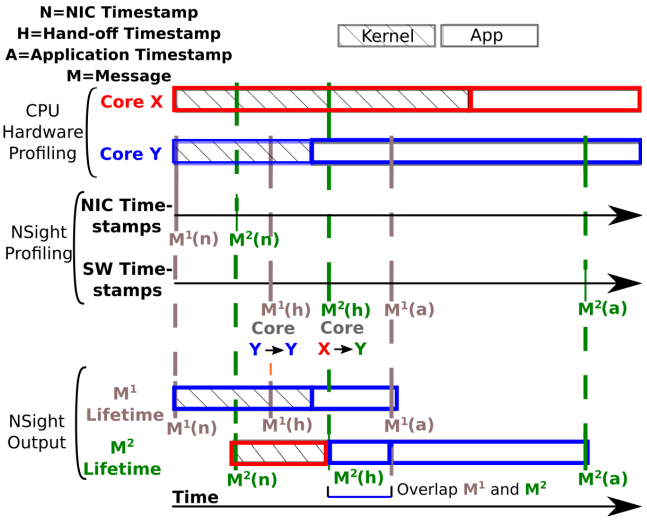


Figure 7: We cannot reconstruct message lifetimes using CPU profiling and NIC timestamps alone. Instead, we place CPU-profile timelines in the context of each message by collecting *per-message* NIC timestamps ($M^1(n)$, $M^2(n)$), Software timestamps at application ($M^1(a)$, $M^2(a)$), and cross-core hand-off timestamps along with the core information ($M^1(h)$ Core **Y**→**Y**, $M^2(h)$ Core **X**→**Y**). The superscript of each timestamp corresponds to the message ID assigned by NSight. With this context, we see that M^1 is received at NIC at $M^1(n)$ and processed on core **Y** through $M^1(h)$, till it is received by App at $M^1(a)$. M^2 is processed on core **X** and then handed-off to the App on core **Y** at $M^2(h)$. At Core **Y**, M^2 waits for M^1 to be processed before it is received by the App at $M^2(a)$.

cores. We only see the process contexts (kernel, application) and individual functions (not shown), but not messages.

Key idea 2, Message profiling: To construct message lifetimes, we augment CPU profiling with *per-message* timestamps and core numbers. Figure 7 shows the information collected by NSight profiling to construct two message lifetimes, M^1 and M^2. For each message (for example, M^2), we seek to get three timestamps: a NIC timestamp ($M^2(n)$), a core hand-off timestamp ($M^2(h)$), and an application timestamp ($M^2(a)$). The NIC and application timestamps allow us to capture the start and end of a message's lifetime on the end-host; for instance, M^2's lifetime is from $M^2(n)$ to $M^2(a)$. The core hand-off timestamp ($M^2(h)$) along with core information (Core **X**→**Y**), helps identify the *per-core* system activity that a message encounters in its lifetime; for example, M^2 is processed on Core **X** between $M^2(n)$ to $M^2(h)$, and then on Core **Y** between $M^2(h)$ to $M^2(a)$. Crucially, these timestamps are sufficient to produce a single timeline of all system activity related to the processing of a message.

We now explain how these timestamps can be obtained and how they suffice to reconstruct detailed message lifetimes. The per-message NIC hardware-timestamps and application software-timestamps can be taken at the application send/receive operations. They help *order* messages, so we can assign message IDs, M^1 and M^2. Messages *sent* from end-hosts are ordered by their application timestamps. Messages *received* at end-hosts, like M^1 and M^2, are ordered by NIC timestamps, $M^1(n)$ and $M^2(n)$. The per-message *hand-off* timestamps and core information can be collected at points where messages cross software-processing and core boundaries. In kernel network stacks, there is one boundary where messages are handed-off between kernel and application, like `sock_def_readable` in Linux. User-space network stacks can have similar boundaries [47, 55] while others do not [26, 48, 58].

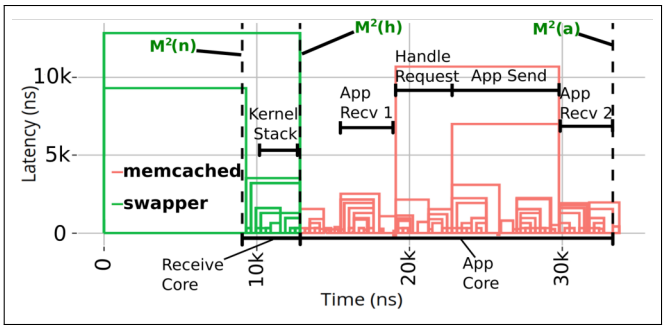


Figure 8: NSight presentation of message lifetime of M^2. The X-axis shows time in nanoseconds and captures message processing latency from $M^2(n)$ to $M^2(a)$. System activity is captured as nested 'boxes' on the timeline. Each box represents a function traced by CPU profiling. The left and right vertical boundaries of each box corresponds to the function `call` and `return` timestamps. The Y-axis shows individual function latencies in nanoseconds. The horizontal black lines and annotations (e.g., `App Recv`) are added for clarity.

In our example in Figure 7, there is an overlap between lifetimes of M^1 and M^2 on core **Y** from $M^2(h)$ to $M^1(a)$. M^2 has to wait for the application on core **Y** to complete processing M^1 before it can be processed. This overlap shows inter-message interference or head-of-line blocking. We can similarly detect unrelated system activity or application interference that appear in message lifetimes.

Figure 8 describes NSight's presentation of M^2. Between timestamps $M^2(n)$ and $M^2(h)$, M^2 is processed by core **X** (`Receive core`). After $M^2(h)$, M^2 is processed by core **Y** (`App core`) where M^2 waits for the application, `memcached`, to process M^1 (`App Recv 1` to `App Send`), after which M^2 is received (`App Recv 2`).

4.2 Diagnosing high message latencies

Profiling even for brief periods of time, will leave us with hundreds of thousands of message lifetimes. To diagnose why some message lifetimes are longer, like we did in Figure 3, we must identify *anomalous* system activity that slow down those

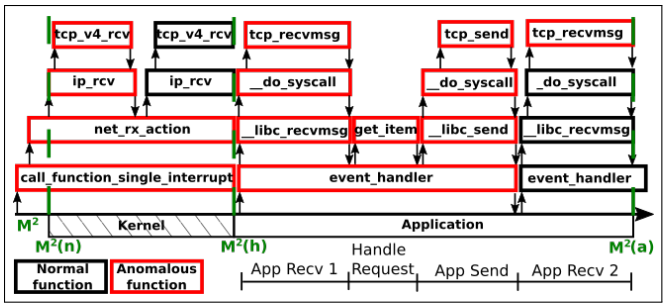


Figure 9: M^2-message-lifetime shown in greater detail by zooming into part of the call stack. When functions within M^2 are compared to those in M^1, many functions shown in red appear anomalous. For instance, `call_function_single_interrupt` and its nested functions appear to take longer or occur more frequently. The *cause* for these deviations is that `ip_rcv` has been called twice, once for receiving M^1 and a second time for receiving M^2 due to head-of-line blocking.

messages relative to others, by comparing their lifetimes. Two typical types of anomalies in message lifetimes are functions that take longer and functions that occur more frequently in some lifetimes compared to others; for example, `App Recv` occurs twice in M^2 in Figure 8. Deeply nested end-host stacks can result in nesting of anomalies of different types, leading to a third challenge.

Challenge 3 (C3): Due to nesting, the same latency deviation can be explained by multiple anomalies. Figure 9 explains this problem. When compared to M^1, most functions in M^2 appear anomalous! Some take longer, like the first invocation of `event_handler`; others appear more often, like `__libc_recvmsg`; and the rest are unexpected, like `__libc_send`, a `send` in the middle of *receiving* M^2.

Key idea 3, Anomaly disambiguation: To reduce ambiguities from nesting, we only report anomalous functions that cannot already be *explained* by their nested functions. To determine whether an anomalous function is explained by nested anomalies, we use a heuristic. If the nested anomalies together account for more than 80% of the latency deviation of the parent function (see §5.2 for why), we conclude that the nested anomalies explain the parent anomaly and omit the parent anomaly as a reason for deviation.

Figure 9 describes how the latency deviation in `call_function_single_interrupt` is accounted for by a nested anomalous `ip_rcv` call. Therefore, `ip_rcv` is listed as a root cause but not `call_function_single_interrupt`.

5 Design and implementation

In this section, we describe how the three key ideas from §4 realize the goal of network latency diagnosis in microsecond-regimes. NSight is composed of two subsystems. The first is a profiling subsystem, that tracks broad CPU activity and

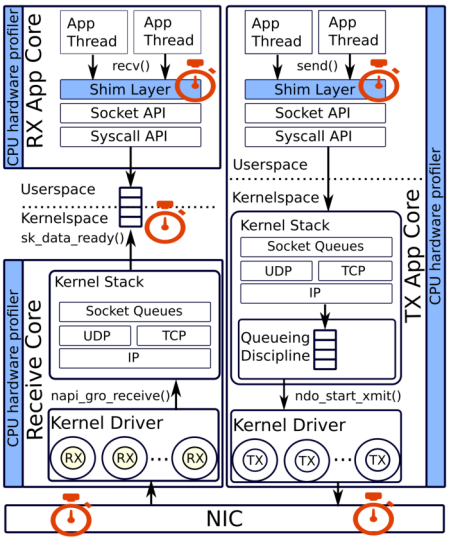


Figure 10: NSight profiling in Linux. The unshaded parts of this figure are the scope of activity that we want to profile and automatically diagnose over. We run CPU profiling on all cores to collect system activity *(G1)* and identify anomalies. To establish *causality* linking observations from the CPU profiler to messages, we collect timestamps and core information for each message on their way in and out of the system and across cores with the shim layer.

passage of messages through end-host stack (§4.1, ***Message profiling***). It also tracks the relationship between NIC, CPU profiling and software time-domains so that the observations from different devices can be aligned into a single timeline (§4.1, ***Time reconciliation***). Put together, it is responsible for capturing *all system activity (G1)* during the profiling period with *nanosecond-precision (G3)* and *low-overhead (G4)*. The second is an analysis subsystem that reconstructs network-message lifetimes and diagnoses network latency deviations within them. To do so, it analyses anomalous system activity in network-message lifetimes, identifies root causes, and attributes precise deviations to these root causes (§4.2, ***Anomaly disambiguation***). The profiling and analysis subsystems together *automate (G2)* network latency diagnosis.

5.1 NSight profiler

Figure 10 explains how we get broad information from CPU hardware profiling *(G1)* and combine it with per-message profiling information from a shim layer to establish a causal link between system behavior and message lifetimes (§4.1, ***Message profiling***). Typical CPU profiles collect system activity at function granularity and list *all* function `call` and `return` times, their execution context and core numbers with nanosecond granularity *(G3)*. Independent of the CPU profiler, the shim layer intercepts messages, irrespective of the application, to collect timestamps at three points in the stack, shown

in Figure 10, as metadata for each message. Core numbers are collected at the kernel–userspace boundary. For socket-based stacks, the shim layer also collects socket file descriptor numbers to detect head-of-line blocking that arises when application threads are multiplexed across multiple sockets. We quantify overheads from profiling in Section 6 *(G4)*.

To reconcile independent observations from the CPU profiler and the shim layer into a single timeline, §4.1, ***Time reconciliation*** polls the conversion between the clocks for the duration of profiling from a user-thread.To construct message lifetimes accurately, the user-thread must detect *all conversion changes* and align the observations at all points in time. We quantify the accuracy of this scheme in §6 *(G3)*.

Profiler implementation and deployment. The shim layer is implemented using standard Linux and socket APIs, with 1055 lines of C code. It can be dynamically linked by *unmodified* applications using `LD_PRELOAD`; statically linked applications might need to be modified, however.

We extend the Linux NIC timestamp framework to obtain timestamps at the kernel–userspace message hand-off boundary by patching 40 lines of the 5.4 Linux kernel (§4.1, **C2**). VMA stack has no such boundary and needs no modification.

NSight is built on top of the Intel-PT CPU profiler, whose traces are available through `perf`. `perf` exports Intel-PT timestamps from `TSC` to `sched_clock` timedomain. We modify 443 lines in `perf` to use the time reconciliation parameters and export CPU profiler timestamps directly in software time domain (`CLOCK_REALTIME`). The thread that polls these parameters is implemented in 363 lines of C code (§4.1, **C1**).

§7 shows how NSight is effective even when users turn it on for only a few seconds at a time. To capture random events across time, users must turn on NSight repeatedly. We have ambitions of using NSight for continuous profiling, but the current buffering implementation in Intel-PT limits such use.

5.2 NSight analysis

The analysis subsystem consists of three parts. The first part reconstructs message lifetimes from profiling data (§4.1, ***Message profiling***). The second part detects anomalous system activity during these lifetimes. The third part sifts through the anomalies to identify root causes for latency deviations within message lifetimes (§4.2, ***Anomaly disambiguation***, *G2*).

Identifying anomalous system activity. In §4.2 we mentioned three types of anomalous system activity that contribute to latency deviations: functions that take longer, functions that are called more frequently, and unexpected functions that show up in some message lifetimes compared to others.

There are three other classes of anomalies that slow down message lifetimes. The first class consists of *entire program contexts* that are unexpected but show up in message lifetimes as a result of scheduling decisions or interrupts. The second class is defined by the *absence of system activity* that is seen when the CPU is idling. This anomaly occurs when the CPU

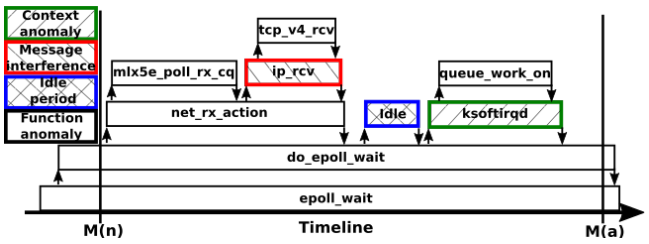


Figure 11: Message lifetime with a richer set of nested anomalies. {`mlx5e_poll_rx_cq`, `ip_recv`, `Idle`, `ksoftirqd`} are sufficient to explain the causes of latency deviations seen in this nested stack (§4.2, ***Anomaly disambiguation***).

waits for an event, like a memory read due to a cache miss, and is often indicative of resource bottlenecks. The third class is *cross-message interference* in the network stack.

The algorithm that classifies system activity within message lifetimes as anomalous or normal runs in four phases.
The first phase compares message lifetimes belonging to the same application and identifies *unexpected program contexts* that occur in a minority of message lifetimes. OS and application interference is usually identified in this phase.
The second phase identifies *gaps in system activity* that are not associated with any function or program context, like Figure 5. It also identifies the cause for each gap from the last function call *preceding* the gap. Figure 4 is an example result.
The third phase compares message lifetimes belonging to the same application and identifies individual *functions* that are slower, more frequently called, or unexpected. Figure 8 presented several anomalous functions identified in `M2` lifetime. Error handling code paths, like `TCP` retransmission, and application bottlenecks are usually identified in this phase.
The final phase identifies overlaps *between* messages, similar to how we detect overlap between `M1` and `M2` in §4.1, ***Message profiling***. This phase detects cross-application network interference when the overlap is between messages belonging to different applications, and head-of-line blocking when the overlap is between messages of the same application.

Attributing root causes to anomalies. §4.2, **C3** discussed how nesting ambiguates latency-deviation attribution. Often, only one of the anomalies in a deeply nested stack is sufficient to *explain the latency deviation due to the stack and identify corrective action*. In such cases, listing the nested anomalies as root causes only ambiguates diagnosis.

We now revisit this challenge in the context of an example in Figure 11 that has an anomalous program context (`ksoftirqd`) and cross-application message interference (`ip_rcv`). It is unnecessary to flag nested anomalies *within* anomalous program contexts or cross-application message interference because the corrective action to address the deviation is clear: the scheduling policy must be revisited to avoid these anomalies. Therefore, the algorithm will not flag `queue_work_on` or `tcp_v4_rcv` even if they are anomalous.

§4.2, ***Anomaly disambiguation*** described how we do not report anomalous parent functions if 80% percent of their latency deviation is already explained by the nested anomalies. When we report nested anomalies instead of their parent anomaly, we will not be able to explain some portion of the latency deviation. This is due to the fact that nested function latencies seldom make up 100% of the parent function latencies. We define the fraction of the latency deviation explained by NSight diagnosis as its *coverage*. For example, if a parent function takes 1000 ns longer than normal, and nested function takes 900 ns longer than normal, reporting only the nested function as root cause will result in 90% coverage. We evaluate NSight's coverage in §6.

Analysis implementation. The algorithms in the analysis subsystem are implemented with 2189 lines of R code. The visualisations comprise 1768 lines of R.

The precision of Intel-PT is limited because it profiles in *batches*, a few CPU cycles at a time. Latencies of functions whose `call` and `return` times are within the same batch can be under-reported to take no time at all! On the other hand, small latencies, corresponding to the batch granularity, can be added between batches, giving the appearance of an idling CPU. Such under-reporting and bogus gaps in system activity obfuscates anomaly detection. NSight analysis algorithms therefore ignore differences in latency smaller than the batch granularity (up to 322 ns in our system).

Instead of directly reporting anomalous functions such as `ksoftirqd` or `ip_recv` that are hard to interpret as root causes, we categorize them by functionality and report a single root cause, like `OS threads` or `Receive processing`. Each category is suggestive of a class of corrective actions that apply to all functions in that category. Table 1 shows 4 examples of categories used in this paper.

The process of categorization is partly automated. For example, process contexts are automatically derived from `perf`. We categorize 1350 functions in Linux by hand, using the contextual information from their names in a user configurable CSV file. We also introduce head-of-line blocking as a category. To do so, we automate summarization of all functions that are executed when processing messages with *minimum latency*. When these functions occur more frequently or their latencies deviate (for example, NIC interrupt processing takes longer) in message lifetimes of the same application, NSight shows head-of-line blocking as one of the root causes. We verify the latency deviations attributed to head-of-line blocking by cross-referencing message lifetimes to identify overlaps.

6 Evaluation

Our work on NSight is motivated by the paucity of *full-stack*, *lightweight* and *high-fidelity* network latency diagnosis tools that can be used to diagnose latencies in the microsecond regime. In this section, we examine to what extent the ideas in this paper address this gap.

Category	Anomalies
`NGINX` head-of-line blocking	`NGINX` process context Functions that were involved in processing the fastest network messages.
OS Threads	`ksoftirqd`, `kthreadd`, `kworker`, `swapper`
Receive Processing	Kernel/Driver packet processing (e.g. `ip_rcv`, `net_rx_action`, `mlx5e_poll_rx_cq`)

Table 1: Category examples and corresponding anomalies

To provide *full-stack* visibility, §4.1, ***Time reconciliation*** aligns observations from the CPU profiler and shim layer that use independent clocks. §6.1 examines the accuracy of time reconciliation which is crucial for tracking causality. To be *lightweight*, §4.1, ***Message profiling*** relies on hardware profiling while introducing software profiling *latency*-overheads at a few points in the end-host stack. §6.2 examines the overheads of this profiling scheme for two reasons; first, to determine if it can produce reliable diagnosis *despite* the overheads and second, if NSight can be used in production. Finally to be *high-fidelity* yet unambiguous, §4.2, ***Anomaly disambiguation*** only reports a subset of anomalies that can explain a majority of latency deviations in messages as root causes. §6.3 examines the extent to which this technique is successful especially in the microsecond regime.

6.1 Time reconciliation correctness

Software clock changes make reconciling system activity, captured by CPU profilers, and message lifetimes, captured by shim layer, hard. To align system activity and message lifetimes correctly, §4.1, ***Time reconciliation*** must capture *all* software-clock change events and use the correct conversion between CPU profiling and software clocks at all points in time. If old or incorrect conversion is used, the system activity and message lifetimes will be incorrectly lined up, introducing spurious or missing system events in message lifetimes.

To test the accuracy of §4.1, ***Time reconciliation*** , we design a benchmark that continuously captures CPU profiling (`TSC`) and software timestamps(`CLOCK_REALTIME`) one after the other. When we use the conversion parameters captured by NSight's user-space thread to convert all the CPU profiling timestamps to software timestamps, we expect to construct a linear timeline from the interspersed converted and measured software timestamps; that is, consecutive timestamps must *always advance* in time. If the old or incorrect conversion parameters are used in any time window, we detect a deviation from the linear timeline, showing that events observed across CPU profiling and the shim layer will be reordered.

Across multiple runs on different machines, over 10,000,000 conversions for each run, the consecutive converted and measured software timestamps always advance in time, never deviating. In each run, we observe that the software clock changes 4000+ times. This shows that the proposed time reconciliation maintains the ordering of events in message lifetimes even with software clock changes. We note

All numbers in µs. h = high load, l = low load				
Tool	median (h)	99.9th (h)	median (l)	99.9th (l)
Baseline	30.3	112.6	10	14.4
Intel-PT	30.8 (2%)	120.4 (7%)	10.6 (5%)	15.3 (6%)
NSight	31.1 (3%)	132.8 (18%)	11 (10%)	16.2 (12%)
eBPF-1	38.6 (27%)	157.6 (40%)	11.8 (18%)	17.3 (20%)
eBPF-2	41.8 (38%)	165 (46%)	13.2 (31%)	18.6 (29%)
eBPF-4	51.9 (71%)	556 (393%)	14.1 (41%)	19.4 (35%)
eBPF-8	59.1 (95%)	565 (402%)	15.5 (54%)	21 (45%)
Ftrace	201.8 (565%)	1060 (841%)	40.1 (298%)	66.4 (359%)

Table 2: Overhead of profiling tools on median and tail measurements. eBPF-*n* is eBPF used to profile *n* functions.

that a stronger test for time reconciliation, in which we take two timestamps *at the same time* and test their equivalence is impossible. Capturing timestamps takes time, and is the reason for a majority of NSight's profiling overheads.

6.2 Message profiling overheads

Latency overheads of profiling tools can perturb message lifetimes and obfuscate latency *diagnosis*. This is why these tools are only used for confirming hypotheses rather than diagnosis [15, 28, 32, 43, 45]. Even though NSight perturbs message lifetimes, it does not share this challenge because NSight is built on top of CPU profiling which *profiles NSight itself*! When NSight profiling slows down message lifetimes, it will show up in system activity captured by §4.1, ***Message profiling*** and §4.2, ***Anomaly disambiguation*** will detect it as the root cause. *Perf Idle (A)* in Figure 4 is an example where the CPU idles during NSight profiling introducing latencies.

Latency overheads of profiling tools also inhibit their use for *latency measurement in production environments*. To be useful in the microsecond-regime, we expect that this overhead should not be beyond a few microseconds.

To evaluate the latency overhead of NSight, we run a benchmark using `memcached` and record the receive latency of requests, measured from the time they arrive at the NIC to when they are received by `memcached`; this is the baseline measurement. A peak 4 core load on our system is 500k requests per second (rps); for this experiment we measured overheads across two loads on 4 cores, a low load (40k rps, 8% of peak), and a high load (300k rps, 60% of peak).

Table 2 shows the result of the experiment. Intel PT adds 2-7% over all measurements; Gathering software timestamps and core information with NSight adds another 1-11% totaling 3-18% overhead. This shows that NSight can be turned on in production for brief periods of time without perturbing median latencies by more than a few microseconds.

In contrast, as Figure 1 showed, profiling even *a single function call*, like `__sys_recvmsg`, using eBPF (eBPF-1) adds more overhead than NSight. As we increase the number of functions calls profiled with eBPF, its overhead increases (See eBPF-2, eBPF-4 and eBPF-8). Over all experiments, eBPF-1 adds 18-40% latency overhead. Ftrace, that profiles the full stack like NSight, has the largest impact on performance (up to 841% overhead). The high latency overheads of these tools make them impractical for use in production environments.

The current design for §4.1, ***Time reconciliation*** burns an entire core for the user-thread. This overhead can be prohibitive in production environments. Thankfully, the overhead is avoidable because software clocks change relatively slowly, once every 4 ms in Linux. If the software clock changes are tracked directly from the time synchronization protocol, there is no need for an extra core during profiling.

6.3 Coverage after anomaly disambiguation

For high-fidelity, latency diagnosis must be able to report root causes for all latency deviations seen in message lifetimes, even if the deviations are in the order of microseconds. We measure fidelity in terms of coverage, defined as the latency deviation explained by diagnosis as a fraction of overall latency deviation. However, §4.2, ***Anomaly disambiguation*** leads to less than 100% coverage. Trading off some coverage for getting rid of false negatives is still reasonable because NSight can be used *iteratively* to improve coverage; in each iteration the most conspicuous root causes remaining can be discovered with NSight and corrected for (See next section).

By not reporting parent anomalies, when 80% or more of their deviation is explained by their nested anomalies, we get a minimum coverage of 69% and a median coverage of 96% across all experiments and all observed message-latencies. Only 10 messages across our experiments have a coverage less than 87%. This shows that highlighting only anomalies that explain 80% or more of their parent's latency deviation as root causes reduces false negatives and yet allows for a majority of root causes to be discovered in the first iteration.

7 Latency diagnosis with NSight

We now describe the iterative process by which NSight can quickly diagnose the causes of poor performance. Let us start with an initial system configuration that runs `memcached` in which large `memcached` tails are observed. Profiling the system with NSight identifies the prominent causes of tails. Users can mitigate or eliminate the causes found and profile the *reconfigured system* with NSight to identify the remaining causes of tails. Three such iterations help reduce `memcached` 99.9999th percentile latency from 15.3 ms to 182 µs in our setup. Unfortunately, some of the mitigations we use increase median latencies by a few microseconds. NSight helps identify *which* mitigations cause this increase by comparing profiling data collected *across* iterations.

We now describe these iterations with NSight and the notable causes of network latency in our system. We present diagnosis results only for `memcached` server *receive* latencies because the majority of end-host delays are known to show up on the receive path [35, 39, 78]).

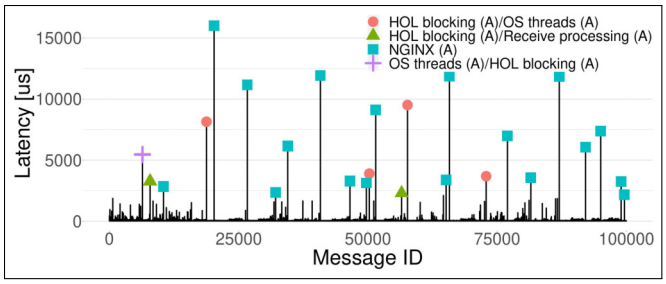


Figure 12: Balloon plot showing the top causes of tail latency with the initial configuration. The tallest balloons are blue squares, identified as *NGINX (A)* in the legend; this means NGINX interferes with memcached on the application core (A). The balloons are spaced apart, indicating that their causes are independent and can be addressed separately.

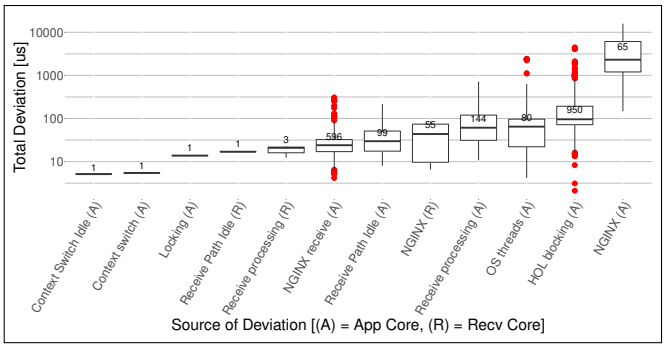


Figure 13: Global box plot showing the causes of tail latencies with the initial configuration. The number of tail messages impacted by each cause is shown on top of the boxes. This presentation helps identify the most important causes to pursue after one iteration of NSight profiling; pursuing both, causes that result in the largest deviations *and* causes that impact the *most tails*, can lead to the biggest latency reductions.

7.1 First iteration

Initial configuration. Our setup consists of two Linux machines (2x14 Intel Xeon Gold 5120, 192 GB RAM), running kernel version 4.18 (Ubuntu 18.04) connected by 100Gbps interfaces to a 3.2Tbps Ethernet switch. memcached, a latency sensitive workload (similar to [20, 33, 55]) runs alongside NGINX, the interfering workload. Both applications use the default configuration and share 4 cores. The workload consists of memcached requests arriving at 160-190k requests per second (60-80% of expected memcached throughput across 2 cores in our system), and NGINX requests arriving at 50-60k requests per second (60-80% of expected NGINX throughput on a single core). ntp and ptp were disabled in our setup when we collected the experimental results in this section.

Initial diagnosis. To use NSight, users can collect a profiling sample of a few seconds and look at the initial result. In our setup, this allows us to profile 100k memcached request-responses. The initial result, Figure 12, a balloon plot similar to Figure 3, shows the distribution of tail messages and their causes. The largest tails are caused by NGINX interference on the application core, *NGINX (A)*. The remaining tails are due to three causes, mainly head-of-line blocking of application threads, *HOL blocking (A)*, in combination with interference due to *OS threads (A)* and *Receive processing (A)* at the application core. These causes are defined in Table 1.

A second presentation, the box plot in Figure 13, summarizes the causes (X-axis) sorted by the *median* total deviation added to each tail message. The number of messages impacted by each cause, shown on the boxes, represents how *pervasive* the cause is. We notice that the most conspicuous causes impacting the most messages are to the right of *Receive processing (R)*, starting with *NGINX receive (A)* that impacts 596 tail messages. Going after these can increase the latency reduction achieved with this iteration.

Of the causes in Figure 13, we find that *HOL blocking (A)* impacts the most tail messages (950), indicating that there is a lack of I/O parallelism in memcached. When we examine the *tail* message lifetimes slowed down by *HOL blocking (A)* (the top outliers in the box plot), we see memcached *sends* delaying memcached request-*receives* by as much as 1 ms. To understand *why*, we look at memcached code and find that memcached threads process up to 20 requests per socket, sending responses for each, *before* processing the next request. This is interesting because papers [20, 55] have conjectured that it is sufficient to use microsecond granularity core-scheduling to improve memcached latencies, but in fact memcached itself foils that plan. The way to improve memcached latencies is to first modify memcached to introduce additional I/O parallelism as NSight identifies here.

7.2 Second Iteration

Second configuration. The next step is to mitigate or eliminate the causes identified in the previous diagnostic step. To eliminate *NGINX (A)* interference, we pin memcached to two cores and NGINX to a third core; similarly, to eliminate interference due to *Receive processing (A)* and *NGINX receive (A)*, we pin kernel receive activity to a fourth core and configure RSS to send all receive traffic to that core (Similar to IOKernel [55]). To mitigate *HOL blocking (A)*, we limit memcached-requests per socket to 2 (down from 20) and limit memcached server threads to one per core.

Second diagnosis. Having applied the second configuration we rerun NSight. Figure 14 and Figure 15 are the analogous presentations to Figure 12 and Figure 13. The largest latency deviations in Figure 15 come from *Paging/Paging Idle (A)*. The message lifetimes impacted by these causes show repeated calls to change_protection and change_prot_numa each taking up to 400 µs. The documentation for change_prot_numa() says that this code is a mechanism to identify beneficial page migrations; interestingly, it creates

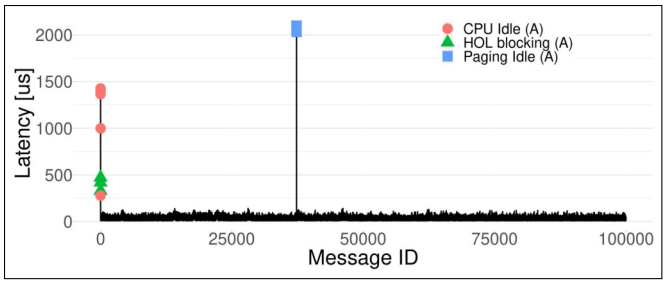


Figure 14: Balloon plot with the second configuration. Bunching of balloons shows system effects that impact message-bursts. Paging causes the largest tails. CPU idle activity and head-of-line blocking assail the initial few messages.

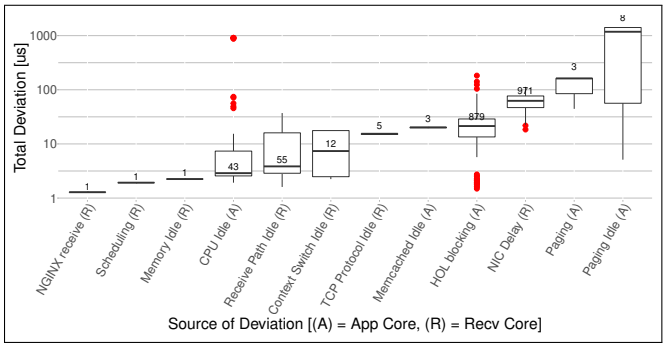


Figure 15: Global box plot with the second configuration. Alongside Paging and CPU idling that cause a few tails, this graph shows that interrupt coalescing (*NIC delay (R)*) and head-of-line blocking are most pervasive and worth pursuing.

deviant latencies. This suggests that architectural changes are needed to identify page migrations *without* causing tails. NSight can play a role by making it easy to confirm that the new architecture does not introduce latency deviations.

We also find that a few *CPU idle (A)* outliers in Figure 15 add up to 0.6 ms to tail messages; these correspond to the initial balloons in Figure 14. The lifetimes of these messages show large gaps in system activity *between* connection set up functions, `dispatch_conn_new()` called on the *receive core* to which we pinned the kernel receive activity, and `conn_new()` called on the `memcached` core. When we look at this code, we find that `memcached` registers an event handler for connection setup using libevent. When a new connection message is received (on the *receive core* in our setup) an event is dispatched to the handler on another thread that must be scheduled on the *application core*. The *delay in scheduling the connection handler* causes tail latencies during startup.

7.3 Third iteration

Third configuration. We now mitigate the causes found in Figure 15. We disable `autonuma` feature to confirm the *Paging/Paging Idle (A)* deviations, and adaptive interrupt coalescing to confirm *NIC Delay (R)* deviations, even though doing so might lead to worse performance. To speed up connection setup, we increase priority of new connection events by changing one line in `memcached`. Another cause we identified after the second iteration but before the third, was removed by disabling the LRU replacement feature; for compactness, we condense this additional iteration into the third iteration.

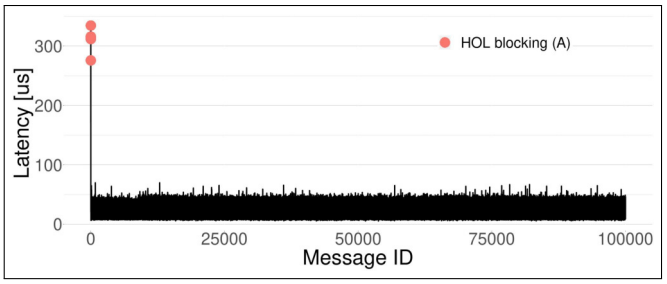


Figure 16: Balloon plot with the third configuration. A few balloons still appear, but their absolute latency (350 µs) is tiny compared to tails seen with the initial configuration (16 ms), and no balloons occur once the system is warmed up.

Third diagnosis. Having applied the third configuration we rerun NSight. The balloon plot Figure 16 shows that all the significant outliers are in the start up phase. The tail latencies of the initial messages are much lower than those seen with the second configuration in Figure 14 (350 µs vs. 1.4 ms). They are not caused by *CPU Idle (A)*, as they were with the second configuration, but by *HOL blocking (A)*. Overall, the tails are an order of magnitude smaller compared to the 1.1 ms-16 ms tails originally seen with the initial configuration in Figure 12.

7.4 Analysis of diagnosis and configurations

We now confirm tail latency improvements due to the diagnosis by running experiments with all three configurations, initial §7.1, second §7.2, and third configuration §7.3, for a longer duration without NSight profiling. We measure the latency of 10 million requests, using each configuration 10 times. Figure 17 shows the CDF of the receive latencies with these configurations; the left graph shows all the latencies and the right shows the tail latencies. With the third configuration, we see 99.9th percentile latency improve by 43× (2.2 ms to 51 µs). The 99.999th percentile latency is 67 µs and 99.9999th percentile latency is 182 µs (down from 15.3 ms). Both, the second and third configurations improve the tail latencies compared to the initial configuration but at the cost of *increasing* latencies in the first 60% of messages.

Diagnosing latency increases in lower percentiles. NSight analyses latency anywhere on a latency curve, not just the tail. Since the deviations in Figure 17 are worst around the 25th percentile © (13.3 µs with initial but 24.7 µs with the third configuration), users can configure NSight to focus on the 25th percentile. NSight will analyse a slice of

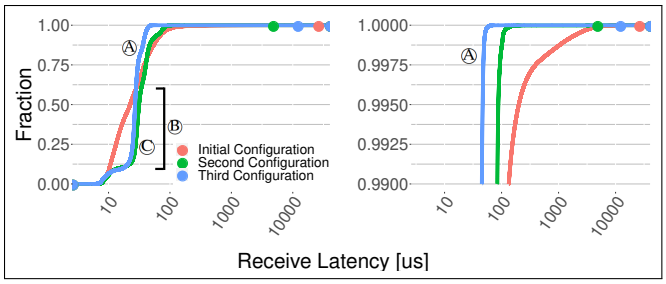


Figure 17: Full CDF (left) and p99-100 (right) of `memcached` receive latencies in longer runs (10 million requests, 10 repetitions) for all 3 configurations. The third configuration improves tail latencies beyond the 60th percentile Ⓐ but *adds* small latencies to messages between the 10th and 60th percentiles Ⓑ, with the maximum latencies being added *around* the 25th percentile Ⓒ; a proper solution instead of our expeditious mitigations could get the benefit of tail reduction without penalizing the common case.

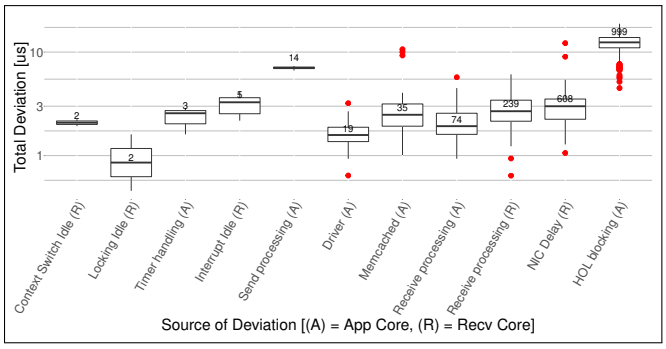


Figure 18: Global box plot comparing 25th percentile messages in the third iteration with those in the first iteration. To focus on causes that impact the *span* of messages around 25th percentile Ⓒ in Figure 16, the boxes are sorted by *number of messages impacted*. Head-of-line blocking is the most pervasive cause of the latency increase.

messages between the 20th and 30th percentiles. Since the latency increases occur *across iterations*, users can compare message lifetimes across iterations with NSight to identify the causes. We configure NSight to compare the 25th percentile messages in the third §7.3 and first iterations §7.1 to diagnose latency increases; the results in the rest of the section use this configuration. In this setting, latency deviation is defined as latencies that get worse around the 25th percentile in the third iteration compared to those in the first iteration.

Since *all* the messages around the 25th percentile are similarly impacted, we look for the *most pervasive causes*. Therefore, we turn to a global box plot that presents the causes *sorted by the number of messages impacted*, Figure 18. The most pervasive cause of latency, impacting all but one of the thousand messages around the 25th percentile in the third iteration relative to the first iteration, is *HOL blocking (A)*. The messages also experience *NIC delay (R)* relative to messages in the first iteration. This is surprising because we disabled adaptive interrupt coalescing in the third iteration §7.3.

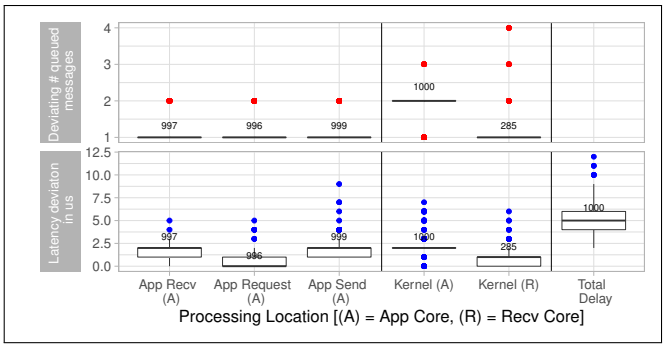
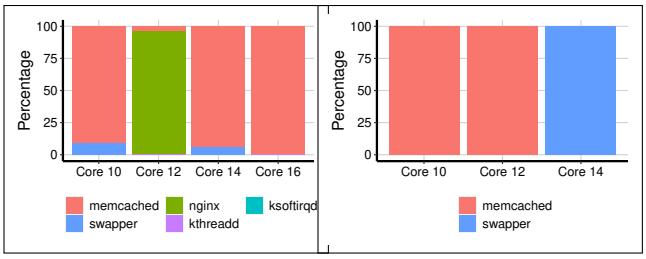


Figure 19: Queuing breakdown showing relative queuing ahead of 25th percentile messages in the third versus the first iteration. Deviations are shown for select functions (X-axis) for which we can measure the queue depth ahead of each message, by counting function occurrences in message lifetimes. The top half shows deviations in *queue depth*; a dot or line at 4 means that there are *4 more messages ahead of the deviant message relative to the reference*. The bottom half is a box plot for resulting latency deviations. The functions are categorized into application vs. kernel, send vs. receive vs. request processing. The count of messages impacted is shown on top of each plot. This graph shows that the 25th percentile messages experience more queuing in the third iteration.

To identify *why* the 25th percentile messages of the third iteration experience head-of-line blocking relative to the first iteration, we consult NSight's queuing breakdown described in Figure 19. It shows that a majority of the 25th percentile messages have at least one more message ahead of them in the third iteration relative to the first iteration (top half) and this introduces latency deviations (bottom half). *App Send (A)* shows more latency deviation than other categories. *Kernel (A)* and *Kernel (R)* measure send/receive queuing in the kernel. Because the second configuration (§7.2) isolated kernel receive activity from the *application* core, *Kernel (A)* shows latency deviations only due to *sending* responses. Receive queuing shown in *Kernel (R)* impacts fewer messages.

Together, deviations in *App Send (A)* and *Kernel (A)* show that *sending responses takes longer* in the third iteration even though *fewer responses* (reduced to 2 per socket in §7.2) are sent back per socket relative to the first iteration. This shows that the application core cannot keep up in the third iteration.

To find *why*, we consult NSight's core context summaries for the iterations, shown in Figure 20. It shows the percentage of time the *message lifetimes* spend in each processing context. We see that `memcached` uses three cores to process the 25th percentile messages in the first iteration, Figure 20a, compared to two in third iteration, Figure 20b. This confirms that the



(a) First iteration (b) Third iteration

Figure 20: NSight core-context summary showing the process contexts (legend) active in the 25th percentile *memcached message lifetimes* on each core (X-axis), and the percentage of time they are active (Y-axis). `memcached` has three cores available in the first iteration vs. two cores in the third iteration, exacerbating head-of-line blocking in the third iteration.

threads are backlogged in the third iteration because of the *lack of available CPU*; the mitigation of *pinning* `memcached` threads to cores (§7.1) increased head-of-line blocking for the 25th percentile messages in the third iteration.

Figure 20b also shows that in the third iteration, the core used for kernel receive activity is mostly idle/sleeping (`swapper` is the default idle task) waiting for a NIC interrupt, whereas in the first iteration the cores are always running, processing `memcached` requests or receiving messages in the kernel. This explains why we see deviations due to *NIC Delay (R)* in Figure 18 despite disabling adaptive interrupt coalescing; *waking the core* takes time and delays the NIC interrupt. This is an example of complex NIC–CPU scheduling interactions that NSight captures (§1). Waiting for the NIC interrupt at low loads puts the receive core to sleep *since it has nothing else to do*, and waking it up delays the NIC interrupt! Thus, the mitigation of pinning the kernel receive activity to a core in §7.2 adds latencies at lower loads to the common case.

8 Diagnosing VMA network stack

NSight can diagnose problems in different applications such as `redis` and different network stacks such as VMA network stack. We now describe the key causes of network tail latencies we found with unmodified `memcached` and `redis` on top of the VMA user-space network stack.

System configuration. For experiments with `memcached`, we pin `memcached` servers to 4 cores and increase the load (400k request/s on 4 cores). For experiments with `redis`, a single-threaded server, we profile a single core `redis` instance using the standard `redis-benchmark` (110k request/s on 1 core). Since these applications are already pinned to cores, studying application interference with `NGINX` is irrelevant and we do not include it in contrast to the Linux study.

Diagnosis. We now describe the key sources of network latency in VMA found using the same diagnostic strategy we used in the Linux study, guided by NSight's graphs. As expected, the overall tail latency distribution improves with VMA in comparison to Linux. But surprisingly, the outliers for `memcached` are more severe. While the median `memcached` server request receive latency is 8.38 µs and the 99.9th percentile latency is 45.3 µs, the worst message latency is 34.5 ms! The median, 99.9th and worst `redis` request receive latencies are 1.63 µs. 145.1 µs, and 1.2 ms. Following are the most prominent causes of tails in VMA.

VMA epoll mechanism. NSight diagnostic graphs show that some `memcached` messages are delayed for up to 25 ms *in the NIC*! In this case, even though the message is received by the NIC, the epoll implementation of VMA does not pick it up. The exact reason for this behavior is unclear, but we posit that either the NIC hardware delays reporting the arrival or the stack waits for a message for a specific socket.

OS interference. We find that the default Linux scheduling policies frequently puts polling based stacks to sleep for short amounts of time (4 µs). In the case of some `memcached` messages that are severely delayed, we detect a kernel stack overflow, that puts all but one of the application threads to sleep for up to 12 ms with the lone thread handling the panic. This is unexpected behavior that seems to suggest a bug.

Buffer management. VMA ring buffer management causes frequent shorter latency deviations. It fills up the RX buffer queue with unused buffers and removes used send-buffers from the TX queue in bursts, adding deviations of up to 2.8 ms (though more frequently in the range of 60-150 µs).

9 Limitations and future work

We have already noted three limitations of NSight. First, NSight cannot be used for continuous profiling due to Intel-PT buffering implementation (§5.1). Second, CPU profilers capture system activity in batches of CPU cycles; NSight cannot capture latency deviations smaller than a batch (§5.2). Finally, consuming a core for §4.1, ***Time reconciliation*** is unnecessary if software clock changes are tracked by `ptp`. Another limitation of NSight is that it produces 600MB-1GB of compressed raw profiling data per second. Decompressing the profiling data to a usable format increases the size by 10-20x. Reducing the amount of data produced and speeding up analysis will reduce the time between NSight iterations.

We are expanding NSight's scope to RDMA-based stacks, and more general purpose performance diagnosis to analyze Linux's core operations [63]. We are also using NSight to characterize the design space for low-latency network stacks. We plan to make the tool available as open source.

Acknowledgements

We thank our shepherd, Robert Ricci, anonymous reviewers, Jon Howell, Amin Vahdat, Vyas Sekar, Marcos Aguilera, Ben Pfaff, Ming Liu, Adriana Szekeres, Naama Ben David, Nadav Amit, Amy Tai, Irina Calciu, Jayneel Gandhi, Ana Klimovic, Lukas Humbel and Michael Wei for their insightful feedback.

References

[1] ebpf. Onlin., https://ebpf.io/.

[2] F-stack: High performance network framework based on dpdk. http://f-stack.org/.

[3] Ftrace. Onlin., https://www.kernel.org/doc/Documentation/trace/ftrace.txt.

[4] Perf: Performance analysis tools for linux. Onlin., http://man7.org/linux/man-pages/man1/perf.1.html.

[5] Seastar: High-performance server-side application framework. http://seastar.io/.

[6] Mohammad Mejbah ul Alam, Tongping Liu, Guangming Zeng, and Abdullah Muzahid. Syncperf: Categorizing, detecting, and diagnosing synchronization performance bugs. In *Proceedings of the Twelfth European Conference on Computer Systems*, EuroSys '17, page 298–313, New York, NY, USA, 2017. Association for Computing Machinery.

[7] Paul Barham, Austin Donnelly, Rebecca Isaacs, and Richard Mortier. Using magpie for request extraction and workload modelling. In *Proceedings of the 6th Conference on Symposium on Operating Systems Design and Implementation - Volume 6*, OSDI'04, page 18, USA, 2004. USENIX Association.

[8] Adam Belay, George Prekas, Ana Klimovic, Samuel Grossman, Christos Kozyrakis, and Edouard Bugnion. IX: A protected dataplane operating system for high throughput and low latency. In *11th USENIX Symposium on Operating Systems Design and Implementation (OSDI 14)*, pages 49–65, Broomfield, CO, October 2014. USENIX Association.

[9] Zachary Benavides, Keval Vora, and Rajiv Gupta. Dprof: Distributed profiler with strong guarantees. *Proc. ACM Program. Lang.*, 3(OOPSLA), October 2019.

[10] M.Y. Chen, E. Kiciman, E. Fratkin, A. Fox, and E. Brewer. Pinpoint: problem determination in large, dynamic internet services. In *Proceedings International Conference on Dependable Systems and Networks*, pages 595–604, 2002.

[11] Shuang Chen, Christina Delimitrou, and José F. Martínez. Parties: Qos-aware resource partitioning for multiple interactive services. In *Proceedings of the Twenty-Fourth International Conference on Architectural Support for Programming Languages and Operating Systems*, ASPLOS '19, page 107–120, New York, NY, USA, 2019. Association for Computing Machinery.

[12] Intel Cooperation. *Intel 64 and IA-32 Architectures Software Developer's Manual - Volume 3B*. Intel Corporation, August 2007.

[13] Mathieu Desnoyers and Michel Dagenais. The lttng tracer: A low impact performance and behavior monitor for gnu/linux. *OLS (Ottawa Linux Symposium)*, 01 2006.

[14] The Kernel development community. Timestamping. Onlin., https://www.kernel.org/doc/html/latest/networking/timestamping.html.

[15] Jaana Dogan. Want to debug latency? https://rakyll.medium.com/want-to-debug-latency-7aa48ecbe8f7.

[16] Benjamin Donie. iostat. Onlin., http://man7.org/linux/man-pages/man1/iostat.1.html.

[17] Srikar Dronamraju. Uprobe-tracer: Uprobe-based event tracing. Onlin., https://www.kernel.org/doc/Documentation/trace/uprobetracer.txt.

[18] Úlfar Erlingsson, Marcus Peinado, Simon Peter, Mihai Budiu, and Gloria Mainar-Ruiz. Fay: Extensible distributed tracing from kernels to clusters. *ACM Trans. Comput. Syst.*, 30(4), November 2012.

[19] Rodrigo Fonseca, George Porter, Randy H. Katz, Scott Shenker, and Ion Stoica. X-trace: A pervasive network tracing framework. In *Proceedings of the 4th USENIX Conference on Networked Systems Design and Implementation*, NSDI'07, page 20, USA, 2007. USENIX Association.

[20] Joshua Fried, Zhenyuan Ruan, Amy Ousterhout, and Adam Belay. Caladan: Mitigating interference at microsecond timescales. In *14th USENIX Symposium on Operating Systems Design and Implementation (OSDI 20)*, pages 281–297. USENIX Association, November 2020.

[21] Junzhi Gong, Yuliang Li, Bilal Anwer, Aman Shaikh, and Minlan Yu. Microscope: Queue-based performance diagnosis for network functions. In *Proceedings of the Annual Conference of the ACM Special Interest Group on Data Communication on the Applications, Technologies, Architectures, and Protocols for Computer Communication*, SIGCOMM '20, page 390–403, New York, NY, USA, 2020. Association for Computing Machinery.

[22] Susan L. Graham, Peter B. Kessler, and Marshall K. Mckusick. Gprof: A call graph execution profiler. *SIGPLAN Not.*, 17(6):120–126, June 1982.

[23] Sangjin Han, Scott Marshall, Byung-Gon Chun, and Sylvia Ratnasamy. Megapipe: A new programming interface for scalable network i/o. In *Proceedings of*

the 10th USENIX Conference on Operating Systems Design and Implementation, OSDI'12, page 135–148, USA, 2012. USENIX Association.

[24] Stephen Ibanez, Alex Mallery, Serhat Arslan, Theo Jepsen, Muhammad Shahbaz, Nick McKeown, and Changhoon Kim. The nanopu: Redesigning the cpu-network interface to minimize rpc tail latency, 2020.

[25] Intel. Intel vtune profilder. Onlin., https://software.intel.com/en-us/vtune.

[26] Intel Corporation. Data plane development kit. https://www.dpdk.org/. April 2021.

[27] Calin Iorgulescu, Reza Azimi, Youngjin Kwon, Sameh Elnikety, Manoj Syamala, Vivek Narasayya, Herodotos Herodotou, Paulo Tomita, Alex Chen, Jack Zhang, and Junhua Wang. Perfiso: Performance isolation for commercial latency-sensitive services. In *2018 USENIX Annual Technical Conference (USENIX ATC 18)*, pages 519–532, Boston, MA, July 2018. USENIX Association.

[28] Alexey Ivanov. Optimizing web servers for high throughput and low latency. https://dropbox.tech/infrastructure/optimizing-web-servers-for-high-throughput-and-low-latency.

[29] Alan D. Brunelle Jens Axboe and Nathan Scott. blktrace. Onlin., http://man7.org/linux/man-pages/man8/blktrace.8.html.

[30] Masami Hiramatsu Jim Keniston, Prasanna S Panchamukhi. Kernel probes. Onlin., https://www.kernel.org/doc/Documentation/kprobes.txt.

[31] Nikolai Joukov, Avishay Traeger, Rakesh Iyer, Charles P. Wright, and Erez Zadok. Operating system profiling via latency analysis. In *Proceedings of the 7th Symposium on Operating Systems Design and Implementation*, OSDI '06, page 89–102, USA, 2006. USENIX Association.

[32] Theo Julienne. Debugging network stalls on kubernetes. https://github.blog/2019-11-21-debugging-network-stalls-on-kubernetes/.

[33] Kostis Kaffes, Timothy Chong, Jack Tigar Humphries, Adam Belay, David Mazières, and Christos Kozyrakis. Shinjuku: Preemptive scheduling for microsecond-scale tail latency. In *16th USENIX Symposium on Networked Systems Design and Implementation (NSDI 19)*, pages 345–360, Boston, MA, February 2019. USENIX Association.

[34] Anuj Kalia, Michael Kaminsky, and David Andersen. Datacenter rpcs can be general and fast. In *16th USENIX Symposium on Networked Systems Design and Implementation (NSDI 19)*, pages 1–16, Boston, MA, February 2019. USENIX Association.

[35] Rishi Kapoor, George Porter, Malveeka Tewari, Geoffrey M. Voelker, and Amin Vahdat. Chronos: Predictable low latency for data center applications. In *Proceedings of the Third ACM Symposium on Cloud Computing*, SoCC '12, New York, NY, USA, 2012. Association for Computing Machinery.

[36] Antoine Kaufmann, Tim Stamler, Simon Peter, Naveen Kr. Sharma, Arvind Krishnamurthy, and Thomas Anderson. Tas: Tcp acceleration as an os service. In *Proceedings of the Fourteenth EuroSys Conference 2019*, EuroSys '19, New York, NY, USA, 2019. Association for Computing Machinery.

[37] Chung Hwan Kim, Junghwan Rhee, Hui Zhang, Nipun Arora, Guofei Jiang, Xiangyu Zhang, and Dongyan Xu. Introperf: Transparent context-sensitive multi-layer performance inference using system stack traces. *SIGMETRICS Perform. Eval. Rev.*, 42(1):235–247, June 2014.

[38] John Levon. Oprofile. Onlin., https://oprofile.sourceforge.io/news/.

[39] Jialin Li, Naveen Kr. Sharma, Dan R. K. Ports, and Steven D. Gribble. Tales of the tail: Hardware, os, and application-level sources of tail latency. In *Proceedings of the ACM Symposium on Cloud Computing*, SOCC '14, page 1–14, New York, NY, USA, 2014. Association for Computing Machinery.

[40] ARM Limited. *ARM CoreSight Architecture Specification v3.0*. Intel Corporation, August 2017.

[41] Xiaofeng Lin, Yu Chen, Xiaodong Li, Junjie Mao, Jiaquan He, Wei Xu, and Yuanchun Shi. Scalable kernel tcp design and implementation for short-lived connections. In *Proceedings of the Twenty-First International Conference on Architectural Support for Programming Languages and Operating Systems*, ASPLOS '16, page 339–352, New York, NY, USA, 2016. Association for Computing Machinery.

[42] Inc. Linux Kernel Organization. Linux. https://www.kernel.org/.

[43] Dan Luu. Sampling v. tracing. https://danluu.com/perf-tracing/.

[44] Jonathan Mace, Ryan Roelke, and Rodrigo Fonseca. Pivot tracing: Dynamic causal monitoring for distributed systems. In *2016 USENIX Annual Technical Conference (USENIX ATC 16)*, Denver, CO, June 2016. USENIX Association.

[45] Marek Majkowski. The story of one latency spike. https://blog.cloudflare.com/the-story-of-one-latency-spike/.

[46] Ilias Marinos, Robert N.M. Watson, and Mark Handley. Network stack specialization for performance. *SIGCOMM Comput. Commun. Rev.*, 44(4):175–186, August 2014.

[47] Michael Marty, Marc de Kruijf, Jacob Adriaens, Christopher Alfeld, Sean Bauer, Carlo Contavalli, Michael Dalton, Nandita Dukkipati, William C. Evans, Steve Gribble, Nicholas Kidd, Roman Kononov, Gautam Kumar, Carl Mauer, Emily Musick, Lena Olson, Erik Rubow, Michael Ryan, Kevin Springborn, Paul Turner, Valas Valancius, Xi Wang, and Amin Vahdat. Snap: A microkernel approach to host networking. SOSP '19, page 399–413, New York, NY, USA, 2019. Association for Computing Machinery.

[48] Mellanox. Messaging accelerator (vma). Onlin., https://docs.mellanox.com/display/VMAv902.

[49] Microsoft. Event tracing for windows. Onlin., https://docs.microsoft.com/de-de/windows/win32/etw/about-event-tracing.

[50] Microsoft. Perfmon: Performance monitor on windows. Onlin., https://docs.microsoft.com/en-us/windows-server/administration/windows-commands/perfmon.

[51] Sun Microsystems. Dtrace. Onlin., http://dtrace.org.

[52] David Miller. ethtool. Onlin., https://man7.org/linux/man-pages/man8/ethtool.8.html.

[53] MIPS. Pdtrace. Onlin., https://www.mips.com/develop/tools/navigator-probes/, August 2021.

[54] OpenZipkin. Zipkin: A distributed tracing system. Onlin., https://zipkin.io/.

[55] Amy Ousterhout, Joshua Fried, Jonathan Behrens, Adam Belay, and Hari Balakrishnan. Shenango: Achieving high CPU efficiency for latency-sensitive datacenter workloads. In *16th USENIX Symposium on Networked Systems Design and Implementation (NSDI 19)*, pages 361–378, Boston, MA, February 2019. USENIX Association.

[56] P4. In-band network telemetry. Onlin., https://p4.org/p4-spec/docs/INT_v2_1.pdf.

[57] Aleksey Pesterev, Jacob Strauss, Nickolai Zeldovich, and Robert T. Morris. Improving network connection locality on multicore systems. In *Proceedings of the 7th ACM European Conference on Computer Systems*, EuroSys '12, page 337–350, New York, NY, USA, 2012. Association for Computing Machinery.

[58] Simon Peter, Jialin Li, Irene Zhang, Dan R. K. Ports, Doug Woos, Arvind Krishnamurthy, Thomas Anderson, and Timothy Roscoe. Arrakis: The operating system is the control plane. In *11th USENIX Symposium on Operating Systems Design and Implementation (OSDI 14)*, pages 1–16, Broomfield, CO, October 2014. USENIX Association.

[59] V. Prasad, William Cohen, F. Eigler, M. Hunt, J. Keniston, and B. Chen. Locating system problems using dynamic instrumentation. 01 2005.

[60] George Prekas, Marios Kogias, and Edouard Bugnion. Zygos: Achieving low tail latency for microsecond-scale networked tasks. In *Proceedings of the 26th Symposium on Operating Systems Principles*, SOSP '17, page 325–341, New York, NY, USA, 2017. Association for Computing Machinery.

[61] Linux PTP. The linux ptp project. Onlin., http://linuxptp.sourceforge.net/.

[62] Henry Qin, Qian Li, Jacqueline Speiser, Peter Kraft, and John Ousterhout. Arachne: Core-aware thread management. In *13th USENIX Symposium on Operating Systems Design and Implementation (OSDI 18)*, pages 145–160, Carlsbad, CA, October 2018. USENIX Association.

[63] Xiang (Jenny) Ren, Kirk Rodrigues, Luyuan Chen, Camilo Vega, Michael Stumm, and Ding Yuan. An analysis of performance evolution of linux's core operations. In *Proceedings of the 27th ACM Symposium on Operating Systems Principles*, SOSP '19, page 554–569, New York, NY, USA, 2019. Association for Computing Machinery.

[64] Patrick Reynolds, Charles Killian, Janet L. Wiener, Jeffrey C. Mogul, Mehul A. Shah, and Amin Vahdat. Pip: Detecting the unexpected in distributed systems. In *Proceedings of the 3rd Conference on Networked Systems Design & Implementation - Volume 3*, NSDI'06, page 9, USA, 2006. USENIX Association.

[65] Luigi Rizzo. netmap: A novel framework for fast packet i/o. In *2012 USENIX Annual Technical Conference (USENIX ATC 12)*, pages 101–112, Boston, MA, June 2012. USENIX Association.

[66] Steven Rostedt. Kernelshark. Onlin., https://kernelshark.org/.

[67] Muhammad Shahbaz, Sean Choi, Ben Pfaff, Changhoon Kim, Nick Feamster, Nick McKeown, and Jennifer Rexford. Pisces: A programmable, protocol-independent software switch. In *Proceedings of the 2016 ACM SIGCOMM Conference*, SIGCOMM '16, page 525–538, New York, NY, USA, 2016. Association for Computing Machinery.

[68] Benjamin H. Sigelman, Luiz André Barroso, Mike Burrows, Pat Stephenson, Manoj Plakal, Donald Beaver, Saul Jaspan, and Chandan Shanbhag. Dapper, a large-scale distributed systems tracing infrastructure. Technical report, Google, Inc., 2010.

[69] Livio Soares and Michael Stumm. Flexsc: Flexible system call scheduling with exception-less system calls. In *9th USENIX Symposium on Operating Systems Design and Implementation (OSDI 10)*, Vancouver, BC, October 2010. USENIX Association.

[70] Brent Stephens, Aditya Akella, and Michael Swift. Loom: Flexible and efficient NIC packet scheduling. In *16th USENIX Symposium on Networked Systems Design and Implementation (NSDI 19)*, pages 33–46, Boston, MA, February 2019. USENIX Association.

[71] Brent Stephens, Arjun Singhvi, Aditya Akella, and Michael Swift. Titan: Fair packet scheduling for commodity multiqueue NICs. In *2017 USENIX Annual Technical Conference (USENIX ATC 17)*, pages 431–444, Santa Clara, CA, July 2017. USENIX Association.

[72] Uber Technologies. Jaeger: open source, end-to-end distributed tracing. Onlin., https://www.jaegertracing.io/.

[73] VMware. Vprobes. Onlin., https://www.vmware.com/products/beta/ws/vprobes_reference.pdf.

[74] Kit Po Wong, Chi Ping Tsang, and Wan Yee Chan. Sherlock—a system for diagnosing power distribution ring network faults. In *Proceedings of the 1st International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems - Volume 1*, IEA/AIE '88, page 109–115, New York, NY, USA, 1988. Association for Computing Machinery.

[75] Wenfei Wu, Keqiang He, and Aditya Akella. Perfsight: Performance diagnosis for software dataplanes. In *Proceedings of the 2015 Internet Measurement Conference*, IMC '15, page 409–421, New York, NY, USA, 2015. Association for Computing Machinery.

[76] Minlan Yu, Albert Greenberg, Dave Maltz, Jennifer Rexford, Lihua Yuan, Srikanth Kandula, and Changhoon Kim. Profiling network performance for multi-tier data center applications. In *Proceedings of the 8th USENIX Conference on Networked Systems Design and Implementation*, NSDI'11, page 57–70, USA, 2011. USENIX Association.

[77] Fang Zhou, Yifan Gan, Sixiang Ma, and Yang Wang. wperf: Generic off-cpu analysis to identify bottleneck waiting events. In *13th USENIX Symposium on Operating Systems Design and Implementation (OSDI 18)*, pages 527–543, Carlsbad, CA, October 2018. USENIX Association.

[78] Noa Zilberman, Matthew Grosvenor, Diana Andreea Popescu, Neelakandan Manihatty-Bojan, Gianni Antichi, Marcin Wójcik, and Andrew W. Moore. Where has my time gone? In *Passive and Active Measurement*, pages 201–214, Cham, 2017. Springer International Publishing.