Tracing and Its Observer Effect on Concurrency

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Abstract

Execution tracing has an *observer effect*: the act of tracing perturbs program behaviour via its overhead, which can in turn affect the accuracy of subsequent dynamic analysis. We investigate this observer effect in the context of concurrent behaviour within JVM-based programs. Concurrent behaviour is especially fragile as task-scheduling ordering can change, which could even lead to deadlock via thread starvation under certain conditions. We analyse three dimensions of overhead, compute volume, memory volume, and uniformity, using a configurable-overhead tracer and a concurrency-performance analyser. We argue that uniformity is a key, and underappreciated, dimension of overhead that can have qualitative effects on program behaviour. Experimental results show that overhead significantly affects real-world concurrent behaviour and subsequent analysis, at times unintuitively.

CCS Concepts: • Software and its engineering → Software performance; Dynamic analysis; • Theory of computation → Concurrency; Program analysis; • General and reference → Performance; Measurement.

Keywords: Performance analysis and monitoring, Dynamic program analysis, Concurrency, Execution tracing

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1 Introduction

Execution tracing is used to capture precise and fine-grained data about a program's behaviour. These data can be used to better understand and optimise program behaviour and

to enable automatic program analysis. It is especially useful for performance analysis, which depends on data from real executions.

However, execution tracing naturally has an *observer effect* (also known as a *probe effect*); the act of tracing itself perturbs the behaviour being observed. This is caused by overhead incurred by tracing. The effect can be substantial enough that the recorded behaviour is significantly distorted from the untraced behaviour. Any analysis, manual or automatic, on sufficiently distorted data is inherently flawed and may lead to invalid conclusions.

There are many dimensions along which overhead can be evaluated, we consider three in particular:

Compute volume The amount of direct compute overhead (i.e. CPU cycles) introduced.

Memory volume The amount of memory consumed by the tracer. This indirectly incurs compute overhead by increasing page faults and can directly incur overhead if it consumes memory bandwidth in a bandwidth-constrained application.

Uniformity How uniformly overhead is incurred across threads (concurrent uniformity) and across time (temporal uniformity).

While all three inform the design of new execution tracers (such as which dimensions to prioritise for optimisation), they also elucidate the relative fragility of concurrent behaviour and analysis.

We argue that understanding the uniformity of overhead is essential to understanding its effect on program behaviour (Section 2). The common amortising mindset that “tracing adds $x\%$ overhead” is misguided as it does not account for the nuanced nature of overhead, instead assuming it is a consistent slow down of the program. Importantly, overhead can qualitatively affect a program's behaviour.

In this paper we investigate the effect of tracing-overhead on *program concurrent behaviour* – how and when a program uses concurrency – and execution duration in real-world Java programs. We also consider how distorted-behaviour in traces affects the accuracy and validity of subsequent concurrency-performance analysis. Various *metrics* are suitable for exploring the effect of the overhead dimensions above. We focus on four key metrics:

MTU Mean thread usage – effectively the integral of thread use over time, divided by total time.

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A-MTU Active threads MTU – *active* threads are those progressing computation at a given time.

W-MTU Waiting threads MTU – a thread is *waiting* when it is waiting on another thread to finish some work.

WCD Wall-clock duration of a program execution.

The key research questions addressed in this paper are:

1. How does the observer effect inherent in execution tracing affect program concurrent behaviour?
2. How do the various dimensions of tracing-overhead (compute, memory, and uniformity) differ in their effects?
3. How is subsequent concurrency-performance analysis affected by the observer effect?

To investigate these questions, we developed a low-overhead JVM tracer, *Covetr* (*Configurable OVERhead TRacer*), and augmented it to generate configured additional overhead (Section 3). To investigate the effect of tracing-overhead on subsequent program analysis we use a concurrency-performance analyser, *Rehype*, that we introduced in a previous paper [16] (summarised in Section 3.2).

Managed runtimes, and the JVM in particular, make it significantly easier to instrument and trace programs in a fast and safe way. Though native programs can be similarly instrumented, there is less available tooling and it is easier to introduce errors and inefficiencies. In particular, managed runtimes enable runtime instrumentation (e.g. during class loading), provide debug symbols (e.g. function signatures) by default, and (almost) automatically integrate inserted tracing code (e.g. JVM bytecode) into existing error handling and JIT compilation. Moreover, instrumentation tools can take advantage of greater runtime information (e.g. program state) to decide when and how to instrument and trace code.

Initial experimental results (Section 4) suggest that: the hypothesised observer effect does exist and can significantly affect concurrent behaviour; overhead dimensions vary in their effects; and increased overhead reduces analysis accuracy. While the results are specific to concurrent behaviour and concurrency-performance analysis, we suggest that the observer effect is broadly relevant to many forms of dynamic analysis.

The aim of this paper is to demonstrate the existence and relevance of the tracing observer effect on concurrent behaviour and analysis. We believe its relevance to dynamic analysis warrants further investigation. While the experimental evidence we present is a first step on this path of investigation, there is significant scope for further experimentation and analysis.

Finally, we position this paper among related work in Section 5 and conclude in Section 6.

2 Uniformity in Tracing

We wish to challenge an implied assumption in the statement “tracing adds $x\%$ overhead”, the assumption is that such

overhead does not significantly affect program behaviour, it merely slows the program (i.e. wall/user-clock duration) – as though the processor, memory, and I/O speed had all been equally slowed. Tracing-overhead is not equivalent to a slower processor, it is not uniform as the overhead is only incurred when events are traced and events are not traced uniformly. Thus, even given uniform per-event overhead, the impact of tracing-overhead will be non-uniform.

Furthermore, as tracing-overhead fundamentally interacts with the broader system, by consuming limited resources, it will have a greater impact at points of resource contention and bottlenecks. Any such impact is further amplified as points of contention have the greatest opportunity for distorting program behaviour.

Thus, while the apparent outcome of tracing may be $x\%$ longer execution duration, the qualitative effect on behaviour may be greater. For example, task-scheduling may be affected, which could, in the worst case, lead to deadlock via thread starvation¹. Similarly, increased overhead may cause a program to change modes of operation, e.g. an adaptive bitrate streaming system [19] choosing to degrade the quality of video segments. So, though $x\%$ might be acceptable in some instances (e.g. for non-performance-analysis applications, such as record/replay), it may not be so innocuous in other instances.

3 Method

In our experiments we use two systems: a configurable-overhead tracer and a concurrency-performance analyser.

3.1 Configurable-Overhead Tracer

Covetr is an execution tracer that takes in a *trace-config* and generates a *trace-log*. The trace-config specifies which functions of the target program should be traced. *Covetr* generates function and concurrency framework events (e.g. task-spawn events; other concurrency events, such as OS thread wait/wake, are not necessary as the task framework events provide sufficient information for our analysis). The vast majority of events generated are function-entry and -exit events. These contain a nanosecond time-stamp², a function identifier, and id for the thread that the event occurred on.

Covetr consists of two primary components, the *instrumenter* and the *tracer*. The instrumenter is essentially an aspect-oriented-programming tool that is configured by the trace-config. It intercepts class loading within the JVM and modifies class bytecode to insert tracing code. The tracer is an in-process utility that receives calls from tracing code and records corresponding events on disk as a trace-log.

¹<https://wiki.sei.cmu.edu/confluence/display/java/TPS01-J.+Do+not+execute+interdependent+tasks+in+a+bounded+thread+pool>

²We assume the system clock is monotonic and consistent across threads (i.e. time-stamps can be compared). However, our method does not rely on this (time-stamps are not used for ordering).

The tracer is designed for minimal overhead, prioritising low compute volume. To achieve this, it uses a client-server architecture with a single server and one client for each JVM thread. The clients generate logs of per-thread events and the server writes these to disk on a background thread. Logs are transferred using a bespoke *lockless buffer exchange protocol*.

Lockless buffer exchange. Each client uses two buffers, the *active* and *inactive* buffers. Each buffer has a boolean flag that indicates whether the client or the server has *control* of the buffer. The *active* buffer is always controlled by its containing client. Clients write new events to their *active* buffer. When a client's *active* buffer fills, the client attempts to swap its *active* and *inactive* buffers. If a client controls its *inactive* buffer, the buffers are swapped and the client sets the new *inactive* buffer to be controlled by the server. However, if a client's *inactive* buffer is controlled by the server when its *active* buffer fills, the client will expand its *active* buffer.

The server runs a periodic loop checking for client *inactive* buffers flagged as controlled by the server, when it finds one, it writes the buffer to disk. The server uses two further techniques to minimise occurrences of clients expanding their *active* buffers. First, the server can request specific clients swap their buffers before their *active* buffer reaches capacity. When a client generates an event, it checks its swap-request flag, if set, the client immediately swaps its buffers. Second, the server has an additional *exchange* buffer which is given to a client in place of its *inactive* buffer when the server takes the *inactive* buffer. This enables clients to swap their buffers, even if the server is still writing their *inactive* buffer to disk.

Configurable overhead. For this work, we extend the trace-config with an *overhead-config* specifying that additional synthetic overhead is to be incurred when recording an event – basically it is easier to add tracing-overhead than to remove it! The overhead-config can specify both additional *computation* (simulated by hash operations on a sequence of random bytes) and additional *memory allocation* (malloc) by the tracing process, and also whether allocation has a corresponding free (allocating but not freeing memory enables isolating the effect of memory overhead from the allocation compute overhead). Ideally, we would like to be able to configure *uniformity of tracing-overhead*, however, as a uniform baseline is not possible (Section 2), we instead experiment with uniformity by adjusting which functions are instrumented (Section 4.1).

3.2 Concurrency-Performance Analyser

Rehype [16] takes a *trace-log*, generated by *Covetr*, and produces suggestions as to how the program's concurrency might be refactored to improve performance (such as inlining a task to reduce the amount of time threads in the program spend waiting). We call these suggestions *changes*

and denote them using δ , here treated as maps from trace-logs to trace-logs.

Given a trace-log t , *Rehype* produces a set of changes Δ and an *estimated trace-log* $\delta(t)$, for each change $\delta \in \Delta$. These approximate the trace-log the program would generate with δ implemented on the source code. Then, given a performance metric μ and writing the value of μ for t as $\mu(t)$, *Rehype* calculates the estimated proportional improvement (EPI) of a change as:

$$\text{EPI}_{\mu}^{\delta}(t) = (\mu(\delta(t)) - \mu(t)) / \mu(t) \quad (1)$$

The experimental situation below is slightly more complex as we have a range of traces t obtained by varying *overhead-config* in the tracer.

4 Experimental Results

We perform experiments to investigate the three research questions (see Introduction). We define the various overhead configurations used in experiments in §4.1, describe the experimental metrics in §4.2, report on the experiments in §4.3, and discuss experimental limitations in §4.4.

To investigate the real-world effects of tracing-overhead, we perform all experiments on an industrial Java API server, *Acme*. *Acme* uses a task-based concurrency model (centred on substantial usage of Java's standard thread pool interface, *ExecutorService*), has approximately 500k LoC, and has been in production for five years. Experiments execute a synthetic series-of-requests workload which simulates the standard use of *Acme* on a non-loaded machine. This provides a consistent workload to evaluate the effects of various overhead configurations.

All experiments were run on a Linux benchmarking machine with specifications: Intel Core i7-8700 CPU @ 3.20GHz, 32GB RAM, Clear Linux OS [1] 34630. Intel TurboBoost was disabled, the CPU scaling_governor parameter was set to performance, and hyper-threading was enabled as it provides a more realistic basis for concurrency analysis. Software: Java OpenJDK 1.8.0_292, Rust 1.50.0-nightly (*Covetr* is implemented in Rust). Experiments were run using Docker [13] containers³, Docker version 20.10.6. Max JVM heap size was 8.36GB.

4.1 Configurations

We use two baseline configurations:

base: instruments only concurrency constructs (such as thread-pool and task events) necessary to capture concurrent behaviour.

³Docker containers simplify benchmark environment management and consistency. On Linux, Docker containers have been shown to have negligible impact on CPU and memory speeds [2] (unlike virtual machines).

std: standard, but unoptimised, configuration used by *Rehype* to identify changes for *Acme*. This configuration extends base by instrumenting all functions in *Acme* (i.e. the `com.acme` package, but not third-party library code).

We denote additional overhead configurations using their overhead type and volume (Section 3.1):

co-[x]: Extends `std` with *compute* overhead by performing [x] hashes on each event; e.g. `co-2` performs two hashes each event.

db-[x]: Add *compute* overhead by performing hashes on each event, as `co-[x]` does. However, unlike `co-[x]`, `db-[x]` only instruments third-party library functions that are primarily called during concurrent phases of *Acme* (specifically, database access functions) instead of those instrumented by `std`. We use this to demonstrate the effect of overhead during phases with greater concurrency.

ma-[x] and ml-[x]: Extends `std` with *memory* overhead by allocating [x] bytes on each event; `ma` immediately frees the memory, while `ml` does not. These allow experiments to isolate memory use effects from the compute overhead of allocation (§3.1).

4.2 Metrics

We evaluate experiments on summary metrics of thread usage and wall-clock duration (WCD) as the overhead configuration is varied. We calculate the mean thread usage (MTU) across an execution for all occupied threads, *active* threads (A-MTU), and *waiting* threads (W-MTU). A thread is occupied when it is processing a task (as opposed to being idle in a thread pool); it is *active* when it is progressing computation; it is *waiting* when it is paused waiting for the result of another task. We derive additional metrics below to further evaluate the effects of overhead.

Metrics μ are naturally defined on trace-logs t . However, our experiments only vary configurations c and not other inputs, hence it is convenient to regard μ also as functions of c . The same applies to EPI (§3.2).

Idea 1. We compare configurations c using the value of a metric relative to the base configuration (i.e. $\mu(c) / \mu(\text{base})$). These derived metrics provide a direct measure of the distortion caused to concurrent behaviour by configurations' overhead. We define the relative effect (RE) of a metric μ as the absolute distance of the metric to the base version. That is, given a configuration c , the μ -relative effect (μ -RE) is:

$$\mu\text{-RE}(c) = \left| \frac{\mu(c)}{\mu(\text{base})} - 1 \right| \quad (2)$$

The ratio of MTU-RE to WCD-RE (shown in Fig. 2b) is useful as a measure of the proportional effect on concurrency and duration:

$$\text{MTU-RE-to-WCD-RE-ratio}(c) = \text{MTU-RE}(c) / \text{WCD-RE}(c) \quad (3)$$

Idea 2. To evaluate the effect of overhead on *Rehype*'s analysis accuracy, we compare the EPI (Eq. 1) for changes that are identified by `std` (as base does not record enough data) and additional overhead configurations. Specifically, for a given configuration, we calculate the relative EPI (REPI) for each change both it and `std` identify and then take the mean REPI (MREPI) across all such changes. In short, MREPI diverging from 100% indicates overhead is affecting analysis accuracy (REPI represents the affect on accuracy for a single metric).

Assuming metric μ , we write Δ^c for the changes identified by *Rehype* in a trace-log under overhead configuration c , and define $\Delta = \Delta^c \cap \Delta^{\text{std}}$. The REPI of change $\delta \in \Delta$ indicates the reduction in accuracy for that change caused by the configuration's overhead:

$$\text{REPI}_\mu^\delta(c) = \text{EPI}_\mu^\delta(c) / \text{EPI}_\mu^\delta(\text{std}) \quad (4)$$

The MREPI is then the average reduction in accuracy caused by the overhead over common changes Δ :

$$\text{MREPI}_\mu(c) = \frac{1}{|\Delta|} \sum_{\delta \in \Delta} \text{REPI}_\mu^\delta(c) \quad (5)$$

Idea 3. Finally, the time-series metric of thread usage over a program execution (its *concurrent profile*) is useful to illustrate concurrent behaviour; its graphical form gives the shape of concurrency throughout an execution – i.e. when and how many threads are used. Two executions of the same program, with the same input and environment, should have almost identical concurrent profiles in the absence of overhead; Fig. 1b shows the concurrent profiles of three executions of *Acme*, under different overhead configurations.

4.3 Experiments

We devise separate experiments for each research question (see Introduction). The key takeaway is that: tracing-overhead can significantly distort program behaviour (to amplify or suppress concurrency), even when execution duration is largely unaffected.

RQ.1. How does the observer effect inherent in execution tracing affect program concurrent behaviour? To investigate this question we use the plainest form of overhead, compute volume, and correlate it with a change in MTU, reflecting a distortion to the program's concurrency. This correlation is illustrated in Fig. 1a (all raw values are provided in Table 1). The figure also shows that, for *Acme*, increased overhead decreases the MTU – making the program *appear* less concurrent. It is important to understand that while *Acme* does *behave* less concurrently (a greater proportion of the execution is spent on a sequential phase) given overhead, this is not reflective of its behaviour in a normal state without overhead (thus it merely *appears* less concurrent).

The intuition behind the reduction in apparent concurrency is that a particular sequential phase of execution within

Figure 1. The effect of compute overhead on program concurrent behaviour. All configurations were executed 20 times.

Acme generates more trace events and thus incurs more overhead. This is shown in Fig. 1b; the co-1k profile has an amplified sequential phase (approximately between 30% and 95% of the execution progress), while the base and std profiles appear more concurrent throughout. In those profiles, tracing incurs less overhead and so does not amplify the sequential phase as significantly.

Fig. 1a also illustrates how concurrency distortions can affect the apparent concurrent efficiency of a program. The W-MTU decreases more than the A-MTU, suggesting (if taken at face value) that the program is more efficiently using concurrency (as *waiting* threads are an inefficient use of resources [16]), than it does when executed without overhead.

Finally, Fig. 1c illustrates the change in maximum recorded concurrent thread use (MaxTU) due to overhead. A MaxTU change results from a task-scheduling change. This reflects a qualitative effect on program behaviour due to overhead. Note that the effect is not monotonic (though it appears so for the db-* configurations due to the increased overhead on background threads), rather, qualitative effects can be chaotic.

RQ.1. Answer: the observer effect can significantly distort the concurrent behaviour of a program. Furthermore, overhead can have qualitative effects that are not monotonic.

RQ.2. How do the various dimensions of tracing-overhead (compute, memory, and uniformity) differ in their effects? We discuss this question in two parts: (i) the subtleties between compute and memory overhead; and (ii) uniformity and its fundamental nature. The difference between compute and memory overhead is primarily exhibited by the difference between MTU and WCD. The effect on MTU is bounded, while the effect on WCD is not.

Given a maximum recorded concurrent thread use MaxTU such that $\text{MaxTU} > 1$, the MTU is always less than it and greater than 1 (if the program does not deadlock), i.e. for a given configuration c , $1 < \text{MTU}(c) < \text{MaxTU}$. Moreover, the effect of increasing or decreasing overhead begins to level

off as it nears these bounds. This effect is seen in Figs. 1a, 2a, and 2c.

The WCD metric, however, has no such bound, it can continue to increase indefinitely (though it can never go negative). In fact, WCD-RE naturally accelerates as overhead increases and becomes the bottleneck in the program's execution, this is seen in Fig. 2d. The fact that co-* and db-* configurations affect duration significantly is unsurprising as they directly add to the compute time. What is interesting, however, is that ml-* configurations do not show the same significant increase in WCD, despite it having levels of MTU-RE equivalent to the db-* configurations. This difference is seen in the ratio of MTU-RE to WCD-RE (Fig. 2b).

We have argued that overhead **uniformity** cannot exist (Section 2). Yet, demonstrating the effect of uniformity in isolation would require a uniform baseline. A purely-uniform baseline cannot exist and a practically-uniform baseline cannot practically exist (practical uniformity could be constructed in a toy example, but not in a real-world system). As such, we must instead observe the effect of uniformity in other experiments, such as Fig. 1b. Here, the std and co-1k configurations track the same functions, however, the functions are not uniformly invoked across the execution. As co-1k incurs greater overhead, its profile shows that the functions are disproportionately invoked in the sequential phase.

Uniformity, as a dimension of overhead, is important to consider as it intrinsically affects the behavioural distortion caused by overhead. It is present in all of our experiments as it determines where overhead is incurred. While the experiments so far have depressed concurrency (relative MTU less than 100%) the inverse distortion, an apparent increase in overall concurrency (relative MTU greater than 100%), can also be observed. For example, Fig. 2c shows the MTU for db-* configurations. These configurations increase the apparent concurrency by adding overhead to database access functions, which *Acme* primarily calls in background threads.

Figure 2. The effect of various overhead configurations. All configurations were executed 20 times.

Whether distortion amplifies or depresses concurrency depends on which functions in the program generate the most trace events and when/where they are called (in concurrent or sequential phases). While this could, theoretically, result in uniformity if all threads produce identical events and overhead is perfectly uniform, such a scenario is unrealistic. In real programs, the number of events traced on each thread (concurrent uniformity) and at different times (temporal uniformity) will vary substantially causing overhead to be non-uniform (let alone naturally occurring non-uniformity due to tracing environment (e.g. cache behaviour)). Hence, in real programs, increased overhead correlates directly to increased concurrent behaviour distortion (i.e. increased MTU-RE).

RQ.2. Answer: increased compute and memory overhead correlates to increased MTU-RE and WCD-RE (though they are not proportional to each other), while uniformity controls the *shape* of the concurrent distortion. However, it is impractical to experimentally isolate overhead uniformity in real-world systems.

RQ.3. How is subsequent concurrency-performance analysis affected by the observer effect? Increased overhead reduces the accuracy of *Rehype*'s estimations (Section 3.2). Fig. 3 illustrates this via two charts. The first (Fig. 3a) illustrates the reduced accuracy of estimations as the MREPI (Eq. 5) of multiple performance metrics (MTU, A-MTU, W-MTU, and duration) for three ml-* and co-* configurations⁴. The second (Fig. 3b) shows the percentage of changes identified for the std configuration that were identified by other configurations. The change in the set of identified changes

(a) The effect of overhead on *Rehype*'s estimation accuracy (Eq. 5). Note that A-MTU and WCD overlap almost entirely.

(b) The percentage of changes identified for the std configuration that are also identified for other configurations (i.e. $|\Delta^c \cap \Delta^{\text{std}}| / |\Delta^{\text{std}}|$ for a given configuration c).

Figure 3. The effect of overhead on *Rehype*'s analysis. All configurations were executed 20 times.

for configurations with additional overhead represents a qualitative effect on the analysis. This shows that overhead can have a qualitative effect on concurrent behaviour (task-scheduling Fig. 1c) and, separately, a qualitative effect on subsequent analysis.

The effect of overhead is compounded in estimated trace-logs (§3.2), as they inherit both the behaviour distortions

⁴The db-* configurations are omitted as they do not instrument enough functions for *Rehype* to identify changes.

from the trace-log they are based off and the reduced accuracy of estimation due to overhead. The end result is an estimate of program behaviour, for a given change, that is far from the real behaviour the program would exhibit with the change implemented and zero tracing overhead. This results in developers having reduced (human) confidence in the validity of the estimations which can lead to reduced adoption of changes (even if they are, in fact, beneficial).

That being said, we find that, generally, *Rehype* is able to identify many changes as beneficial (in binary terms) despite the concurrency distortions. We hypothesise that this is due to the relative-improvement approach of *Rehype*'s analysis.

RQ.3. Answer: analysis accuracy decreases as overhead increases, which matches intuition. This has been experimentally shown for *Rehype* and we suspect it holds for other analysis tools.

4.4 Limitations

These experimental results are limited to a single system *Acme*, running a single simulated workload, using four base metrics (MTU, A-MTU, W-MTU, and WCD), and analysed by *Rehype*. We argue that evaluation of tracer overhead to understand its various dimensions is important and that we have presented some initial results in these experiments. Future work should provide further rigour by evaluating more real-world systems, more program behaviour metrics, and more dynamic analysers.

5 Related Work

The observer effect has been previously studied in relation to performance analysis by Mytkowicz et al. [14] and synchronisation errors by Gait [3]. Mytkowicz et al. analysed how it can perturb performance data and system measurements so that a manual analysis (by a “performance analyst”) may draw incorrect conclusions. Gait investigated how it modifies the frequency of occurrence of synchronisation errors in concurrent programs (inserting variable length delays affects when (and whether) synchronisation errors occur). Our work differs in that we specifically consider concurrent behaviour distortions and the effect on automatic concurrency-performance analysis.

More broadly we consider three areas of related work: various major strands of dynamic capture tools; tracing tools that treat overhead as a first-class problem; and research that investigates the effect of overhead in related domains.

Dynamic capture tools vary in the patterns and volumes of overhead incurred. At one end are profiling tools (e.g. *perf* [10] and *Flight Recorder* [8]), which perform low-overhead periodic sampling to provide a rough snapshot of program performance behaviour; incurring small amounts of periodic overhead. At the other end are execution control systems (e.g. *PIN* [7]) that run programs in a managed environment and intercept CPU instructions; incurring large

amounts of overhead constantly. In between there are: 1) kernel instrumentation tools (e.g. *DTrace* [5] and *BPFs* [4]) which insert probes in the Linux kernel to trace kernel events; 2) high-level tracing tools (e.g. *Ruby Tracer* [18]) which incur greater overhead to provide a simpler developer interface; and 3) dynamic instrumentation tools (e.g. *Valgrind* [15]) that incur high overhead (*nullgrind*, a minimal *Valgrind* configuration, has been reported [17] to incur more than 5x overhead on average) but provide a fine-grained tool for analysis of program behaviour, similar to execution control systems. In terms of overhead, *Covetr* exists between kernel instrumentation tools and high-level tracing tools, it traces more information than kernel tools, but is significantly more optimised than high-level tracers.

Mashtizadeh et al. [12] present *Castor* (a record/replay system) and Payer et al. [17] present *memTrace* (a memory tracing system), both are examples of systems that treat **overhead as a first-class problem**. Both leverage OS and hardware acceleration to achieve low overhead. For example, Payer et al. trace 32-bit code in 64-bit architectures, allowing *memTrace* to use an additional 2^{32} memory addresses beyond those that are used by the target program, as well as the extra registers available in *x86_64* (over *x86*), meaning that the tracer and program operate on disjoint registers and memory regions. *Castor*, along with numerous hardware acceleration techniques, achieves low-overhead by being selective in what it records. Specifically, they only record sources of non-determinism (such as system calls). This is a key difference between *Castor* and *Covetr*; *Covetr* must record even deterministic events (e.g. function entry and exit) to capture enough performance information to accurately estimate the effect of changes and enough program information to identify sensible source-level changes.

Finally, the effect of **various forms of overhead** has been investigated in other fields. For example, the effect of cache overhead on allocation-heavy programs (Grunwald et al. [6]) and sorting algorithms (LaMarca and Ladner [9]), the effect of network overhead on cluster computing (Martin et al. [11]), and the impact of address translation on performance (Zhou et al. [20]).

6 Conclusion

Execution tracers have an observer effect: the act of capturing data perturbs the data captured. Tracing overhead has numerous dimensions, we considered three: compute, memory, and uniformity. Experimental results show tracing-overhead distorts the concurrent behaviour of a program, quantitatively and qualitatively, and can affect the accuracy and validity of subsequent analysis. Fundamentally, uniformity cannot exist in tracing and non-uniformity must be accepted, understood, and mitigated in execution tracers.

Table 1. Experimental data. (All values are relative to the base configuration; “90% $\pm$ 1.60%” indicates a mean of 90 with a standard deviation of 1.60.)

	Config.	MTU	A-MTU	W-MTU	WCD
Baseline configurations	base	100.00% $\pm$ 0.92%	100.00% $\pm$ 0.99%	100.00% $\pm$ 1.20%	100.00% $\pm$ 0.94%
	std	90.53% $\pm$ 1.60%	96.87% $\pm$ 1.38%	86.34% $\pm$ 2.24%	114.16% $\pm$ 3.67%
co-* configurations	co-2	86.26% $\pm$ 1.39%	95.37% $\pm$ 1.28%	80.22% $\pm$ 2.25%	129.05% $\pm$ 6.02%
	co-5	79.48% $\pm$ 2.92%	94.24% $\pm$ 1.97%	69.70% $\pm$ 3.76%	145.36% $\pm$ 11.12%
	co-10	74.78% $\pm$ 2.39%	92.85% $\pm$ 1.38%	62.81% $\pm$ 3.54%	164.93% $\pm$ 12.04%
	co-20	66.17% $\pm$ 1.12%	89.49% $\pm$ 0.70%	50.73% $\pm$ 1.87%	210.15% $\pm$ 7.78%
	co-50	53.50% $\pm$ 1.32%	85.17% $\pm$ 0.64%	32.53% $\pm$ 1.93%	342.26% $\pm$ 25.47%
	co-100	45.64% $\pm$ 0.46%	82.74% $\pm$ 0.41%	21.08% $\pm$ 0.78%	552.55% $\pm$ 21.35%
	co-200	40.70% $\pm$ 0.37%	81.08% $\pm$ 0.22%	13.96% $\pm$ 0.61%	970.68% $\pm$ 10.87%
	co-500	36.69% $\pm$ 0.19%	80.11% $\pm$ 0.23%	7.94% $\pm$ 0.34%	2251.81% $\pm$ 9.67%
	co-1k	35.32% $\pm$ 0.11%	79.88% $\pm$ 0.12%	5.81% $\pm$ 0.15%	4384.03% $\pm$ 10.16%
ma-* and ml-* configurations	ma-50	89.01% $\pm$ 1.84%	96.33% $\pm$ 1.94%	84.17% $\pm$ 2.22%	116.81% $\pm$ 3.76%
	ma-100	89.68% $\pm$ 1.53%	96.06% $\pm$ 1.31%	85.45% $\pm$ 2.00%	116.17% $\pm$ 2.95%
	ma-200	89.02% $\pm$ 1.07%	95.84% $\pm$ 0.96%	84.50% $\pm$ 1.62%	115.69% $\pm$ 2.73%
	ma-500	89.53% $\pm$ 1.92%	97.04% $\pm$ 2.10%	84.57% $\pm$ 2.10%	117.00% $\pm$ 4.28%
	ma-1k	89.43% $\pm$ 1.42%	96.35% $\pm$ 1.15%	84.85% $\pm$ 1.91%	117.99% $\pm$ 3.01%
	ma-2k	87.69% $\pm$ 1.61%	95.10% $\pm$ 1.66%	82.80% $\pm$ 2.22%	122.57% $\pm$ 3.84%
	ma-5k	87.63% $\pm$ 1.54%	95.72% $\pm$ 1.67%	82.28% $\pm$ 2.04%	121.79% $\pm$ 4.75%
	ma-10k	87.08% $\pm$ 1.17%	95.54% $\pm$ 1.63%	81.49% $\pm$ 1.62%	121.21% $\pm$ 3.86%
	ma-20k	87.41% $\pm$ 1.18%	95.77% $\pm$ 1.59%	81.88% $\pm$ 1.46%	121.08% $\pm$ 5.26%
	ma-50k	87.50% $\pm$ 0.96%	95.64% $\pm$ 1.29%	82.12% $\pm$ 1.31%	122.41% $\pm$ 5.23%
	ma-100k	88.13% $\pm$ 1.33%	95.53% $\pm$ 1.15%	83.24% $\pm$ 2.07%	119.80% $\pm$ 3.46%
	ma-200k	87.43% $\pm$ 1.63%	95.80% $\pm$ 1.50%	81.90% $\pm$ 2.47%	121.01% $\pm$ 5.03%
	ma-500k	87.49% $\pm$ 1.10%	95.87% $\pm$ 1.37%	81.96% $\pm$ 1.29%	118.74% $\pm$ 4.13%
	ml-50	88.00% $\pm$ 1.73%	95.82% $\pm$ 1.81%	82.83% $\pm$ 2.09%	120.06% $\pm$ 4.21%
	ml-100	86.87% $\pm$ 1.85%	95.26% $\pm$ 1.49%	81.33% $\pm$ 2.48%	121.09% $\pm$ 4.83%
	ml-200	86.94% $\pm$ 1.65%	95.65% $\pm$ 2.17%	81.18% $\pm$ 2.10%	126.00% $\pm$ 5.58%
	ml-500	84.73% $\pm$ 1.88%	95.81% $\pm$ 1.50%	77.41% $\pm$ 2.61%	132.06% $\pm$ 5.67%
	ml-1k	80.28% $\pm$ 2.28%	94.42% $\pm$ 1.67%	70.93% $\pm$ 3.28%	144.29% $\pm$ 8.91%
	ml-2k	74.63% $\pm$ 1.25%	92.21% $\pm$ 1.42%	63.00% $\pm$ 2.23%	161.66% $\pm$ 6.11%
	ml-5k	66.35% $\pm$ 1.96%	89.12% $\pm$ 0.82%	51.30% $\pm$ 3.10%	202.27% $\pm$ 6.28%
	ml-10k	65.88% $\pm$ 1.84%	89.10% $\pm$ 1.09%	50.53% $\pm$ 2.69%	206.75% $\pm$ 15.52%
	ml-20k	65.98% $\pm$ 1.35%	89.09% $\pm$ 0.88%	50.71% $\pm$ 2.20%	202.13% $\pm$ 7.85%
	ml-50k	65.83% $\pm$ 1.19%	89.05% $\pm$ 0.86%	50.48% $\pm$ 1.97%	201.92% $\pm$ 8.20%
	ml-100k	65.89% $\pm$ 1.51%	89.10% $\pm$ 1.02%	50.55% $\pm$ 2.40%	205.33% $\pm$ 8.27%
	ml-200k	64.80% $\pm$ 1.84%	88.40% $\pm$ 0.83%	49.20% $\pm$ 2.82%	207.58% $\pm$ 8.52%
	ml-500k	63.08% $\pm$ 1.98%	87.86% $\pm$ 0.97%	46.69% $\pm$ 2.95%	221.45% $\pm$ 18.00%
db-* configurations	db-10	104.49% $\pm$ 1.45%	104.62% $\pm$ 1.12%	104.40% $\pm$ 2.01%	109.90% $\pm$ 1.12%
	db-20	108.82% $\pm$ 1.82%	110.72% $\pm$ 1.50%	107.56% $\pm$ 2.73%	119.25% $\pm$ 1.18%
	db-50	113.13% $\pm$ 1.56%	115.79% $\pm$ 1.10%	111.36% $\pm$ 2.22%	143.31% $\pm$ 2.98%
	db-100	116.58% $\pm$ 1.92%	118.97% $\pm$ 1.30%	115.00% $\pm$ 3.19%	181.33% $\pm$ 2.70%
	db-200	116.38% $\pm$ 2.12%	116.07% $\pm$ 1.75%	116.58% $\pm$ 2.92%	256.41% $\pm$ 11.48%
	db-500	120.81% $\pm$ 2.34%	114.65% $\pm$ 1.47%	124.88% $\pm$ 3.26%	443.83% $\pm$ 4.31%
	db-1k	123.61% $\pm$ 2.17%	114.08% $\pm$ 1.42%	129.92% $\pm$ 3.18%	772.98% $\pm$ 12.43%
	db-2k	128.35% $\pm$ 1.17%	113.17% $\pm$ 0.50%	138.39% $\pm$ 1.99%	1418.88% $\pm$ 11.30%
	db-5k	130.97% $\pm$ 0.20%	113.52% $\pm$ 0.23%	142.51% $\pm$ 0.22%	3388.99% $\pm$ 14.55%
	db-10k	130.82% $\pm$ 0.46%	112.63% $\pm$ 0.20%	142.85% $\pm$ 0.70%	6667.10% $\pm$ 37.46%

Furthermore, we have argued that uniformity is an essential, and understudied, dimension of overhead that warrants further investigation.

In future work we plan to evaluate tracing-overhead on more real-world programs and against more metrics. We also plan to investigate how tracing-overhead can qualitatively affect application functionality, such as in adaptive video streaming where overhead may cause video quality negotiation to have a different outcome.

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