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Abstract

Performance and Dynamism in User-extensible Compiler Infrastructures

MLIR is a modular compiler framework that provides core infrastructure to be leveraged and extended by users implementing their own compilers, an inherently dynamic design as a result of the underlying heterogeneous data structure whose shape is known only at runtime. This approach presents an inherent optimization boundary, as the dynamic structures cannot be precisely reasoned about before runtime to guarantee the validity of optimisations, meaning static ahead-of-time compilation provides fewer benefits. Previous compiler frameworks accept the limitations of this optimization boundary, leveraging only the remaining optimizations offered by static ahead-of-time compilation, yet still incurring the costs of long build times and reduced flexibility, suggesting dynamic languages might be more suitable. We examine performance bottlenecks incurred by dynamic languages for code rewriting tasks in xDSL, a Python-native compiler framework inspired by MLIR. We find that both the inherent dynamism of these rewriting tasks over runtime heterogeneous data structures and modern interpreter optimisations narrow the performance gap between static and dynamic languages, using both traditional measurement techniques and a novel tool for performance profiling bytecode instructions. Our research challenges the status quo of implementing user-extensible compiler frameworks in static, ahead-of-time compiled languages. Instead, we motivate the use of dynamic languages, demonstrating that they balance compilation performance with the flexibility and fast build times.

Contents

List of Abbreviations

FFI Foreign Function Interface. 38, 61

GCC GNU Compiler Collection. 16

GEMM General Matrix Multiply. 18, 57

GIL Global Interpreter Lock. 35

IR Intermediate Representation. 8, 12, 14, 16, 17, 22–27, 29, 44, 46, 49, 56, 60

IRDL Intermediate Representation Definition Language. 17, 41

JIT just-in-time. 11, 19, 32, 51–53, 63

MLIR Multi-Level Intermediate Representation. 8, 9, 11–13, 16, 17, 21–30, 39–48, 54, 56–61, 63, 64

PEP Python Enhancement Proposal. 49, 51

PyPI Python Package Index. 32, 33, 38

RISC Reduced Instruction Set Computer. 16, 56

RTTI Run-time Type Information. 9, 43, 57

SSA Static Single Assignment. 12, 16, 18

VM Virtual Machine. 49

vtable Virtual Method Table. 55, 56

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Chapter 1

Introduction

Compilers are a critical component of computing systems, providing an abstraction from high-level programming languages to the underlying machine ISA. Released in 1987, `gcc` was a popular open-source compiler [1], but its monolithic and tightly-coupled design impacted its re-usability. The LLVM compiler framework [2] addressed these problems with a human-readable and language-independent textual IR in Static Single Assignment (SSA) form [3], which could be analysed and transformed by a sequence of passes, made available as a re-usable C++ library. Recently, MLIR [4], has furthered these goals by enabling users to cheaply extend compilers with their own abstractions.

Compiler extensibility is critical for handling the heterogeneous hardware and exotic optimisations of modern workloads. To implement this, MLIR uses dynamic, pointer-chasing data structures and algorithms to represent its IR. For example, pattern rewriting in MLIR traverses and pattern matches on a linked list representation of SSA values. This further inhibits optimisations, both as a result of dynamism and not being amenable to other transformations such as vectorisation. These factors motivate challenging the status quo of LLVM and MLIR implementing user-extensible compiler frameworks in static, ahead-of-time compiled languages.

xDSL [5] is a reimplementation of MLIR's core data structures and IR definitions in Python, a dynamically typed, interpreted language. Using Python allows xDSL to take MLIR's goal of user extensibility to even further extremes by leveraging its dynamic features such as runtime meta-programming. In addition to this, xDSL's interpreted nature avoids MLIR's long build times, and its dynamic typing matching the dynamic nature of the user-extensible compiler framework workload. However, using Python also has drawbacks, most notably in relation to runtime performance. This work examines the performance of the pattern rewriting component of the xDSL compiler framework, focussing on the impact of dynamism and contrasting against the current state-of-the-art, MLIR.

The performance of a program is constrained both by the details of its implementation and the runtime of its language. These two properties are deeply interlinked, making

them difficult to measure independently. To disentangle them, we manually optimise and specialise xDSL's implementation of pattern rewriting (Figure 1.1, ①), resulting in an 7× performance uplift. We then confirm that the performance of the specialisation is constrained only by the language runtime by examination of the dispatched bytecode of micro-benchmarks. This bytecode examination process revealed a gap in the provision of fine grained performance profilers for Python. To address this gap, we developed ByteSight, native tracing performance profiler for Python bytecode. We then use this tool to quantify the impact of recent performance enhancements made to CPython for this specialised implementation (Figure 1.1, ②). This describes the best-case for the performance of pattern rewriting in xDSL, which can then be compared against MLIR.
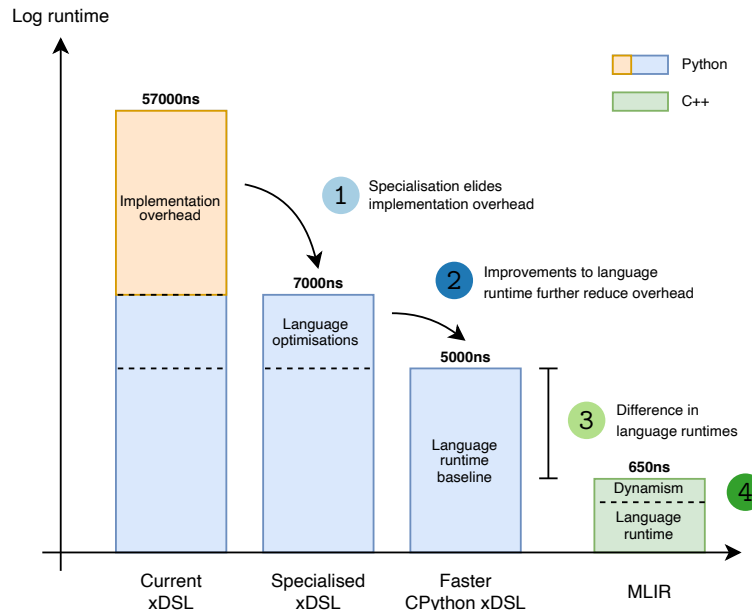
Figure 1.1: Closing the gap between xDSL and MLIR pattern rewriting performance. xDSL's performance can be improved by changes to both its implementation and language runtime. C++ has less of a performance advantage for MLIR than other workloads due to the costs associated with dynamism.

A key difference between the Python and C++ runtimes is their degree of language dynamism. MLIR's C++ runtime incurs overhead when dynamically dispatching functions (Figure 1.1, ③), which is worsened by prohibiting ahead-of-time performance optimisations. In contrast, almost every bytecode operation evaluated by the Python interpreter is dynamic, each incurring an overhead checking runtime information. As such, we expect the difference in performance between language runtimes (Figure 1.1, ④) to be smaller for more dynamic workloads. To corroborate this, we measure the difference in performance between pattern rewriting workloads using xDSL and MLIR, and assess the contribution of overheads incurred by dynamism. This measurement procedure uniquely leverages

xDSL's sidekick compilation functionality to ensure the comparability of performance measurements by driving them with the same textual IR, even for implementation details internal to each framework. Finally, we critically evaluate the degree to which this motivates the use of Python for implementing user-extensible compiler frameworks.

The contributions of our work are as follows:

- An examination of the current performance of pattern rewriting workloads in the CPython language runtime (chapter 3).

- A tool to examine CPython bytecode dispatch in program runs, facilitating the analysis of costs incurred by dynamism (chapter 4).

- A specialisation of the current xDSL implementation for pattern rewriting workloads, demonstrating the best-case performance of CPython for such applications (chapter 5).

- An exploration of optimisation techniques to shrink the performance gap between dynamic and static languages for pattern rewriting workloads (chapter 6).

- A quantitative comparison of the performance of user-extensible compiler frameworks implemented in static and dynamic languages, focussing on the impact of dynamism (chapter 7).

Chapter 2

Background

Compilers are the interface between application code and the underlying hardware on which it is executed. With the end of Dennard scaling and the slow-down of Moore's law [6], the design of computer hardware increasingly relies on heterogeneous accelerator hardware to achieve performance goals within power and area budgets [7]. This has been accompanied by a stratospheric increase in the amount of compute being used for the training and inference of large machine learning models [8]. Together, these two factors make the development of compilers which can perform high-level optimisations and target exotic accelerator hardware critical for delivering the performance goals of modern applications. Since both the optimisations and underlying hardware are fast-changing, the development velocity of the compiler is crucial to deliver state-of-the-art models with delay (Figure 2.1) [9]. This motivates the development of shared compiler infrastructure which increases development velocity, for example by having short build times, a simple syntax, and a convenient API.
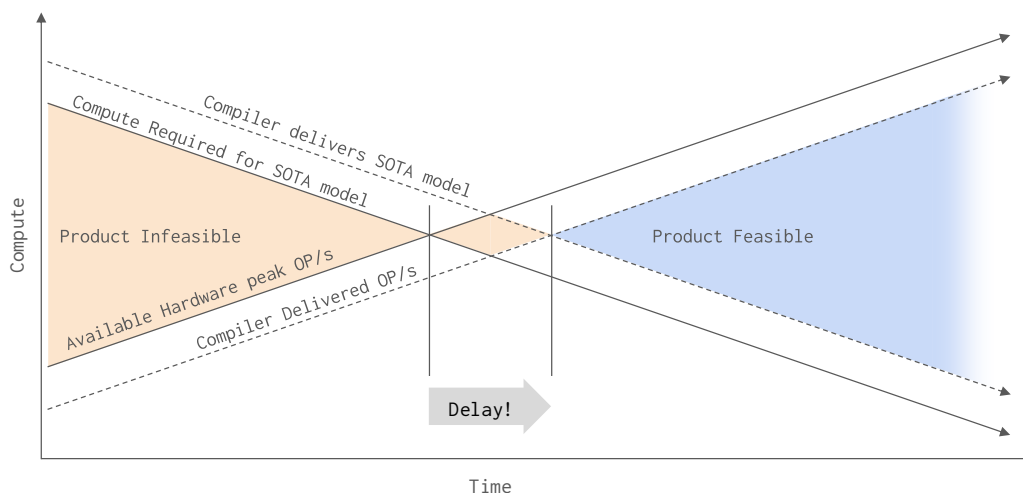
Figure 2.1: Compilers are lagging behind the development of both machine learning hardware and workloads. Figure created by Anton Lydike based on a slide from Sean Silva's talk at the March 2025 Cambridge Compiler Social.

Early compilers such as Grace Hopper's A0 and the ALGOL compiler were standalone programs, specific to individual languages [10]. Researchers then generalised these standalone programs into shared infrastructure, for example with the SUIF project [11]. The GNU Compiler Collection (GCC) project adopted these ideas, providing a popular and open-source shared infrastructure for the compilers of several languages, including C, C++, and FORTRAN. However, its monolithic and tightly-coupled design limited the reusability of its components [1], presenting a research gap in the field.

2.1   The LLVM project

In 2004, Lattner and Adve published "LLVM: A Compilation Framework for Lifelong Program Analysis and Transformation" [2], productising a collection of good ideas in compiler design. One of LLVM's key contributions was a human-readable textual IR, contrasting the binary IRs of `gcc` at the time. This IR has a language- and target-independent RISC-like instruction set in SSA form [3], making LLVM re-usable across different frontends and backends, while benefitting from shared infrastructure. Modular transformation passes can be defined to modify this IR. These passes can be composed to implement sophisticated optimisation pipelines, as each pass operates on the same IR structures. These desirable properties lead to LLVM's widespread adoption, but the demands of modern workloads present a number of challenges for LLVM. For example, LLVM's low-level IR is not well suited to abstract over the high-level operation rewrites required to optimise machine learning workloads. In addition to this key infrastructure such as parsing and printing must be implemented by hand, slowing development velocity.

2.2   Multi-level intermediate representation (MLIR)

Multi-Level Intermediate Representation (MLIR) addresses these modern challenges, providing "compiler infrastructure for the end of Moore's law" [4]. Its key contribution is allowing users to easily define multiple levels of abstraction supporting heterogeneous recursively nested structures, referred to as dialects. This contrasts the fixed low-level abstractions and homogeneous flat structures of LLVM IR, whose shape is known at runtime, resulting in less dynamic dispatch and control flow. As a result of this, MLIR allows different problem domains to define their own operations and transformation passes while sharing common infrastructure. This facilitates efficiently expressing optimisations at the most appropriate abstraction level, which can then each be applied, lowering from high-level domain-specific representations to low-level hardware-specific ones. Lowering leverages pattern rewriting, a declarative way to express transformations as patterns which match IR constructs and replace them with lowered versions. Traits abstract across properties shared by IR components [12], facilitating these user-extensible pattern rewrites on custom dialects. The provision of common infrastructure including documentation

generation, parsing and printing logic, and location tracking further reduces the engineering effort required to develop complex optimisations and support custom hardware targets.

MLIR is implemented in C++, providing desirable performance characteristics, but having a verbose syntax and long build times. This is partially mitigated by Intermediate Representation Definition Language (IRDL), "a domain-specific language to define IRs" [13], implemented as a SSA-based dialect of MLIR. IRDL provides a declarative system for defining dialects, operations, and types which can be dynamically loaded at runtime.

2.3 xDSL

xDSL is a Python-native compiler framework, originally written as a re-implementation of MLIR's data structures and associated logic. As a result of its similar data structures and shared textual IR, xDSL can be used as a side-kick compiler for MLIR, facilitating modular replacement of individual components of its pipeline. This is achieved with a DSL implementation in Python of IRDL. In contrast to MLIR, xDSL prioritises developer productivity through Python's easy-to-use syntax and fast build times, along with first-class support for user-extensibility which allows adding new operations at runtime. This design choice has benefits for modern compiler developers, where improvements to developer productivity are critical to minimise delay for state-of-the-art workloads (Figure 2.1).

2.4 Dynamic languages and workloads

Programming language design is a game of trade-offs, with a wide variety of design choices incurring differing benefits and costs. One such choice is the degree of dynamism, defined by Williams et al. as "allowing properties of programs to be defined at run-time" [14]. As such, static languages fix properties ahead of time, whereas dynamic languages offer more flexibility at runtime. These trade-offs for features including dynamic dispatch and runtime meta-programming are discussed in the literature (Related work, section 8.3).

In addition to considering support for dynamism as a property of a programming language, it can be helpful to classify a workload as dynamic or static. For example, General Matrix Multiply (GEMM) operations which underpin modern machine learning systems rely on streaming data in a statically known order. This is well-suited to ahead-of-time compilation, as it is amenable to optimisation passes requiring no runtime information, such as code motion or vectorisation [15]. In contrast, pattern rewriting in user-extensible compiler frameworks relies on pointer chasing data structures with a high degree of dynamism. The SSA representation of the code being rewritten is structured as a doubly linked list, with the applications of the rewriting semantics to this list known only dynamically at runtime. This dynamic, pointer-chasing workload is inherently memory bound, having irregular access patterns with high latencies [16]. As such, optimisations to computational

throughput have minimal impact on overall performance, as the bandwidth ceiling upper bounds performance [17]. Furthermore, it precludes many optimisations leveraged by ahead-of-time statically compiled languages such as C++ to accelerate their performance for other workloads.

2.5   CPython internals

Python is a high-level, dynamically typed-checked programming language, known for its readable syntax and extensive library support [18]. The language has many implementations, from its reference implementation, CPython, to alternatives such as PyPy's JIT compiler [19]. CPython operates by compiling Python source code into a stack-based bytecode. This bytecode is executed by a virtual machine in an interpreter loop, fetching and evaluating the compiled sequence of instructions one at a time. This approach limits performance compared with static ahead-of-time compiled languages by the overhead of the virtual machine and having fewer opportunities for ahead-of-time optimisation. However, it also provides great flexibility, supporting Python's dynamic type system and runtime meta-programming capabilities. The Faster CPython project is an ongoing effort to improve the performance of Python by applying techniques such as adaptive optimisation and JIT compilation. For such efforts, it is critical to have a suite of programs with which to benchmark performance. In Python, this is provided by PyPerformance, "an authoritative source of benchmarks for all Python implementations" [20].

2.6   JIT compilation

In their paper "A Brief History of Just-In-Time", Aycock defines just-in-time (JIT) compilation as "translation that occurs after a program begins execution" [21]. He argues that JIT compilation approaches aim to accrue the benefits of both ahead-of-time compilation and interpretation, combining the performance traditionally associated with compilation with the portability and access to runtime information of interpretation.

2.6.1   JIT compilation to machine code

While just-in-time (JIT) compilation can refer to any program translation occurring at runtime, it often refers specifically to the dynamic generation of machine code just before execution. Compilation during runtime exposes information from actual program behaviour which is not available to traditional ahead-of-time compilers. This allows JIT compilers to optimise the generated machine code, and unblocks the optimisation of dynamic runtimes for which there is insufficient information to optimise ahead-of-time.

A major bottleneck for traditional JIT compilation is the speed of compiler optimisation passes, which can lead to delays during program execution. In their paper "Copy-and-Patch

Compilation", Xu and Kjolstad present a novel approach to avoid this runtime cost [22], while still generating high quality machine code. Instead of compiling code from scratch at runtime, a library of machine code stencils for common operations is constructed ahead of time, with holes left for runtime-specific information such as memory addresses. During program execution, the JIT then "patches" these holes to generate executable machine code without incurring the runtime cost of traditional optimising compilers such as LLVM.

2.6.2 Adaptive optimisation

In addition to generating machine code on-the-fly, runtime information can be used to adapt program execution to the current workload. A significant overhead in the performance of dynamically typed languages is checking types at runtime, which is required to select the matching operation implementation for the type. While this type information cannot be known ahead of time in dynamically typed languages, information collected at runtime can be used to optimised the type-checking process. This adaptive optimisation approach relies on the assumption that if a variable has had a fixed type for a sufficient span of time previously, it is likely that it will have the same type in future. For example, while a variable being used as an integer counter in a loop can take any value, if its type in the earlier iterations has always been an integer, it is likely to remain an integer throughout later iterations. In an interpreted language, this assumption can be leveraged to replace general instructions with faster, specialised variants. A concrete implementation of this is Python's specialising adaptive interpreter, discussed in section 6.1.

Chapter 3

Compiler framework performance

In this chapter, we measure the runtime performance of two user-extensible compiler frameworks: MLIR and xDSL. The usefulness of these measurements are three-fold. First, we provide insight into the performance of the current versions MLIR and xDSL in relation to each other. Second, we identify the components of xDSL's implementation which contribute most to its overall runtime, and as such are good targets for optimisation (chapter 5). Finally, we isolate small, self-contained components of the implementation which are comparable between MLIR and xDSL, through which the impact of dynamism can be examined (chapter 7).

3.1   Methodology

Accurate performance measurement is a fundamental yet notoriously fickle discipline in systems research. In this section, we discuss our experimental methodology, including: the hardware and software setup; the selection of workloads examined; and additional infrastructure constructed. Through this, we aim to justify our experimental procedure and facilitate reproducibility of results.

3.1.1   Experimental setup

We measured all experimental results for this work with the same experimental setup: an AWS EC2 virtual machine (Table 3.1a). This choice benefits experimental replicability, making it easy for future researchers to provision their own AWS EC2 instance with a similar machine configuration, and hence performance characteristics. However, there are also drawbacks associated with using virtualised cloud infrastructure for performance measurements. Unlike bare-metal machines, the added layer of indirection of the hypervisor adds noise and confounding effects to the performance measurements. We use the subset of machine configuration available through the hypervisor to minimise noise, for example by pinning workloads to individual virtual cores and disabling address space randomisation.

Following these mitigations, the experimental setup is a fair compromise of leveraging available resources and empowering reproducibility for slightly reduced experimental precision. Finally, the ubiquitous use of cloud resources, especially for compilation workloads in build servers, makes this choice and its associated properties representative of real-world applications.

Table 3.1: Summary of the experimental setup used for performance measurement.

(a) Hardware configuration.

Configurable	Configuration
AWS instance type	c5a.4xlarge EC2
Operating system	Ubuntu 24.04
Linux kernel version	6.8.0-1029-aws
CPU name	AMD EPYC 7R32
Logical CPU cores	16
Clock frequency	2799.99 MHz
L1 Data Cache	32 KiB
L1 Instruction Cache	32 KiB
L2 Unified Cache	512 KiB
L3 Unified Cache	16384 KiB
RAM [GB]	16

(b) Software configuration.

Configurable	Configuration
CMake version	3.28.3
Ninja version	1.11.1
Python interpreter	CPython 3.10.17
C++ compiler	clang 18.1.8
xDSL commit SHA	e1b12a2
MLIR commit SHA	6516ae4

In addition to the underlying experimental hardware, the software configuration of the machine significantly contributes to its performance characteristics. As such, we similarly provide a description of the language versions and build tools, along with the exact `git` SHAs of the compilation frameworks that we compare in this chapter (Table 3.1b). Experiments in later chapters ablate across both language and framework versions, with these versions being noted explicitly when changed.

3.1.2 Experimental workloads

One novel contribution of xDSL is the concept of sidekick compilation frameworks: "an approach that uses multiple frameworks that interoperate with each other by leveraging textual interchange formats [...]" [5]. We leverage xDSL's interoperability with MLIR's textual IR to construct workloads which can be applied to both frameworks. This guarantees directly comparable performance measurements at the pipeline phase and function level, driven by the shared representation. Without sidekick compilation, for example comparing two more disparate user-extensible compiler frameworks such as MLIR and Pliron [23], this comparison would be constrained to only end-to-end measurement, obscuring the impact of variables such as dynamism on the performance properties.

MLIR facilitates the representation of algorithms of varying complexity across a wide range of abstraction levels. In this case, we define workloads as the combination of a segment of IR and a rewriting optimisation transforms it. This can be used to drive both frameworks' command line optimiser tools and internal phases and functions within the frameworks. Although real-world workloads vary in structure, a common use-case for MLIR is ingesting IR, applying rewriting operations to it, and finally passing the transformed IR to LLVM for code generation. Since this IR is often provided in a binary format in production environments, as opposed to a textual one more commonly used during development, rewriting machinery constitutes a high proportion of the executed logic. Because of this, workloads representative of these real-world use-cases should exercise common operations in rewriting machinery, such as walking through operations, checking their traits, and replacing them in their parent block. In addition to this, using basic dialects through which most IR are lowered such as `arith` and `builtin` is similarly beneficial. As such, we select constant folding as our main experimental workload to fulfil these requirements.

Constant folding

Stoltz et al. define constant folding as "a well-known static compiler technique in which values of variables which are determined to be constants can be passed to expressions which use these constants" [24]. It has been leveraged for both performance and space improvements since the earliest optimising compilers. Despite this, it remains relevant even over more modern, exotic optimisations due to its simplicity, efficient implementation, and high impact on generated IR. In addition to this, procedural generation of IR which can be constant folded is simply parameterised in length (section B.1), facilitating experiments examining performance scaling. We show an example IR segment with three constants below (Listing 3.1).

```
1  builtin.module {
2    %0 = arith.constant 865 : i32
3    %1 = arith.constant 395 : i32
4    %2 = arith.addi %1, %0 : i32
5    %3 = arith.constant 777 : i32
6    %4 = arith.addi %3, %2 : i32
7    "test.op"(%4) : (i32) -> ()
8  }
```

```
1  builtin.module {
2    %0 = arith.constant 2037 : i32
3    "test.op"(%0) : (i32) -> ()
4  }
```

(a) Unfolded IR amenable to constant folding.   **(b)** Constant folded IR.

Listing 3.1: Folding three integer constants over arithmetic addition in MLIR's textual IR.

3.1.3 Measurement infrastructure

In order to facilitate the efficient and reproducible measurement of xDSL's performance characteristics, we developed infrastructure to drive our benchmarks with a variety of measurement tools and profilers. In addition to their usefulness for understanding and optimising compiler performance, the benchmarks composing the performance experiments also provide an opportunity to augment the development process of the xDSL project. Benchmarks can be used to characterise the performance impact of changes to the xDSL codebase, making it easier to avoid unnecessary performance regression. As such, we provide a command line interface for developers to run the benchmarks, with further functionality which supports a variety of profiling tools[1]. Furthermore, our benchmarks interface with Airspeed Velocity [25], a tool which runs benchmarks across repository commits. The xDSL website then tracks the results of this tool, providing a dashboard for the performance characteristics of xDSL over time[2].

3.2 End-to-end benchmarks

The simplest metric for the performance of a system is its overall runtime. Both xDSL and MLIR provide two APIs in the form of a command line tools and a programmatic interface. Although real-world workloads typically pass binary IR to a subset of the programmatic interface, this does not fully exercise the overall functionality of the system. In contrast, measuring the end-to-end runtime of the command line optimiser for textual IR captures a large proportion of the functionality, including debugging tools such as parsing and printing the textual IR. This makes them a good candidate for this simple metric of end-to-end runtime.

End-to-end measurements are well-aligned metrics of performance for real-world workloads, but are limited by their coarse granularity. Conveniently, the structure of modern compiler frameworks facilitates more detailed breakdowns, even for end-to-end runs. LLVM's key contribution of a human-readable textual IR facilitates splitting compilation into a sequence of discrete re-usable phases, which can be measured independently. As such, compilers having LLVM's pedigree, such as MLIR and xDSL, can be modelled as a pipeline – parsing the input, applying optimisation transformations, and generating a lowered output. This allows us to break down end-to-end benchmarks into components of finer granularity.

For MLIR, we invoke `mlir-opt constant_folding.mlir --canonicalize --mlir-⌋ timing`. By default, this prints results to four decimal places, which is insufficiently granular to time printing very short IR segments. As such, we modify MLIR's implementation to print more decimal places. In order to guarantee statistical significance following this change, we measure across ten repeats. Since we are sampling a single variable, we take

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[1] `https://github.com/xdslproject/xdsl/blob/main/benchmarks/README.md`
[2] `https://xdsl.dev/xdsl-bench/`

the arithmetic mean of these values, with an uncertainty given by their standard deviation. For xDSL, we leverage our custom benchmarking infrastructure (subsection 3.1.3), which drives each phase canonicalizing the workload and records precise timings. We then calculate the average and uncertainty by the same procedure, in order to plot these wall times for each framework and the slowdown between them (Figure 3.2a).

(a) All pipeline phases of MLIR are faster than xDSL.

(b) xDSL's parser and canonicalizer incur around 50× slowdown, whereas the printer slows down only 2× for small workloads.
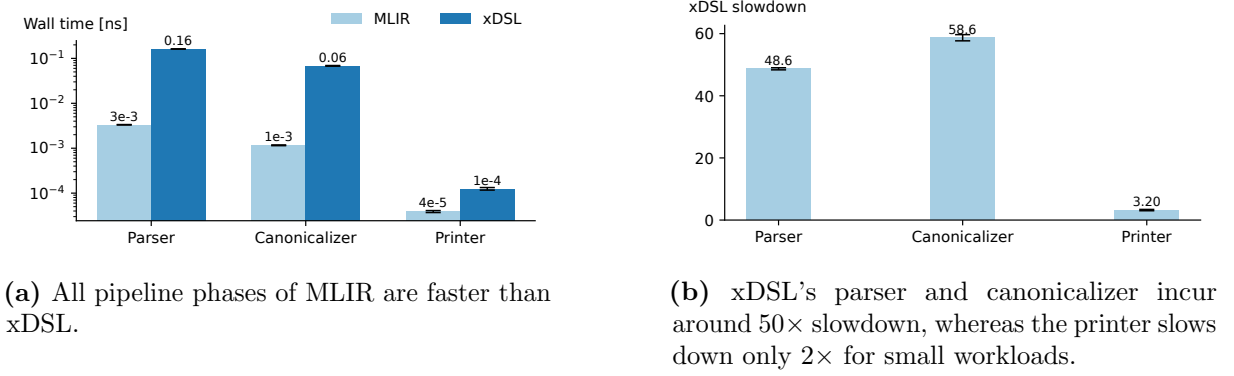
Figure 3.2: Performance comparison of constant folding 1000 integer addition operations (section 3.1.2) between xDSL and MLIR.

Despite its simplicity, this initial experiment reveals a number of interesting insights. Firstly, the slow-down from xDSL to MLIR for the first two passes is approximately 50×. This provides an initial baseline for the overhead incurred by the combination of xDSL's language runtime and implementation details over the MLIR implementation. Secondly, the slow-down for the printer is much lower than the other two phases, at only 3×. The constant folded output is very short, containing only two IR instructions (Listing 3.1b) for any length input of that schema. As such, the overhead of writing to the standard output is greater than the processing time for those few operations. In contrast, the logic implement parsing and canonicalization rewrites is much longer than any fixed overhead they incur, such as the parser reading the IR from a file.

Since the parser represents a majority of the total runtime for both frameworks, it appears an attractive candidate for optimisation as a corollary of Amdahl's law [26]. Of any pipeline phase, improving the parser by a fixed proportion yields the greatest runtime reduction. Despite this, we select the pattern rewriting phase, which implements the canonicalizer, for further investigation. Compilers designed to meet the demands of modern workloads heavily focus on optimising IR through rewriting. For example, the XLA machine learning compiler takes a binary input representation as input, which it then lowers through MLIR dialects applying rewrite optimisations in order to generate efficient code targeting accelerator hardware [27]. This process only relies on parsing and printing logic for debugging, as its main code generation flow operates entirely on binary representations. As such, optimising these components is a less attractive research direction, as it would only affect the performance of development and testing infrastructure. Furthermore, the rewriter is a much more dynamic workload, with its control flow necessarily determined

at runtime based on the contents of the IR being optimised. This further makes it a more suitable candidate for examination through the lens of the impact of dynamism on user-extensible compiler frameworks.

3.3   Micro-benchmarks

Micro-benchmarking refers measuring the performance of fast, granular, and isolated segments of code. The term was coined by Saavedra et al. in their 1995 paper [28] "Performance Characterization of Optimizing Compilers". As such, we are in good company in our application of micro-benchmarking approaches to this problem domain. Micro-benchmarks have many desirable properties. Since they run quickly, they can cheaply be repeated for statistical confidence. Furthermore, their fine granularity makes them tractable to reason about – providing useful information to optimise the component of the system they measure. However, a key difficulty of micro-benchmarking is ensuring alignment with overall system performance. For example, the selection of code paths to micro-benchmark may introduce bias, making them less representative of the overall system. In addition to this, their performance may be inflated as a consequence of warmed caches and JIT optimisations across repeats, which would not occur during normal operation [29]. As such, micro-benchmarking is a useful tool for deeply understanding the performance of software, but must be used carefully to ensure the validity of its results.

As discussed in our related work (Section 8.1), Amini and Nui's talk "How Slow is MLIR" [30] discusses a set of micro-benchmarks for key operations in the MLIR compiler, such as traversing the IR and creating operations. These micro-benchmarks were used to inform the optimisation of MLIR's data structures and for comparison with traditional LLVM-based compilers. The implementation of the micro-benchmarks allude to an underlying design goal in MLIR by their measurement of asymptotic scaling properties[3]. This design goal is asymptotically optimal performance for its underlying data structures. However, data structures with these characteristics often incur constant-time penalties. This causes overhead for small workloads, where, unlike the asymptotic case, the cost is not amortised. As such, micro-benchmarks may not be representative of the system's overall performance, revealing possibility for the optimisation of code co-designed using them. Despite this, they can still provide useful insight into MLIR's performance characteristics. We implement micro-benchmark workloads for the xDSL equivalent to those for MLIR presented in the keynote, and compare the results of these benchmarks between the two implementations, giving insights into their relative performance.

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[3]`https://github.com/joker-eph/llvm-project/blob/6773f8/mlir/unittests/Benchmarks/Cloning.cpp#L66`

3.3.1 Implementation

Unfortunately, the implementation and build instructions for the "How Slow is MLIR?" micro-benchmarks were not published with the talk. However, the source code can be found on a branch of their fork of LLVM[4]. We provide a copy of this source code and instructions for running the benchmarksto enhance the replicability of our results and facilitate further performance experiments. We then use this source code to construct comparable micro-benchmarks in Python.

A key design goal of our micro-benchmarks for xDSL is parity with those provided for MLIR, ensuring the validity their direct comparison. As such, we derive their implementation from the MLIR benchmarks, matching test data and function invocations as closely as possible. In addition to being fairly comparable, it is critical that the micro-benchmark results are statistically significant. This is particularly challenging as their execution time approaches the 1ns resolution of the most granular system counters on the benchmarking machine. As such, we measure the total time taken to execute the functions under test 32768 times, evaluating the individual duration by dividing by the number of iterations. As with the traditional benchmarks, we repeat this process ten times, calculating the arithmetic mean and standard deviation as the value and its uncertainty respectively. In the following sections, we discuss the implementations of a number of micro-benchmarks, facilitating discussion of the insights they give into compiler performance across implementations and language runtimes in later chapters.

3.3.2 Operation instantiation

Operations are a central data structure in MLIR and xDSL's IR representation, constituting dialects and composing together into programs. As such, the methods to instantiate operations a very frequently invoked, making them a good candidate for micro-benchmarking. In both MLIR and xDSL, there are two main ways an operation can be constructed: direct creation **1**; or using a builder **2** (Listing 3.3).

---

[4]`https://github.com/joker-eph/llvm-project/tree/benchmarks`

```
1  // Setup
2  OpBuilder b(ctx.get());
3
4  // Benchmark  1
5  OperationState opState(unknownLoc,
   ↪  "testbench.empty");
6
7  Operation::create(opState);
8  // Benchmark  2
9  b.create<EmptyOp>(unknownLoc);
```

(a) "How Slow is MLIR?" C++ implementation.

```
1  # Benchmark  1
2  EmptyOp.create()
3
4  # Benchmark  2
5  EmptyOp()
```

(b) xDSL Python implementation.

Listing 3.3: Micro-benchmark implementations for methods checking an operation has a trait.

The performance characteristics of these implementations differ significantly (Table 3.2). In MLIR, the creation and building mechanisms have approximately the same performance, taking around 150ns to instantiate an operation. In contrast, xDSL's operation building is much slower than direct creation, jumping from $20\times$ to $80\times$ slower. This comes as a result of the trade-off xDSL makes between performance and expressivity, with its builder including a large section of inference and verification logic as a wrapper around the create method. While MLIR disables this verification logic for release builds, it is always enabled in xDSL, facilitating its use case of development and prototyping. We examine the performance impact of disabling verification in the later discussion of workload specialisation (chapter 5).

Table 3.2: Operation instantiation in xDSL is approximately $25\times$ slower than in MLIR when creating instructions in the asymptotic case, but is up to $90\times$ slower when using the builder API.

Mechanism	MLIR [ns]	xDSL [ns]
1 Create	155 ± 14	3770 ± 916
2 Build	153 ± 0.5	12700 ± 1810

3.3.3 Operation trait checks

Traits are a key property of MLIR and xDSL's operations, providing a mechanism to abstract implementation details and properties. In order to allow users of the frameworks to leverage an operation's trait information, both MLIR and xDSL provide helper methods to check whether an operation has a certain trait. These methods are used frequently in common tasks. For example, when pattern rewriting over a block of IR, the matching engine uses the traits of the block's constituent operations to identify valid rewrites.

```
1   // Setup
2   Operation op = b.create<OpWithRegion>(
3       unknownLoc
4   );
5
6   // Benchmark
7   bool hasTrait = op->hasTrait<
8       OpTrait::SingleBlock
9   >();
```

```
1   # Setup
2   op = OpWithRegion()
3
4   # Benchmark
5   has_trait = op.has_trait(SingleBlock)
```

(a) "How Slow is MLIR?" C++ implementation. **(b)** xDSL Python implementation.

Listing 3.4: Micro-benchmark implementations for methods checking an operation has a trait.

These methods can be simply benchmarked for an example workload (Listing 3.4). However, care must be taken when implementing these benchmarks to ensure they are can be equitably compared. For example, the operations must both have the same number of traits, and the target trait must be at the same position in that operation's internal data structure. If this is not true, one implementation may require fewer iterations to perform its workload, invalidating the comparability of the two results. Micro-benchmarks of checking traits for both implementations show a slow-down of approximately $250\times$ from MLIR to xDSL (Table 3.3).

Table 3.3: Trait checks in xDSL are approximately $250\times$ slower than in MLIR in the asymptotic case.

MLIR [ns]	xDSL [ns]
11.7 ± 0.5	1920 ± 695

3.3.4 Summary of micro-benchmarks

These micro-benchmarks provide a number of insights into the baseline performance of xDSL. Firstly, we can see that xDSL's implementation incurs a performance trade-off for the expressivity of its API, with convenient helper methods performing much less well than direct interactions with the underlying data structures. This motivates our work specialising xDSL for a single workload to elide this overhead (chapter 5). Secondly, we begin to quantify the performance overhead of the CPython language runtime over C++ through workloads with trivial implementations such as instantiating empty operations. From this, we can see that CPython 3.10 incurs at least a $25\times$ slowdown over C++. This motivates our work understanding the impact of recent optimisations to CPython such as the specialising adaptive interpreter and baseline JIT (chapter 6), along with the necessary cost of dynamism required to implement Python's semantics (chapter 7).

In addition to the micro-benchmarks matching those provided in "How Slow is MLIR", a subset of which is discussed in detail above, we also developed a further xDSL-only suite to instrument key functions invoked by the pattern rewriter. While these micro-benchmarks are useful in their own right as performance measurements, they also facilitate further experiments. Their small size means they can be reasoned about at the bytecode level (chapter 4), providing useful information about the dynamism of the workload.

Chapter 4

Profiling at the bytecode level

Performance profilers are powerful tools that provide useful information about program control flow and hotspots, facilitating performance optimisation. Our research requires detailed information instrumenting Python's internal evaluation loop to draw comparisons with the C++ language runtime and characterise the cost of dynamism. However, existing profilers do not provide information at this granularity, motivating our work in this area. In this chapter we present ByteSight, a novel tool for performance profiling at the bytecode level, allowing us to look deeper into the performance characteristics of highly dynamic programs whose implementation cannot easily be deferred into lower level languages.

Recent developments to CPython's runtime motivate collecting more fine-grained profiling information. For example, the specialising adaptive interpreter rewrites bytecode at runtime into quickened forms, and the baseline JIT substitutes bytecode for tier two micro-operations – both yielding performance characteristics which cannot be reasoned about with function or line level instrumentation. In addition to this, bytecode performance profiling information helps provide a key missing data point when examining the impact of program dynamism. However, to the author's knowledge, no profilers exist which support measurement at this granularity (Related work, section 8.2). One reason for this conspicuous absence of bytecode level profilers is the difficulty of measuring their very short execution times, in the order of the highest resolution system counter. This difficulty is further worsened by the bytecode dispatch and evaluation being deeply interleaved within the interpreter's execution loop.

ByteSight, our novel tool for the performance profiling of CPython bytecode, addresses this gap in the existing provision. ByteSight is a tracing profiler which operates on the bytecode level of the Python interpreter. It is implemented natively in Python using only the standard library, and its source code is available under the MIT licence on GitHub.It does not require patches to Python's language implementation. This makes it portable, robust across language versions, and simple to install from the Python Package Index (PyPI). In this chapter, we discuss its implementation and provide examples of its use.

4.1   Implementation

By virtue of the flexibility and dynamism of its interpreter's implementation, CPython provides a wide variety of opportunities for instrumenting and introspecting running code. One example of this is the standard library function `sys.settrace`, which associates dynamic, user-defined callback functions with the dispatch of key virtual machine events. These include function calls, line execution, handling exceptions, and even individual bytecode operations (interchangeably referred to as opcodes in the documentation). This callback function receives the event type along with the CPython frame and code objects currently being evaluated by the interpreter, facilitating precise instrumentation of the internal operation of the interpreter. Other possibilities for collecting this information include making custom patches to the CPython implementation, or leveraging the `LLTRACE` feature of the debug build of Python. However, the former is specific to individual language versions, and the latter has a verbose output containing no performance information. Furthermore, both requiring re-compiling the CPython implementation from source, precluding simple installation by users from Python Package Index (PyPI). As such, we chose to leverage `sys.settrace`, accepting the challenges associated with its measurement for benefits it provides in portability and robustness across language versions.

Our tool captures bytecode level profiling information through a custom callback function which records a sequence of timestamps associated with the traced events. From this set of timestamps, we can calculate the execution duration of each emitted opcode. This constitutes profiling information of a higher granularity than existing Python performance profilers. In spite of its name, we leverage the `sys.settrace` function as opposed to its sister function `sys.setprofile`. We do this because `sys.settrace` has supported emitting trace events for opcodes since Python 3.7, whereas `sys.setprofile` only emits events at the function granularity. This approach of leveraging CPython's API provides benefits of robustness across versions and easy installation, but also causes a number of challenges for accurate and precise measurement of very short events.

These challenges come as a result of the callback function itself being a callable Python code object. As such, the infrastructure to invoke and evaluate this function has a significant performance cost, in many cases taking longer than the opcode it is instrumenting. To mitigate this, our custom tracing function (Listing 1) records the timestamp at the earliest point ① and the latest point ④ , allowing the majority of its overhead to be excluded. Properties of the frame are then set to emit events for opcodes but not lines ② , further avoiding extraneous overhead. Finally, a tuple of timestamps for the end of the last trace function and the start of the current one are recorded ③ , upper bounding the duration of opcode execution. This sequence of recorded timestamps can then be used in combination with domain knowledge of the language runtime to calculate individual opcode durations.

```
 1  def _trace__collect_event_timestamps(
 2      self, frame: types.FrameType, event: str, _arg: Any
 3  ) -> Callable[..., Any] | None:
 4      """Trace function to collect opcode timestamps."""
 5      now_timestamp = perf_counter()   1
 6
 7      frame.f_trace_lines = False   2
 8      frame.f_trace_opcodes = True
 9
10      if event == "opcode":
11          self._timestamps.append(   3
12              (
13                  self._prev_event_timestamp,
14                  now_timestamp,
15              )
16          )
17          self._prev_event_timestamp = perf_counter()   4
18
19      return self._trace__collect_event_timestamps
```

Listing 1: Trace callback function generating a sequence of timestamps instrumenting opcode events.

4.1.1 CPython internals

In order to infer opcode durations from the event timestamps emitted tracing function, we must first examine the language runtime implementation with which it is co-designed. In this section, we present a view of CPython 3.10's implementation as a basis for our profiler. In more recent Python versions such as CPython 3.13, aspects of the tracing infrastructure have been refactored. However, since both the API provided by the standard library and the position of the tracing logic in the evaluation loop remain the same, the procedure remains applicable to these newer versions. Code objects in CPython are executed by the _PyEval_EvalFrameDefault function (Listing 4.1a). This begins with initialisation to ready for evaluation a , then enters an unbounded evaluation loop b . This loop decodes the next bytecode instruction c , then switches on it to select the appropriate logic to execute d , and repeats until an exception is thrown or the code object terminates. Having an understanding of the evaluation loop, we can next discuss how it is instrumented.

```
1  PyObject* _PyEval_EvalFrameDefault(PyThreadState *tstate,
   ↪ PyFrameObject *f, int throwflag) {
2      // ... declarations and initialization of local variables, macros
       ↪ definitions, call depth handling, ...  a
3      // ... code for tracing call event
4
5      for (;;) {  b
6          // NEXTOPARG() macro  c
7          _Py_CODEUNIT word = *next_instr;
8          opcode = _Py_OPCODE(word);
9          oparg = _Py_OPARG(word);
10         next_instr++;
11
12         // ... code for tracing opcode events
13
14         switch (opcode) {  d
15             case TARGET(NOP) {
16                 FAST_DISPATCH();
17             }
18             case TARGET(LOAD_FAST) {
19                 // ... code for loading local variable
20             }
21             // ... 117 more cases for every possible opcode
22         }
23     }
24     // ... termination
25 }
```

(a) C implementation snippets, derived from an explanation of the bytecode evaluation by Victor Skvortsov [31].
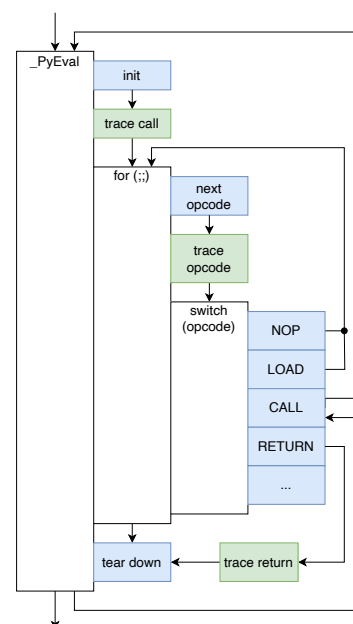
(b) Control flow between evaluation (blue) and tracing (green).

Listing 4.1: Overview of the evaluation loop of CPython 3.10, showing components relating to bytecode evaluation and tracing.

CPython's tracing mechanism works in two phases: registering the callback function, and the invocation of this callback function from the evaluation loop. To register the callback function, users can invoke `sys.settrace`, a standard library function binding to the C implementation of `sys_settrace` in `sysmodule.c:`. This in turn invokes `_PyEval_SetTrace` in `ceval.c`, which updates two fields on the Python Global Interpreter Lock (GIL) thread state struct: `c_traceobj` and `c_tracefunc`. The former is a callable Python code object for the callback function, and the latter points to a "trampoline" function, which invokes this code object with the current frame information. This trampoline is then invoked when events occur in the evaluation loop, including at the start of the frame evaluation for functions, after each opcode is extracted, and on returning from the function (green blocks in Figure 4.1b).

4.1.2   Inferring bytecode duration

Given both the sequence of timestamps and an understanding of their place in CPython's evaluation loop, we can infer our profiler's goal of the time taken to execute each opcode. One way to visualise this is by flattening the block diagram of the evaluation loop

(Figure 4.1b) and annotating it with timestamp measurements (Figure 4.2). From this, we can then construct a system of equations relating the measurements, and derive the durations of each opcode.

(a) Timing function runtime without opcode event tracing.

(b) Timing function runtime, including recording timestamps at the start and end of each opcode event.
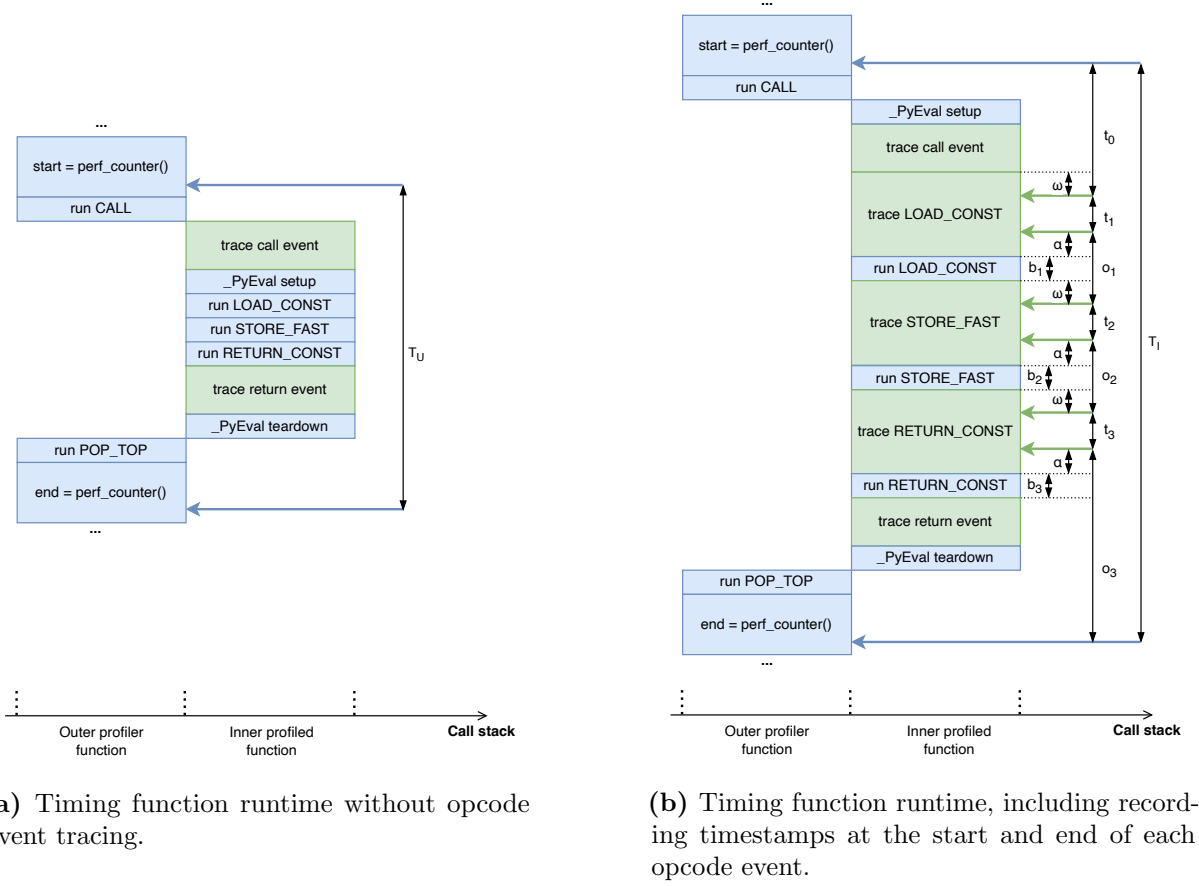
Figure 4.2: Timing Python's evaluation loop with and without instrumentation of opcode events using `sys.settrace`.

By examination of where trace timestamps are recorded, we can see that the duration of the nth bytecode instruction, b_n, is equal to the difference between the recorded timestamp pairs, o_n, and the fixed overheads before and after the tracing function, α and ω respectively (Equation 4.1).

$$b_n = o_n - (\alpha + \omega) \tag{4.1}$$

Furthermore, the measured runtime of the instrumented function, T_I, is equal to the sum of the uninstrumented runtime T_U and the overhead incurred by tracing (Equation 4.2).

$$T_I = T_U + \sum_n (\alpha + \omega + t_n) \tag{4.2}$$

As such, we calculate the sum of the overheads before and after the tracing function, $\alpha + \omega$, under the assumption that they are fixed (Equation 4.3). This assumption is justified by

the calling infrastructure for the tracing function being the same across all opcodes.

$$\alpha + \omega = \frac{T_I - T_U - \sum_n t_n}{n} \tag{4.3}$$

Finally, we can combine this with our initial observation to infer our goal of opcode duration (Equation 4.4).

$$b_n = o_n - \frac{T_I - T_U - \sum_n t_n}{n} \tag{4.4}$$

Beyond the careful co-design of the tracing measurement logic with CPython's implementation, there are a number of confounding effects which must be mitigated to ensure accurate measurement. Firstly, for the profiling information to be useful, the resolution of the most accurate system clock must be sufficient to resolve differences bytecode execution time. On our experimental hardware (subsection 3.1.1) this was true, having a 1ns timer able to resolve differences in opcodes taking around 10ns to execute. However, this is not the case for modern Apple Silicon devices. Their most accurate system timer, `mach_absolute_time` [32], has a resolution of only 40ns and is hence unable to resolve individual bytecode instruction durations of approximately 10ns. This is a physical limitation on measuring such necessarily fast events, and as such can only be resolved by selecting appropriate hardware. Secondly, the CPython language runtime periodically runs housekeeping tasks such as garbage collection, disrupting the flow of bytecode execution and hence adding random noise to our measurements. These can effects can be minimised using techniques from existing performance measurement work such as `timeit` [33] or `pyperf` [34], for example by disabling garbage collection for the duration of profiling. Finally, we repeat and aggregate our experimental measurements for statistical confidence, further minimising machine noise to ensure clean and reliable profiling results.

4.2   Example usage

Having implemented our profiler, we can demonstrate its capabilities on an example workload (Listing 4.3). Each traced event is displayed on its own line, in combination showing the exact sequence of instructions performed by the interpreter when evaluating the function. Function invocations, such as calling `inner_function` ⓧ, are indented by their call stack depth for easy readability. In addition to this, bytecode instructions are formatted following the convention of the standard library, but are annotated with their duration in a comment on the right-hand side of the trace ⓨ.

```
                                    // ======= example:8 `example_function` ========
                                    // >>> inner_function(1)
                                    7          0    LOAD_GLOBAL        0   (inner_function)   // 15   ns
                                               2    LOAD_CONST         1   (1)                // 15   ns
1   import bytesight                           4    CALL_FUNCTION      1   ()                 // 31   ns
2
3   def inner_function(                 // ======== example:3 `inner_function` =========  x
4       x: int | str | float            // >>> assert x
5   ) -> None:                          4          0    LOAD_FAST          0   (x)            // 13   ns
6       assert x                                   2    POP_JUMP_IF_TRUE   4   (to 8)         // 13   ns
7                                              >>  8    LOAD_CONST         0   (None)         // 12   ns
8   def example_function():                    10   RETURN_VALUE           ()             // 31   ns
9       inner_function(1)               // =============================================
10      pass
11      _x = perf_counter()                    6    POP_TOP                ()             // 16   ns
12                                      // >>> pass
13  bytesight.profile_bytecode(         8          8    NOP                    ()             // 15   ns  y
14      example_function                // >>> _x = perf_counter()
15  )                                   9          10   LOAD_GLOBAL        1   (perf_counter) // 15   ns
                                               12   CALL_FUNCTION      0   ()             // 17   ns
                                               14   STORE_FAST         0   (_x)           // 14   ns
                                               16   LOAD_CONST         0   (None)         // 13   ns
                                               18   RETURN_VALUE           ()             // 28   ns
                                    // =============================================
```

(a) Python program.   **(b)** Profiler output.

Listing 4.3: Output of the bytecode profiling tool for a simple Python program, showing the sequence of dispatched bytecode and their individual execution times.

ByteSight provides straightforward mechanism to show the bytecode trace of any Python function. This facilitates debugging control flows in highly dynamic code, which often suffer from "spooky action at a distance", and is educational for the internal workings of Python's interpreter. This functionality is easily accessible by installation from PyPI, contrasting previous approaches which required either re-compiling the Python interpreter or manually implementing the same approach each time. Beyond this, the profiling information of the duration of each opcode is not provided by any existing tools to the author's knowledge. This information provides insight into the relationship between performance and dynamism in Python, and is more generally helpful for understanding and optimising performance critical code which cannot be deferred to a low-level language through Foreign Function Interface (FFI) bindings. In the context of our research, this tool unblocks our work in later chapters characterising and optimising the performance of xDSL.

Chapter 5

Manual specialisation of xDSL

In chapter 3, we constructed a set of experiments to empirically compare the current performance of the xDSL and MLIR compiler frameworks. Our overall aim is to use these experiments to contrast the performance of static and dynamic languages for the implementation of user-extensible compiler frameworks, using MLIR and xDSL as proxies for these two categories respectively. However, the experiments so far measure a combination of the effects of dynamism in the language runtime and implementation details of the framework, with the former obscuring our measurements of the latter. In order to use the frameworks for our aims, our measurements must be as independent of implementation details as possible.

In this chapter, we investigate the performance implications of language dynamism in user-extensible compiler frameworks by examining the impact of specialisation on the xDSL framework. By manually eliminating extraneous computation for specific workloads, we establish a performance baseline for pattern rewriting in xDSL that more accurately reflects the inherent costs of dynamism, independent of implementation overheads. To do this, we manually identify and remove computation performed by the framework which is unnecessary to its execution of this workload. For example, the framework may calculate and check values that are known as runtime invariants for the selected workload, for instance when checking properties of attributes known to be empty. Since this checking does not contribute to the workload's behaviour, it can be removed. Another example is functionality which improves the expressivity of the framework's API, such as runtime type checks to support polymorphism of arguments. Since the workload only uses a single facet of this API, this can also be removed. By eliminating the performance overheads from these unnecessary computations, we reach an implementation representative of the best-case performance of Python for this workload. This specialisation process yields an efficient pattern rewriting workload using xDSL's data structures. This demonstrates the best-case performance of CPython as a proxy for dynamic languages for such applications, facilitating comparison with C++ for insight into the relationship between performance and dynamism in user-extensible compiler infrastructures.

5.1 Micro-benchmarks

An important component of our experimental suite is micro-benchmarks, measuring the performance of procedures fundamental to xDSL and MLIR. Re-using these micro-benchmarks for specialisation allows the isolation of specific dynamic language features, and further provides a mechanism to precisely measure the impact of specialisation. By manually examining the traces of their execution, we can identify and eliminate any unnecessary computation in the current implementation. Having done this, we re-run the micro-benchmarks to quantify the performance of the specialised implementation, facilitating comparison of the language runtime only for compiler framework workloads.

5.1.1 Operation instantiation

The first micro-benchmark discussed in section 3.3 was instantiating operations, one of the central data structures in both xDSL and MLIR. The idiomatic way to do this in xDSL is directly instantiating a new Python object. In xDSL, this process includes a large amount of logic (Figure 5.1, top trace), including verifying attributes and building properties of the operation. However, in many instances this verification is unneeded as it is already known as a runtime invariant, and the building process can similarly be simplified as the structure can be inferred. As such, specialisation to remove this overhead can vastly reduce the complexity and hence improve performance (Figure 5.1, bottom trace).
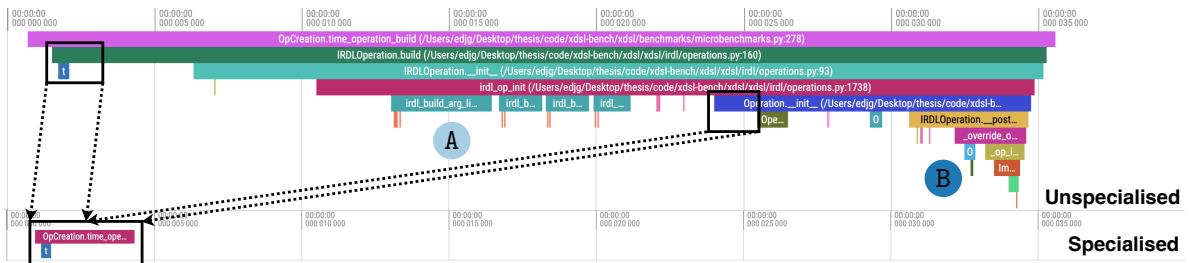
Figure 5.1: The unspecialised `EmptyOp` constructor (top) has a high overhead, including checking known invariants and building empty properties. This overhead can be avoided through specialisation to construct the same operation (bottom).

Examining the above trace, we can visually identify components which take a large proportion of runtime, and may represent unnecessary computation. For example, the xDSL constructor for `IRDLOperation`s invokes logic with significant overhead building and filtering properties of the operation Ⓐ. However, in this workload of the empty operation, this logic does not change the constructed object. Because of this, eliding this logic results in a specialised version of the operation which generates the same output using less computation by applying domain knowledge. In addition to this, MLIR's core operations are not IRDL based, unlike xDSL, meaning this overhead is implementation specific. Similarly, the post-constructor includes logic for context-managed builders Ⓑ,

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which is again unrelated to the empty operation case and not present in MLIR. To avoid this overhead through specialisation, we move from the idiomatic constructor which initialises values to their defaults (Listing 5.2a) to directly modifying xDSL's underlying data structures (Listing 5.2b), where we initialise the defaults explicitly and without unneeded computation. Finally, we leverage an implementation detail of CPython's data model: the `__slots__` attribute [35]. Slots store attributes in a fixed-size array on the object with direct indexing instead using the default `__dict__` mapping from attribute name to value, optimising both lookup speed and space.

```
1  EmptyOp()
```

(a) Instantiation with constructors.

```
1  empty_op = EmptyOp.__new__(EmptyOp)
2  empty_op._operands = ()
3  empty_op.results = ()
4  empty_op.properties = {}
5  empty_op.attributes = {}
6  empty_op._successors = ()
7  empty_op.regions = ()
```

(b) Instantiation by direct manipulation of xDSL's data structures.

Listing 5.2: Unspecialised (left) and specialised (right) approaches to instantiating an `EmptyOp` differ in both length and performance.

Through specialising the implementation to the workload of this micro-benchmark we can achieve significant performance improvements of up to $26\times$ (Table 5.1). A proportion of this speedup is captured by optimisations which C++ is able to make ahead-of-time, but that are invalidated by Python's dynamism. The most salient of these possible optimisations is function inlining calls for the constructor implementation, which would eliminate a significant overhead visible in the Python trace (Figure 5.1). In addition to this, there are further opportunities for optimisations such as instruction combination for more efficient computation, and dead code elimination for compile time invariants [36]. However, the performance improvement comes at the cost of a significantly more complex implementation, contrary to xDSL's design goals of a simple expressive API. We can quantify one cause of this improvement as the specialised code executing fewer, faster bytecode instructions by leveraging our novel bytecode profiling tool (full traces in Appendices E.1, E.2). For example, specialisation reduces the number of bytecode instructions executed from 466 to only 29. Function calls have a much longer duration than other instructions, with their mutation of the call stack taking up to three times longer than loading from a variable. Again leveraging our tool, we can see that specialisation reduces the number of function calls from 65 to 5, further contributing to the performance uplift. By examination of its emitted bytecode (Listing E.2), we can be confident the specialised implementation is near-optimal within the constraints of Python's runtime, as it only constructs the object and sets required fields, performing no other extraneous logic.

Table 5.1: Specialising `EmptyOp` instantiation in xDSL yields performance uplifts of up to 34×, only 2.5× slower than the MLIR reference implementation.

MLIR [ns]	xDSL [ns]	Optimised xDSL [ns]
153 ± 0.5	12700 ± 1810	378 ± 42

5.1.2   Operation trait checks

The second micro-benchmark discussed involved checking traits on operations, and was measured to perform 80× worse in xDSL than MLIR. Similarly to the operation instantiation micro-benchmark, this slow-down comes as a result of a high proportion of method's logic not being required by the core functionality (Figure 5.3a). In this case, this logic improves the expressivity of the API, supporting both concrete objects and types as arguments, along with handling the edge case of unregistered operations. However, this logic lies on the hot path of execution, and again these properties are known as runtime invariants. As such, specialisation can again be leveraged to remove this implementation overhead (Figure 5.3b).

(a) `issubclass` and `isinstance` checks, type `cast`ing, and constructing iterators constitutes over three quarters of xDSL's `has_trait`s runtime.

(b) Specialisation to narrow the interface and optimisation to avoid extraneous work on hot paths can significantly accelerate `has_trait`.

Figure 5.3: Profiling the `has_trait` method before (top) and after (bottom) specialisation with `viztracer` reveals unnecessary computation.

Examining the implementation of this micro-benchmark (Listing 5.4), we can again identify opportunities for specialisation and optimisation. The execution trace shows that checking whether an operation is unregistered (1) accounts for over one third of the micro-benchmark runtime. Through specialisation under the runtime invariant that all operations are registered, this check can be removed – reducing computation. Furthermore, this inspires a general optimisation to xDSL to avoid this check by overloading `UnregisteredOp.has_trait` rather than checking on all code paths. In addition to this, function invocation in Python incurs a performance cost due to the overhead of modifying the stack frame. As such, inlining the call to `get_trait` (2) is another beneficial specialisation. Finally, argument types are dynamically checked (3) and cast (4), incurring

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a performance overhead. However, the type of these arguments are runtime invariants of the caller, so the checks can be specialised away.

```
1  @classmethod
2  def has_trait(
3      cls,
4      trait: type[OpTrait] | OpTrait,
5      *,
6      value_if_unregistered: bool = True,
7  ) -> bool:
8      from xdsl.dialects.builtin import
       ↪  UnregisteredOp  (1)
9      if issubclass(cls, UnregisteredOp):
10         return value_if_unregistered
11
12     return cls.get_trait(trait) is not
       ↪  None  (2)
```

(a) Outer `has_trait` method.

```
1  @classmethod
2  def get_trait(
3      cls,
4      trait: type[OpTraitInvT] |
       ↪  OpTraitInvT
5  ) -> OpTraitInvT | None:
6      if isinstance(trait, type):  (3)
7          for t in cls.traits:
8              if isinstance(t, cast(  (4)
9                  type[OpTraitInvT],
                   ↪  trait
10             )):
11                 return t
12     else:
13         for t in cls.traits:
14             if t == trait:
15                 return
                   ↪  cast(OpTraitInvT,
                   ↪  t)
16     return None
```

(b) Inner `get_trait` method.

Listing 5.4: xDSL methods implementing trait check functionality.

Having specialised xDSL's implementation, we can draw direct comparison between its implementation (Listing 5.5a) and MLIR's (Listing 5.5b), to better understand their relative performance characteristics. In contrast to the original, the specialised implementation directly matches MLIR, with the only difference being approach to checking RTTI. As such, it is well-suited for comparing the performance characteristics of static and dynamic languages independent of implementation details.

```
1  for t in OP.traits._traits:
2      if isinstance(t, TRAIT):
3          return True
4  return False
```

(a) xDSL's modified `has_trait` method.

```
1  TypeID traitIDs[] =
   ↪  {TypeID::get<Traits>()...};
2  for (unsigned i = 0, e =
   ↪  sizeof...(Traits); i != e; ++i)
3      if (traitIDs[i] == traitID)
4          return true;
5  return false;
```

(b) MLIR's `has_trait` method.

Listing 5.5: xDSL and MLIR methods searching trait arrays.

Through specialisation, we achieve a $8\times$ speedup over the original implementation (Table 5.2). However, this again incurs a cost to xDSL's expressivity, sacrificing polymorphic

support for checking traits of both object types and instances. As with operation instantiation, this is contrary to xDSL's design goals. Furthermore, this speedup is less dramatic than operation instantiation, as a result of having less overhead in the original implementation, but can be reasoned about in the same manner with our novel profiling tool (full traces in Appendices E.3, E.4). As before, specialisation reduces the number of bytecode instructions from 89 to 35, with the number of high-overhead `CALL` instructions dropping from 11 to 2.

Table 5.2: Specialising trait checking in xDSL yields performance uplifts of up to 8×, 20× slower than the MLIR reference implementation.

MLIR [ns]	xDSL [ns]	Optimised xDSL [ns]
11.7 ± 0.5	1920 ± 695	239 ± 35

5.2   Pattern rewriting

Having demonstrated specialisation as an approach to examine the performance bound of a language runtime for micro-benchmarks, we can further apply it to real-world workloads such as constant folding. In this section, we specialise a simple pattern rewriter: constant folding over integer addition. These specialised implementations can then be taken as performance baselines for their respective languages, and further analysed through bytecode tracing or disassembly to understand their implementation.

5.2.1   Constant folding

For our first benchmarks of the two frameworks, we measured the end-to-end performance of canonicalization passes applied to an IR with many foldable constants (section 3.1.2). However, canonicalization passes are fairly complex, encompassing a suite of common optimisations, many of which are not applicable to our IR workload. This complexity is detrimental to manual specialisation, resulting in more code requiring transformation by hand. As such, we implement a simple pattern rewriting pass for constant folding over the addition of integers (Listing 5.6). This pass captures common idioms in pattern rewriting, making it a fair proxy for more complex workloads, but is also sufficiently simple to rewrite by hand into a fully specialised form. The rewriter first matches against the integer addition operation to fold ①, exercising operation type checks. Next, it checks the invariant of our workload that both addition operands are constant ②, exercising trait lookups. After this, it gets the value of each operand, exercising operation properties ③. Finally, it replaces the matched operation with a new one, exercising the rewriting mechanism ④.

```python
def match_and_rewrite(self, op: Operation,
    rewriter: PatternRewriter, /):
    # Only rewrite integer add operations  (1)
    if not isinstance(op, AddiOp):
        return

    # Ensure both operands are constants  (2)
    lhs_op = op.operands[0].op
    rhs_op = op.operands[1].op
    if lhs_op.has_trait(ConstantLike) or
        rhs_op.has_trait(ConstantLike):
        return

    # Calculate the result of the addition  (3)
    lhs = lhs_op.value.value.data
    rhs = rhs_op.value.value.data
    folded_op = ConstantOp(
        IntegerAttr(lhs + rhs, op.result.type)
    )

    # Rewrite with the calculated result  (4)
    rewriter.replace_matched_op(
        folded_op, [folded_op.results[0]]
    )
```

(a) xDSL implementation.

```cpp
// Only rewrite integer add operations  (1)
LogicalResult matchAndRewrite(arith::AddIOp op,
    PatternRewriter &rewriter) const override {

    // Ensure both operands are constants  (2)
    arith::ConstantOp lhsConstOp =
        op.getLhs().getDefiningOp<arith::ConstantOp>();
    arith::ConstantOp rhsConstOp =
        op.getRhs().getDefiningOp<arith::ConstantOp>();
    if (!lhsConstOp || !rhsConstOp) {
        return failure();
    }

    // Calculate the result of the addition  (3)
    auto lhsAttr =
        lhsConstOp.getValue().dyn_cast<IntegerAttr>();
    auto rhsAttr =
        rhsConstOp.getValue().dyn_cast<IntegerAttr>();
    if (!lhsAttr || !rhsAttr) {
        return failure();
    }
    APInt lhsValue = lhsAttr.getValue();
    APInt rhsValue = rhsAttr.getValue();
    APInt result = lhsAttr.getValue() +
        rhsAttr.getValue();

    // Rewrite with the calculated result  (4)
    auto resultType = op.getType();
    auto foldedValue =
        rewriter.getIntegerAttr(resultType, result);
    rewriter.replaceOpWithNewOp<arith::ConstantOp>(op,
        resultType, foldedValue);
    return success();
}
```

(b) MLIR implementation.

Listing 5.6: Implementations of pattern rewriters for constant folding over integer addition.

In order to draw fair comparisons between the two frameworks, their implementations of the constant folding pattern rewrite must be equivalent. As such, we provide implementations for both xDSL (Listing 5.6a) and MLIR (Listing 5.6a). Measuring the MLIR implementation is complicated by the fact that its pattern rewriting infrastructure implements constant folding by default. To mitigate this, we manually excise this functionality from the MLIR framework to ensure that our pattern rewriting kernel is the implementation being measured. Having constructed these implementations, we can follow the same specialisation process introduced for the micro-benchmarks to bring the xDSL's performance closer to the best-case for that workload in the Python language.

5.2.2 Specialisation

Although our constant folding pass is less intricate than existing passes such as canonicalization, it is still much more complex than any of the above micro-benchmarks (Figure 5.7a).

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Instead of one or two helper functions in xDSL's API, aspects of the pattern rewriter such as replacing the matched operation have a deep call stack, invoking methods to set many aspects of the IR's object representation. As such, the first step in the specialisation process is manually inlining this call stack, which provides two benefits. Firstly, it avoids the non-negligible overhead of function calls discussed in previous micro-benchmarks, and further worsened by the deep call stack of the more complex implementation. Secondly, it reveals logic that is redundant for the implementation of this workload, which is otherwise hidden across the boundaries of xDSL's API. The inlined implementation can then be specialised to remove this redundant logic, and further leverage runtime invariants of the integer constant addition workload where possible. This yields a specialised implementation with reduced overhead (Figure 5.7b).
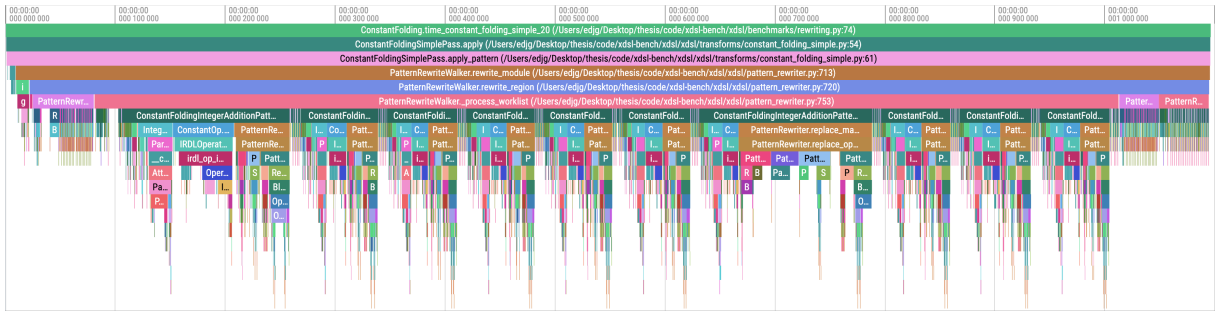
(a) xDSL's existing pattern rewriting infrastructure has a high performance overhead, executing many extraneous operations with a deep call stack.
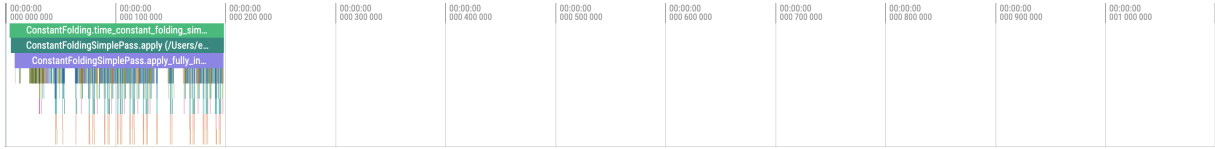
(b) Through specialisation, this overhead can be significantly reduced, performing the exact workload and only invoking inbuilt functions such as set operations and `isinstance` checks.

Figure 5.7: Profiling constant folding pattern rewrites of integer addition before (top) and after (bottom) specialisation with `viztracer` reveals unnecessary computation.

5.2.3   Performance improvement

Through specialising the constant folding implemenation, we achieve a $8\times$ speedup over the original implementation (Figure 5.8). However, this performance uplift comes at the cost of ease of implementation, increasing the constant folding implementation length by $7\times$. As with the specialised micro-benchmarks, we can leverage our novel bytecode profiling tool to explain this improvement in terms of dispatched bytecode instructions, with the workload dropping from 5465 to 977 instructions required to implement its functionality. By examining the implementation and its emitted bytecode instructions, we are confident that it is close to optimal for the workload within the context of xDSL's data structures. In combination with the modifications made to MLIR to similarly avoid extraneous computation, these two implementations are both directly comparable and

complex enough to be representative of real-world workloads. This facilitates their later use for exploring the impact of dynamism on such workloads. Comparison cannot be made with the unmodified version, as MLIR's implementation of pattern rewriting applies constant folding within the framework machinery, clobbering any user-defined constant folding pass.
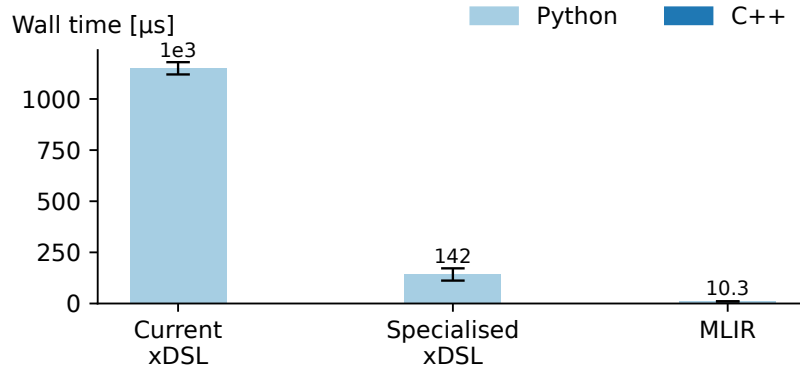
Figure 5.8: Specialisation of constant folding over integer addition in xDSL yields performance uplifts of up to 8×, 14× slower than the MLIR reference implementation.

5.2.4   Optimisations

The majority of changes made during specialisation are applicable only to their specific workload. However, some are more generic to any use case of xDSL, and as such can be applied as stand-alone optimisations. Unfortunately, xDSL is a large codebase, over $150,000$ lines of Python, and as such it is out of scope of this thesis to improve the performance of all of it. Despite this, we demonstrate that the specialisation process lead to generalisable optimisations with measurable performance impact. Through this, we enable performance improvement over time, which can be quantified using our previously introduced measurement infrastructure (subsection 3.1.3). In this section, we discuss two salient examples of these generalised optimisations.

During the specialisation process of trait checking (subsection 5.1.2), we saw that the implementation of xDSL's `has_trait` helper function introduces significant overhead by checking the infrequent case of unregistered operations on the hot path of execution. Since this functionality was not used by the target workload, this could be elided by specialisation for performance. However, it also reveals an optimisation which can be applied to the general case, resulting in a 2.1× speedup on micro-benchmarks and 1.15× speedup within the specialised constant folding workload[1]. Similarly, the specialisation of operation instantiation (subsection 5.1.1) revealed the performance impact of managing the scope of implicit builders, even when they are not being used. As before, this can be generalised to change xDSL's approach from always invoking logic to handle implicit

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[1] https://github.com/xdslproject/xdsl/pull/4242

builders irrespective of whether they are used, to only for operation instantiations which use them, resulting in a $1.06\times$ speedup on micro-benchmarks and $1.01\times$ speedup within the specialised constant folding workload[2].

5.3   Summary

To evaluate whether dynamic languages approach the performance of ahead-of-time compiled languages for implementing user-extensible compiler frameworks, we empirically measure Python's best-case performance for pattern rewriting tasks. By examining specialised implementations of micro-benchmarks and real-world pattern rewriting workloads, we demonstrate that xDSL can achieve performance within $14\times$ of equivalent MLIR implementations. This represents an $8\times$ improvement over xDSL's original implementation, capturing optimisations which can be made automatically by ahead-of-time compilers but not dynamic language runtimes. This specialisation process both eliminates workload-specific redundant computation and avoids costs associated with function invocation, while further revealing generalisable optimisations that benefit xDSL beyond individual workloads. Furthermore, this best-case performance analysis establishes an empirical upper bound for dynamic language performance in compiler infrastructure. In the next chapters, we leverage this performance ceiling as a baseline to examine the effect of both recent improvements to CPython's runtime, and the cost of dynamism in comparison with statically compiled languages.

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[2]`https://github.com/xdslproject/xdsl/pull/4163`

Chapter 6

CPython optimisations for xDSL

Python Enhancement Proposal (PEP) 659 asserts that "Python is widely acknowledged as slow" [37]. This comes partially as an inherent trade-off from the benefits of its interpreted runtime and expressive dynamic semantics, meaning it cannot achieve the general-purpose performance of ahead-of-time compiled languages such as C++ or FORTRAN. However, it is feasible for Python implementations to be competitive with fast implementations of other scripting languages with similar trade-offs, such as JavaScript's V8 or Lua's LuaJIT. The Faster CPython project is an attempt to achieve this goal in Python's reference implementation. Over the course of the recent CPython major versions, new optimisations have been gradually added as part of this project, resulting in incremental performance gains (Table 6.1). This section discusses the details of these optimisations, and their effect on user-extensible compiler workloads in xDSL.

6.1   Specialising adaptive interpreter

Simple interpreters of dynamic languages use generic instructions which can express functionality over a wide array of types. However, this incurs an overhead selecting the specific implementation for the current type at runtime. In 2009, Williams et al. introduced the concept of instruction specialisation in their paper "Dynamic Interpretation for Dynamic Scripting Languages" [14]. This proposes a novel dynamic IR for Lua, whose operations can be specialised to a more performant implementation based on types and control flow encountered at runtime, claiming an average speedup of 1.3×. Following this, Mark Shannon applied the idea to the Python language in his doctoral thesis "The construction of high-performance virtual machines for dynamic languages" [38], demonstrating its viability through the research Virtual Machine (VM) HotPy. This idea was realised in the CPython through Python Enhancement Proposal (PEP) 659's specialising adaptive interpreter, enabled by default in the 2022 minor version 3.11 release.

Table 6.1: Incremental improvements of the geometric mean of speedups across the PyPerformance benchmark suite (full results Appendix A), achieved by optimisations to the CPython interpreter since CPython 3.10.

Python executable		PyPerformance speedup	
Implementation	Feature flag	Baseline	Previous
CPython 3.10.17	None	$1\times$	$1\times$
CPython 3.11.12	None	$1.241\times$	$1.241\times$
CPython 3.13.3	None	$1.312\times$	$1.078\times$
CPython 3.13.3	Experimental JIT	$1.295\times$	$0.988\times$

The specialising adaptive interpreter implements this by replacing instructions which can be optimised by specialisation, such as the generic `LOAD_ATTR`, with an adaptive form, such as `LOAD_ATTR_ADAPTIVE`. Each adaptive instruction maintains an internal counter, incrementing it when the observed usage matches a specialisation opportunity, and decrementing when it does not. When this counter exceeds a threshold, the adaptive instruction replaces itself with the appropriate specialised version, in a process known as a quickening. For example `LOAD_ATTR_ADAPTIVE` becomes `LOAD_ATTR_INSTANCE_VALUE` when the attribute is an instance of the class for previous execution paths of the instruction. If the assumptions required for specialisation are violated later, then the interpreter can fall back to the original instruction implementation to ensure correctness. The optimisation is transparent to users, as no code changes are required, and the interpreter ensures correctness through its fall-back mechanism. The specialising adaptive interpreter's documentation claims a speedup of 10% – 60% [37], matching our recorded geometric mean improvement of 24% for the PyPerformance benchmarks (Table 6.1). This is substantiated by an ablation of the feature across the both previously discussed real-world constant folding workload and micro-benchmarks.

Table 6.2: Execution time per operation improves by a geometric mean speedup of $1.36\times$ across micro-benchmarks and real-world workloads in xDSL when the specialising adaptive interpreter is used (CPython 3.11).

Workload	Execution time [s]		Speedup
	CPython 3.10	CPython 3.11	
Operation instantiation	3770 ± 916	2840 ± 883	$1.33\times$
Specialised operation instantiation	477 ± 385	265 ± 372	$1.8\times$
Trait checking	1920 ± 695	1710 ± 753	$1.12\times$
Specialised trait checking	266 ± 34	191 ± 334	$1.39\times$
Operation traversal	525 ± 3	432 ± 4	$1.21\times$
Constant folding	57000 ± 1895	43000 ± 1340	$1.33\times$
Specialised constant folding	6750 ± 1340	4620 ± 1075	$1.46\times$

We measure the specialising adaptive interpreter to yield a non-negligible speedup of 1.38× across both micro-benchmarks and real-world workloads (Table 6.2). This speedup is greater than the 1.26× recorded across the PyPerformance suite. Since the specialising adaptive interpreter works by quickening highly dynamic instructions into specialised versions, this demonstrates that xDSL as a proxy for user-extensible compiler framework workloads is more dynamic than the baseline of PyPerformance workloads. From this proxy measurement, we hypothesise that user-extensible compiler framework workload is a highly dynamic one, motivating our later quantification of this (chapter 7). The documentation of PyPerformance states "the focus is on real-world benchmarks, rather than synthetic benchmarks, using whole applications when possible." [20], further widening this conclusion to user-extensible compiler framework workloads being more dynamic than the average of a set workload representative of the real-world use of Python. In addition to this, the specialised versions of each workload yield a greater speedup after applying the manual specialisation process described in chapter 5. This shows a further benefit of specialisation in revealing optimisation opportunities by the language runtime.

6.2   Experimental JIT compiler

Another bottleneck of simple interpreted language runtimes is the overhead associated with dispatching and executing bytecode operations. To address this, just-in-time (JIT) compilation can translate frequently executed portions of bytecode into native machine code. This avoids interpreter overhead and allows for further low-level optimizations. CPython's experimental JIT compiler is an implementation of the copy-and-patch machine code generation approach (introduced in subsection 2.6.1), which was added to CPython in 3.13 in 2024. This idea was finally realised in the CPython reference implementation through PEP 744's experimental JIT, optionally enabled by a feature flag in the 2024 minor version 3.13 release.

To implement this, CPython introduced a new internal intermediate representation: tier two opcodes. Tier two opcodes are even more fine-grained that traditional bytecode and as such more amenable to copy-and-patch compilation. When compiling CPython, the LLVM toolchain is used to create small re-usable snippets of machine code for the target machine called stencils, which implement the functionality of these tier two opcodes. At runtime, when bytecode is executed frequently it is marked as hot. Hot bytecode is then translated into a sequence of these more granular tier two opcodes, and optimised by applying transformation passes. The JIT then translates each tier two opcode into executable machine code by copying and patching runtime information into the holes in the pre-compiled stencils. This machine code can then run directly on the processor, replacing the slower interpreter loop to execute the equivalent bytecode instructions. The JIT is experimental and disabled by default in CPython 3.13, but lays the groundwork for significant future performance enhancements. As such, its performance change for many

workloads is minimal or even regressive. As with the specialising adaptive interpreter, we substantiate these claims by an ablation of the feature across the previously discussed real-world workload and micro-benchmarks.

Table 6.3: Execution time per operation improves by a geometric mean slowdown of $0.971\times$ across micro-benchmarks and real-world workloads for CPython 3.13.3 when the experimental JIT is enabled.

	Execution time [s]		
Workload	**JIT disabled**	**JIT enabled**	**Speedup**
Operation instantiation	2990 ± 808	2980 ± 759	$1\times$
Specialised operation instantiation	365 ± 32	391 ± 36	$0.93\times$
Trait checking	1190 ± 553	1220 ± 573	$0.98\times$
Specialised trait checking	221 ± 31	224 ± 30	$0.99\times$
Operation traversal	394 ± 2	427 ± 2	$0.92\times$
Constant folding	44600 ± 1330	47000 ± 1450	$0.95\times$
Specialised constant folding	5400 ± 1225	5250 ± 1275	$1.03\times$

In contrast to the specialising adaptive interpreter, the experimental JIT regresses performance for nearly all workloads (Table 6.3). This aligns with the results recorded for the PyPerformance benchmark suite, which similarly regress when the JIT is enabled. As discussed above, this comes as a result of the JIT's experimental nature, aiming to provide infrastructure for future optimisations rather than immediate gains.

6.3   Summary

In recent years, Faster CPython has introduced two key optimisations which leverage the runtime information as a result of dynamism in the Python interpreter. The first is the specialising adaptive interpreter, which profiles how generic bytecode instructions are used, allowing speculative quickening into a more specialised form. The second is the experimental JIT, which identifies hot code paths at runtime and translates them into optimised native machine code. Beyond these dynamic optimisations which we examine in detail, Faster CPython also makes other optimisations unrelated to dynamism in the language runtime, such as the tail-calling interpreter [39] and memory layout optimisations which further improve performance.
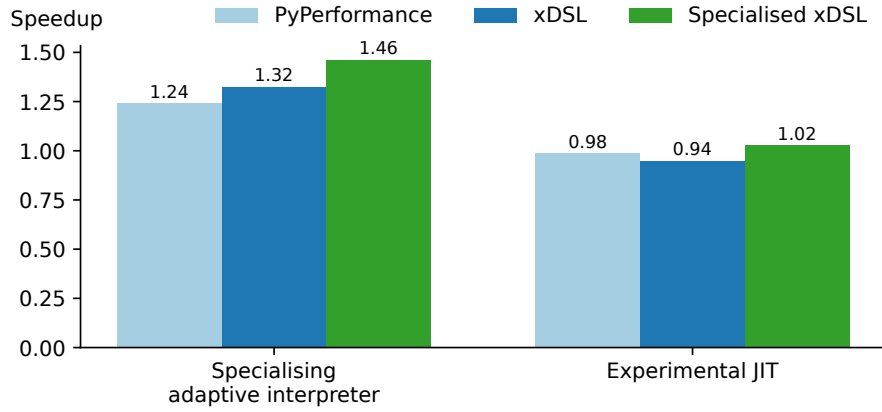
Figure 6.1: Highly dynamic workloads such as constant folding in xDSL exacerbate the performance impact of CPython optimisations leveraging runtime information, with manual specialisation further revealing optimisation opportunities.

Through our empirical measurement, we show that the pointer-chasing, variable control flow workload of the xDSL user-extensible compile framework exacerbates the impact of both of these optimisations leveraging runtime information (Figure 6.1). This can be seen by constant folding in xDSL having a greater speedup than PyPerformance with the specialising adaptive interpreter, but a worse slow-down with the experimental JIT. In addition to this, we show that specialisation of the workloads (chapter 5) reveals further optimisation opportunities, increasing the impact of both of these optimisations.

Chapter 7

Dynamism in compiler frameworks

A key difference between the Python and C++ runtimes is their degree of dynamism. The C++ runtime incurs overhead when dynamically dispatching functions (Figure 1.1, ③), which is worsened by prohibiting ahead-of-time performance optimisations. In contrast, Python dynamically evaluates each bytecode operation individually in its interpreter loop, incurring an overhead each time. As such, we expect the difference in performance between language runtimes (Figure 1.1, ④) to be smaller for more dynamic workloads. In this chapter, we quantify this difference by examining synthetic examples within static and dynamic language runtimes. We then apply this information to understand the difference in performance between pattern rewriting workloads using xDSL and MLIR through the lens of overhead incurred by dynamism.

7.1   Cost of dynamic dispatch

In static languages such as C++, the function calls can often be resolved at compile time. In contrast, dynamic languages such as Python must resolve the address of each function call at runtime, incurring an overhead. However, the address of some function calls can only be known at runtime, for example as a result of object polymorphism. This address then must be resolved during execution by the language runtime in both static and dynamic languages. Furthermore, this information being known only at runtime presents an optimisation boundary, precluding common rewrites such as function inlining which contribute to the performance of ahead-of-time compiled languages. We argue further that the difference between static and dynamic languages is reduced for workloads with insufficient information to resolve function addresses ahead of time. We justify this by examining the mechanisms of dynamic dispatch in Python and C++, and contrasting them through both synthetic examples and our micro-benchmark suite.

C++ uses a Virtual Method Table (vtable) mechanism for method polymorphism, a lookup table which is accessed at runtime through pointer indirection to retrieve the address for

the virtual function implementation. In contrast, Python stores methods and attributes in the `__dict__` object attribute which is searched at runtime, checking parent classes if needed. While both use indirection for dynamic dispatch, Python's approach enables more dynamic behaviour like runtime meta-programming but comes with higher performance costs compared to C++'s more efficient vtable system. We can quantify the performance overhead of this vtable mechanism through a synthetic example (Listing 7.1).

```cpp
class Base {
public:
    int func(int a, int b) { (b)
        return a - b;
    }
    __attribute__((noinline))
    int uninlinedFunc(int a, int b) { (e)
        return a - b;
    }
    virtual int virtualFunc(int a, int b) { (a)
        return a - b;
    }
};

class Derived : public Base {
public:
    int virtualFunc(int a, int b) override {
        return b - a;
    }
};
```

(a) Method definitions.

```cpp
#include <stdlib.h>

int main(int argc, char *argv[]) {
    // Values known only at runtime (c)
    int a = atoi(argv[1]), b = atoi(argv[2]), c
    ↪ = atoi(argv[3]);

    // Setup
    int result = 0;
    Base baseObj;
    Derived derivedObj;
    Base* polyObj = c > 0 ? &baseObj :
    ↪ &derivedObj; (d)

    // Function invocations
    result += baseObj.func(a, b);
    result += baseObj.uninlinedFunc(a, b);
    result += polyObj->virtualFunc(a, b);

    return result;
}
```

(b) Method invocations.

Listing 7.1: Synthetic example of direct and dynamic method dispatch in C++.

This synthetic example exercises polymorphic methods which must be resolved dynamically using a vtable at runtime (a), along with methods which can be statically resolved ahead of time during compilation (b). A challenge when constructing this workload is providing data whose value is known only at runtime. We implement this by taking arguments from the command line (c), as opposed to defining static variables which the compiler could reason about to inform ahead of time optimisations. This is necessary to exercise dynamic dispatch of functions, which requires a polymorphic object whose type is known only at runtime (d). Since this simple synthetic example is amenable to compiler optimisations such as function inlining, we use variable attributes to hint to the compiler that certain methods should not be inlined (e).
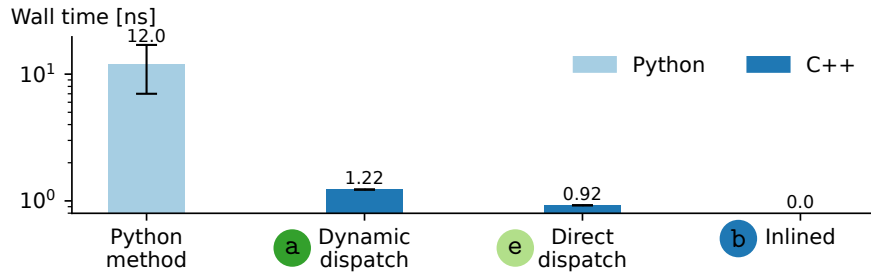
Figure 7.2: Dynamic dispatch generated by `clang -O3` incurs a 30% overhead in comparison with direct dispatch, but remains an order of magnitude more performant than CPython 3.10 method invocation.

Having constructed this synthetic example, we calculate the cost of each method invocation by measuring the runtime of each function and subtracting the runtime of its inlined implementation (Figure 7.2). Dynamic dispatch is 30% slower than direct dispatch, as a result of the overhead constructing and dereferencing through the vtable. Examining the disassembly (Appendix F), this overhead increases the instruction count from 4 to 14, for a total of 10 extra cycles on ARM Reduced Instruction Set Computer (RISC) machines. This observation matches the work of Driesen and Hölzle, who assert the "direct cost" of virtual function calls is up to 10.2 cycles for highly dynamic workloads [40, Figure 18.]. In addition to this Driesen and Hölzle acknowledge there is a further "indirect cost" associated with hidden optimisations, but do not characterise it. An example of such an optimisation hidden by runtime information is the inlining of the function implementation. This code motion represents the remaining 70% of the overhead of dynamic dispatch – significantly greater than the polymorphism machinery. Furthermore, this is a lower bound of this impact, as further optimisations such as vectorisation or dead code elimination could be revealed. Despite both these direct and indirect costs, Python function invocation remains an order of magnitude slower.

Functions which can only be dispatched at runtime are one way a workload can exhibit dynamism. An example of this in the domain of compiler frameworks is the `Operation` objects composing the IR being processed are necessarily only known at runtime, their methods such as verification and printing must be dispatched dynamically. In other cases, MLIR is optimised to avoid this cost. For example, the `TypeID::get<Traits>` function uses template meta-programming to monomorphise the generic function calls. However, this approach is only applicable when there is sufficient information at runtime.

7.2 Run-time type information

In a "A history of C++: 1979–1991", Stroustop states that the original C++ design "deliberately didn't include [mechanisms] for run-time type identification [as] they were almost always misused." [41]. Support for this functionality was later added in C++98 [42], including support for `dynamic_cast`s checked a runtime, and getting the `typeid`

of a polymorphic object. However, this incurs a runtime cost [43], and is brittle in the objects to which it can be applied. A such, LLVM reimplements a subset of this functionality, providing the `dyn_cast` method and `TypeID` data structure, aiming to "strike a balance between performance and the setup required to enable its use" [44]. This is another example of dynamic behaviour, which we again argue incurs additional runtime overhead and precludes optimisations in static languages, closing the gap with dynamic ones. As before, we justify this be examining the details of this mechanism, using our micro-benchmark suite.
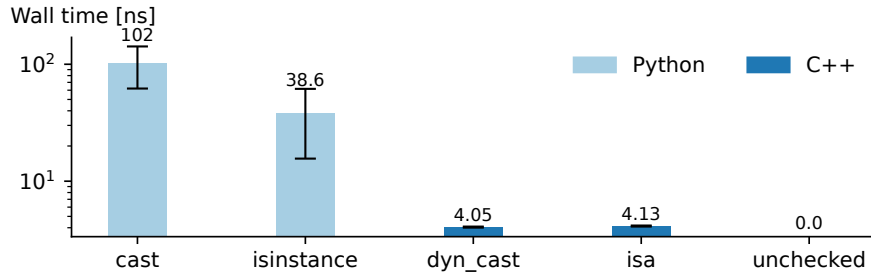
Figure 7.3: Both checking and casting LLVM RTTI have a similar runtime cost, contrasting Python, which is $10\times$ slower for checking and $25\times$ slower for casting.

We measure the duration of micro-benchmarks exercising xDSL and MLIR's RTTI operations (Figure 7.3). LLVM's RTTI implementation is much more performant than Python, leveraging C++ templates to defer as much computation as possible to compile time. In addition to this, type checking and casting have approximately the same performance cost, as they leverage similar mechanisms. In contrast, Python's `isinstance` function is faster than `cast`, as the former is implemented in C as a builtin function, whereas the latter is in Python in the standard library, hence relying on the dynamic dispatch machinery discussed above. However, the implementation of the `cast` function is the identity, doing nothing unless explicitly overridden. Python's dynamic duck typing [45] does not require restructuring data when casting, allowing casting operations and some type checks to be elided. Despite this, the `cast` function incurs a high overhead. In CPython, even empty function calls require at least two expensive bytecode operations, and they cannot be optimised away as they may be overridden dynamically at runtime.

7.3 Dynamic languages for user-extensible compilers

From the previous section we can see that dynamism incurs overhead and precludes ahead of time optimisations. This narrows the performance gap between dynamic and static languages for the implementation of this infrastructure, because the cost traditionally associated with Python's dynamic interpreted runtime is lessened by the commensurate dynamism of the user-extensible compiler framework workload. Contrasting the $60,000\times$ slowdown claimed of C++ implementations of structured workloads such as GEMM [15],

specialised implementations of real-world xDSL workloads demonstrate Python can close this gap to only 10×. In combination with developer productivity being critical for modern compiler engineers to achieve their performance goals (chapter 2), this narrowed gap challenges the status quo of MLIR being implemented static, ahead-of-time compiled C++. Instead, xDSL's approach of using Python improves developer productivity with its expressive syntax and fast build times, empowering fast prototypes during development. We believe that this motivates the use of dynamic languages for the implementation of user-extensible compiler infrastructures.

Chapter 8

Related work

In this chapter, we survey existing literature analysing the performance of compiler frameworks and the Python language, along with the role of dynamism in programming language design. From this, we show the research gaps which this thesis aims to address.

8.1 Compiler framework performance

While compiler designers naturally focus on optimizing the performance of compiled code, the execution time of the compiler itself also has a significant impact on developer productivity. For very large projects such as Firefox, which contains over twenty million lines of code [46], small changes to compiler performance can result in minutes gained or lost for each compilation – significantly impacting developer productivity. Although there has been considerable engineering effort devoted to compiler performance, academic research continues to focus primarily on improving the compiled output rather than the compilation process itself. As such, researchers have not yet fully explored the field, with only a few academic studies examining the performance of compiler frameworks, the most salient of which we discuss below.

Lattner and Adve's original paper proposing LLVM contains a short evaluation of the framework's performance [2, Section 4.1.4]. In this evaluation, the authors compare the runtime of individual transformation passes against `gcc` optimisation level `-O3` across a variety of workloads. The results of this experiment [2, Table 2] report each of LLVM's transformation passes is at least two orders of magnitude faster than `gcc`'s end-to-end compilation across the tested workloads. This demonstrates that analysis and transformations can be performed efficiently, but has a critical flaw. By using end-to-end compilation time for `gcc`, the measurement includes time taken by non-transformation phases such as parsing, printing, and code generation, making it incomparable with the measurements of the transformation passes only for LLVM. Furthermore, since the paper's publication twenty years ago, LLVM has evolved significantly. This evolution brings new complexity,

new performance enhancements, and even new frameworks such as MLIR – changing the calculus of its performance characteristics. This motivated later research to re-examine these performance characteristics of compiler frameworks.

At the 2024 European LLVM Developers' Meeting, Mehdi Amini and Jeff Nui presented their keynote talk "How Slow is MLIR?" [30]. This talk aimed to quantify the feeling in the LLVM community that MLIR incurred a significant performance cost over LLVM alone, and produce metrics against which MLIR could be optimised. The presenters first discuss the implementation details of MLIR, including the design choices made to match common workloads. Next, they provide a set of micro-benchmarks for key functionality provided by MLIR, along with traditional benchmarks for constant folding and loop unrolling workloads. For the micro-benchmarks and constant folding workloads, MLIR is approximately four times slower than traditional LLVM. However, MLIR's more expressive IR representation yields an eighty-eight times speed up over LLVM for loop unrolling.

In addition to performance measurements of the LLVM and MLIR frameworks specifically, there is a body of research examining the performance of compilers more generally. In their 2024 paper, Engelke and Schwarz compare compile-times across frameworks for query compilation [47], finding Cranelift's [48] non-pointer chasing data structures yield a $20 - 35\%$ speedup over LLVM, supporting our hypothesis on the performance impact of dynamism. Engelke's earlier work also touches on compiler performance, proposing low-overhead approaches to binary instrumentation [49], rewriting at runtime [50], and JIT compilation [51] [52]. However, this body of research is much smaller in volume than the literature examining the performance of compiler generated code, despite its critical importance for developer productivity.

Our work differentiates itself from this existing research in two ways. Firstly, the above work focusses only on the performance characteristics of popular frameworks including LLVM, MLIR, and Cranelift. We extend this to also examine xDSL's performance. Secondly, having performance measurements and instrumentation for both MLIR and xDSL, we further extend the domain by contrasting the two frameworks through the lens of dynamism and its impact on performance.

8.2 Python language performance

Driven by Python's immense popularity, significant research effort has been expended developing tools and techniques to characterise its performance. This section discusses a relevant subset of these approaches, and contrasts them with our novel contributions.

8.2.1 Measuring application performance in Python

Reliable and accurate performance measurement is notoriously difficult. As such, its careful execution constitutes the main contribution of systems papers and theses [53] [54]. This

difficulty comes from both sides of the hardware-software interface. For example, hardware optimisations such as hierarchical caches, branch predictors, and power management schemes exhibit complex emergent behaviour [55], making performance measurements less predictable and consistent. Similar confounding effects come from software, from process scheduling in the operating system to garbage collection in language runtimes [56]. Beyond this, advanced interpreters leverage runtime performance information for adaptive specialisation and JIT compilation, further muddling measurements. This phenomenon is explored by Barrett et al.'s "Virtual Machine Warmup Blows Hot and Cold" [29], where interpreter virtual machine warmup is shown to be highly variable, with benchmarks taking over 2000 iterations to reach a steady state. As such, accurate measurement of the performance characteristics of a Python program is more involved than the naïve approach of taking the wall time it takes to execute – requiring additional tools and techniques to guarantee reliable results. Fortunately, Python's strong ecosystem provides a wide variety of tools to achieve this goal, from the simple standard library `timeit` utility [33] to the `pyperf` package [34], with more complex control over confounding effects such as warm-ups and CPU isolation. Our work leverages these tools to make accurate measurements of compiler framework performance.

A key contribution of our research is our application of these tools to produce robust performance measurements and analysis of the xDSL user-extensible compiler frameworks, extending and contrasting similar work for MLIR. In addition to the research contribution of these measurements themselves, our work further supports ongoing research using the xDSL framework by providing re-usable performance benchmarks and associated tooling to measure performance. However, sometimes measurements with finer than end-to-end granularity are required. As such, our tooling also provides a simple user interface for applying performance profilers to these benchmarks.

8.2.2 Profiling to understand Python's performance

Existing profilers for Python typically operate at the function level. For example, Python's standard library provides the `profile` module, a Python-native tracing profiler, along with `cProfile`, a more performant C implementation of the same functionality [57]. These instrument each call event, providing accurate profiling information for each evaluated function. Beyond the standard library, profilers such as `pyinstrument` use statistical sampling rather than tracing to reduce overhead incurred by performance measurement [58]. In addition to this, the recent OSDI best paper winner "Triangulating Python Performance Issues with SCALENE" [59] introduces another profiler which focusses on the FFI boundary between C and Python, a key bottleneck for the best practice of delegating computation to fast low-level implementations. This delegation is particularly effective for structured workloads such as linear algebra, but is less suitable for highly dynamic workloads. Furthermore, profiling information at a finer granularity than the function level is often needed to deeply the performance of a program. `line_profiler` provides

this functionality to a line level [60], but this is still one level of abstraction over the increasingly complex implementation of CPython's interpreter.

We fill this gap in the existing provision with ByteSight, a Python-native tracing performance profiler at the bytecode level. ByteSight extends existing work outputting and rewriting bytecode sequences [61] [62] [63], providing an easily installable package with the novel capability of performance profiling individual bytecode instructions. This contribution also unblocks other work in this thesis, facilitating close examination of specialised implementations and providing information about the performance of individual dynamic bytecode instructions.

8.3 Dynamism in programming languages

One common mechanism providing dynamism in programming languages is dynamic typing. This refers to programming languages where type-checking is performed at runtime, and variables can change type during the course of execution. In their essay "The next 7000 programming languages" [64], Chatley et al. discuss how the landscape of programming languages has changed since Landin's seminal 1966 paper "The next 700 programming languages" [65]. At the time of Landin's paper, there was already a split between dynamically typed languages such as Lisp and statically languages such as C and Algol. Lisp's runtime type checks incurred performance overhead and unexpected runtime type errors, but provided much greater expressivity and hence more productive development than static languages of the time. These trade-offs between static and dynamic languages remain much the same today, with Chatley et al. arguing that dynamically typed languages' expressivity results in "excellent library support", as they are better equipped to express structured data without a fixed schema.

Beyond dynamic typing, there are a wide variety of other mechanisms by which programming languages can provide dynamism. One mechanism is runtime meta-programming, which refers to code which can introspect and manipulate its own behaviour at runtime. An example of this is monkey-patching in Python, which allows the programmatic modification of objects at runtime [66]. Another mechanism is late binding, which refers to resolving method calls at runtime when they are invoked, as opposed to being statically linked ahead of time. Interestingly, ahead-of-time compiled languages typically considered static such as C++ provide this dynamic behaviour in the case of polymorphism. When a method is invoked on an object in an inheritance hierarchy, the correct implementation to execute is resolved at runtime using C++'s vtable mechanism [67]. Driesen and Hölzle quantify the performance overhead of this process in their paper "The Direct Cost of Virtual Function Calls in C++" [40], measuring both a direct cost as a result of the vtable indirection, and an indirect cost from precluded optimisation opportunities. This shows that the dynamic aspects of languages influence the details of their implementation, and the degree to which they can be optimised.

Ahead-of-time compilers rely on static mechanisms such as data-flow analysis to find valid optimisations. As they are run ahead of time, these static analyses have less information to reason about the dynamic runtime behaviour. In this dynamic case, some traditional optimisations cannot be guaranteed to be correct, and hence cannot be leveraged to improve program performance. For example, Hölze and Ungar's paper "Optimizing dynamically-dispatched calls with run-time type feedback" [68] argues that a function which is dynamically dispatched at runtime cannot be optimised through the code motion optimisation of function inlining, as the implementation which will be invoked is not known ahead of time. The authors then aim to address this with an experimental compiler implementing "type feedback", a profile-guided optimisation which inlines dynamically dispatched calls in object-orientated languages. This mirrors later work on instruction specialisation by Williams et al. [14] which lead to Python's specialising adaptive interpreter [37]. However, such approaches are specific to individual aspects of the language runtime, and being ahead of time can only optimise for a prediction of the runtime behaviour. Furthermore, runtime behaviour may differ significantly across inputs for some workloads, making this prediction less representative of real-world behaviour.

Our work applies this body of research to understand the impact of dynamic language features on the performance of dynamic workloads.

Chapter 9

Conclusion

We present performance measurements for the implementation of user-extensible compiler frameworks in dynamic languages through the proxy of xDSL, and contrast this with a replication of existing work measuring the performance of MLIR as a proxy for static language implementations. These measurements find a 110× slowdown for dynamic languages on real-world workloads, but capture the implementation details of the proxies in addition to the language runtimes (chapter 3). To address this, we present specialised versions of micro-benchmarks and a pattern rewriting workload, which. This specialisation process reduces the slowdown between frameworks to 12× (chapter 5). This effort revealed a gap in the tooling provision for highly granular profiling of Python code, leading to our development of ByteSight, a native tracing performance profiler for Python bytecode (chapter 4). ByteSight facilitates developing specialised implementations, and provides insights into the performance impact of dynamism on individual bytecode instructions. Using this tool, we examine optimisation techniques for dynamic language runtimes such as instruction specialisation and JIT compilation, comparing their impact between highly dynamic compiler frameworks with Python's representative suite of real-world workloads. We find that dynamic workloads exacerbate the impact of these optimisations, with instruction specialisation yielding a 10% greater speedup of dynamic over static workloads. This further reduces the slowdown between frameworks to 10× (chapter 6). Finally, we quantify the impact of dynamism on the performance of static and dynamic languages, elucidating the mechanism by which dynamic workloads preclude optimisations and incur overhead and justifying our earlier measurements (chapter 7).

Our work identifies dynamism in user-extensible compiler infrastructures as a result of the heterogeneous data structures used to represent IR, whose structure and contents is known only at runtime. It then quantifies the performance cost this dynamism incurs in their ahead-of-time compiled implementation. We contrast this with implementations in dynamic languages, empirically demonstrating that the performance overhead typically associated with such languages is lessened by both the workload's dynamic nature, and modern optimisation approaches to dynamic language runtimes. This contribution challenges the

status quo of implementing user-extensible compiler frameworks in static, ahead-of-time compiled languages, typified by LLVM's MLIR in C++. Instead, we motivate the use of dynamic languages for these frameworks, showing that implementations such as xDSL which follow this approach present a desirable balance of framework performance with the developer productivity required to deliver modern workloads without delay.

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Appendix A

PyPerformance version comparison

The following section describes the procedure and provides the raw results used to evaluate the speed-ups between CPython versions. Each of the CPython versions was compiled from source with the `--enable-optimizations` and `--with-lto` configuration flags. This compilation was performed on the experimental machine (detailed in subsection 3.1.1) to avoid issues with cross-compilation. The PyPerformance tool runs a suite of benchmarks, each resulting in their own speed-up value (tabulated for each version comparison in Tables A.1, A.2, and A.3). These speed-up values are aggregated into a single speed-up value as the geometric mean. A geometric mean is used because it is less skewed by outlying data. The calculated speed-ups are shown in the main body of the thesis (Table 6.1).

```
 1    py310.json
 2    ==========
 3
 4    Performance version: 1.11.0
 5    Report on Linux-6.8.0-1029-aws-x86_64-with-glibc2.39
 6    Number of logical CPUs: 16
 7    Start date: 2025-06-02 23:12:50.096047
 8    End date: 2025-06-02 23:39:13.222073
 9
10    py311.json
11    ==========
12
13    Performance version: 1.11.0
14    Report on Linux-6.8.0-1029-aws-x86_64-with-glibc2.39
15    Number of logical CPUs: 16
16    Start date: 2025-06-02 22:42:35.309501
17    End date: 2025-06-02 23:09:34.936710
18
19    +-------------------------------+------------+------------+-------------+----------------------+
20    | Benchmark                     | py310.json | py311.json | Change      | Significance         |
21    +===============================+============+============+=============+======================+
22    | async_generators              | 496 ms     | 405 ms     | 1.23x faster | Significant (t=102.94) |
23    +-------------------------------+------------+------------+-------------+----------------------+
24    | async_tree_cpu_io_mixed       | 1.13 sec   | 959 ms     | 1.18x faster | Significant (t=24.21)  |
25    +-------------------------------+------------+------------+-------------+----------------------+
26    | async_tree_eager              | 854 ms     | 607 ms     | 1.41x faster | Significant (t=28.47)  |
```

```
+----------------------------+----------+----------+--------------+-------------------------+
| async_tree_eager_cpu_io_mixed | 1.14 sec | 959 ms   | 1.18x faster | Significant (t=25.07)   |
+----------------------------+----------+----------+--------------+-------------------------+
| async_tree_eager_io        | 1.98 sec | 1.39 sec | 1.42x faster | Significant (t=115.69)  |
+----------------------------+----------+----------+--------------+-------------------------+
| async_tree_eager_memoization | 989 ms | 753 ms   | 1.31x faster | Significant (t=70.85)   |
+----------------------------+----------+----------+--------------+-------------------------+
| async_tree_io              | 1.98 sec | 1.39 sec | 1.42x faster | Significant (t=126.72)  |
+----------------------------+----------+----------+--------------+-------------------------+
| async_tree_memoization     | 989 ms   | 754 ms   | 1.31x faster | Significant (t=80.45)   |
+----------------------------+----------+----------+--------------+-------------------------+
| async_tree_none            | 848 ms   | 607 ms   | 1.40x faster | Significant (t=28.13)   |
+----------------------------+----------+----------+--------------+-------------------------+
| asyncio_tcp                | 907 ms   | 775 ms   | 1.17x faster | Significant (t=6.00)    |
+----------------------------+----------+----------+--------------+-------------------------+
| asyncio_tcp_ssl            | 2.32 sec | 3.63 sec | 1.56x slower | Significant (t=-11.69)  |
+----------------------------+----------+----------+--------------+-------------------------+
| asyncio_websockets         | 643 ms   | 633 ms   | 1.02x faster | Not significant         |
+----------------------------+----------+----------+--------------+-------------------------+
| bench_mp_pool              | 14.4 ms  | 12.8 ms  | 1.12x faster | Significant (t=7.41)    |
+----------------------------+----------+----------+--------------+-------------------------+
| bench_thread_pool          | 1.78 ms  | 1.69 ms  | 1.06x faster | Significant (t=31.34)   |
+----------------------------+----------+----------+--------------+-------------------------+
| chameleon                  | 9.92 ms  | 7.88 ms  | 1.26x faster | Significant (t=53.29)   |
+----------------------------+----------+----------+--------------+-------------------------+
| chaos                      | 130 ms   | 81.1 ms  | 1.61x faster | Significant (t=95.28)   |
+----------------------------+----------+----------+--------------+-------------------------+
| comprehensions             | 29.5 us  | 25.5 us  | 1.16x faster | Significant (t=90.45)   |
+----------------------------+----------+----------+--------------+-------------------------+
| coroutines                 | 35.7 ms  | 28.8 ms  | 1.24x faster | Significant (t=119.60)  |
+----------------------------+----------+----------+--------------+-------------------------+
| coverage                   | 89.0 ms  | 84.8 ms  | 1.05x faster | Significant (t=5.95)    |
+----------------------------+----------+----------+--------------+-------------------------+
| create_gc_cycles           | 1.28 ms  | 1.11 ms  | 1.15x faster | Significant (t=24.86)   |
+----------------------------+----------+----------+--------------+-------------------------+
| crypto_pyaes               | 134 ms   | 85.5 ms  | 1.56x faster | Significant (t=202.03)  |
+----------------------------+----------+----------+--------------+-------------------------+
| dask                       | 525 ms   | 454 ms   | 1.16x faster | Significant (t=21.98)   |
+----------------------------+----------+----------+--------------+-------------------------+
| deepcopy                   | 503 us   | 407 us   | 1.24x faster | Significant (t=59.44)   |
+----------------------------+----------+----------+--------------+-------------------------+
| deepcopy_memo              | 60.3 us  | 45.5 us  | 1.32x faster | Significant (t=77.90)   |
+----------------------------+----------+----------+--------------+-------------------------+
| deepcopy_reduce            | 4.45 us  | 3.59 us  | 1.24x faster | Significant (t=78.19)   |
+----------------------------+----------+----------+--------------+-------------------------+
| deltablue                  | 8.47 ms  | 4.08 ms  | 2.08x faster | Significant (t=150.55)  |
+----------------------------+----------+----------+--------------+-------------------------+
| django_template            | 49.9 ms  | 38.9 ms  | 1.28x faster | Significant (t=45.49)   |
+----------------------------+----------+----------+--------------+-------------------------+
| docutils                   | 3.32 sec | 2.70 sec | 1.23x faster | Significant (t=110.18)  |
+----------------------------+----------+----------+--------------+-------------------------+
| dulwich_log                | 95.2 ms  | 79.0 ms  | 1.20x faster | Significant (t=59.47)   |
+----------------------------+----------+----------+--------------+-------------------------+
| fannkuch                   | 542 ms   | 434 ms   | 1.25x faster | Significant (t=33.10)   |
+----------------------------+----------+----------+--------------+-------------------------+
| float                      | 126 ms   | 86.2 ms  | 1.47x faster | Significant (t=127.64)  |
+----------------------------+----------+----------+--------------+-------------------------+
| gc_traversal               | 3.60 ms  | 3.56 ms  | 1.01x faster | Not significant         |
+----------------------------+----------+----------+--------------+-------------------------+
| generators                 | 60.4 ms  | 55.7 ms  | 1.08x faster | Significant (t=29.61)   |
+----------------------------+----------+----------+--------------+-------------------------+
| genshi_text                | 33.8 ms  | 25.6 ms  | 1.32x faster | Significant (t=85.96)   |
+----------------------------+----------+----------+--------------+-------------------------+
```

genshi_xml	70.6 ms	61.1 ms	1.16x faster	Significant (t=29.82)
go	259 ms	166 ms	1.56x faster	Significant (t=120.34)
hexiom	10.5 ms	7.43 ms	1.41x faster	Significant (t=34.56)
html5lib	106 ms	81.4 ms	1.30x faster	Significant (t=21.53)
json_dumps	14.7 ms	13.6 ms	1.08x faster	Significant (t=21.42)
json_loads	30.2 us	28.4 us	1.06x faster	Significant (t=23.39)
logging_format	11.0 us	7.91 us	1.39x faster	Significant (t=50.52)
logging_silent	197 ns	123 ns	1.60x faster	Significant (t=64.16)
logging_simple	9.95 us	7.10 us	1.40x faster	Significant (t=39.79)
mako	17.3 ms	11.7 ms	1.47x faster	Significant (t=116.59)
mdp	3.51 sec	3.20 sec	1.10x faster	Significant (t=16.77)
meteor_contest	120 ms	109 ms	1.11x faster	Significant (t=58.59)
nbody	150 ms	102 ms	1.47x faster	Significant (t=21.91)
nqueens	111 ms	94.7 ms	1.17x faster	Significant (t=28.95)
pathlib	29.5 ms	27.6 ms	1.07x faster	Significant (t=14.71)
pickle	11.8 us	11.8 us	1.00x faster	Not significant
pickle_dict	28.5 us	29.5 us	1.03x slower	Significant (t=-8.47)
pickle_list	4.17 us	4.16 us	1.00x faster	Not significant
pickle_pure_python	507 us	364 us	1.39x faster	Significant (t=201.27)
pidigits	215 ms	208 ms	1.04x faster	Significant (t=16.13)
pprint_pformat	2.30 sec	1.70 sec	1.35x faster	Significant (t=44.81)
pprint_safe_repr	1.12 sec	825 ms	1.35x faster	Significant (t=62.68)
pyflate	747 ms	463 ms	1.61x faster	Significant (t=105.36)
python_startup	11.0 ms	10.2 ms	1.08x faster	Significant (t=113.04)
python_startup_no_site	7.18 ms	7.62 ms	1.06x slower	Significant (t=-63.11)
raytrace	543 ms	355 ms	1.53x faster	Significant (t=97.20)
regex_compile	204 ms	161 ms	1.27x faster	Significant (t=68.71)
regex_dna	208 ms	182 ms	1.14x faster	Significant (t=45.65)
regex_effbot	3.36 ms	3.23 ms	1.04x faster	Significant (t=7.84)
regex_v8	27.6 ms	24.7 ms	1.12x faster	Significant (t=51.00)
richards	85.1 ms	56.0 ms	1.52x faster	Significant (t=84.28)
richards_super	104 ms	67.5 ms	1.54x faster	Significant (t=81.27)

```
+--------------------------------+------------+------------+--------------+-----------------------+
| scimark_fft                    | 485 ms     | 387 ms     | 1.25x faster | Significant (t=102.78) |
+--------------------------------+------------+------------+--------------+-----------------------+
| scimark_lu                     | 197 ms     | 141 ms     | 1.39x faster | Significant (t=71.19) |
+--------------------------------+------------+------------+--------------+-----------------------+
| scimark_monte_carlo            | 128 ms     | 77.1 ms    | 1.66x faster | Significant (t=127.37) |
+--------------------------------+------------+------------+--------------+-----------------------+
| scimark_sor                    | 232 ms     | 140 ms     | 1.66x faster | Significant (t=112.82) |
+--------------------------------+------------+------------+--------------+-----------------------+
| scimark_sparse_mat_mult        | 6.67 ms    | 4.90 ms    | 1.36x faster | Significant (t=30.12)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| spectral_norm                  | 164 ms     | 131 ms     | 1.25x faster | Significant (t=52.68)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlalchemy_declarative         | 161 ms     | 133 ms     | 1.21x faster | Significant (t=22.47)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlalchemy_imperative          | 24.4 ms    | 21.1 ms    | 1.16x faster | Significant (t=33.55)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlglot_normalize              | 158 ms     | 128 ms     | 1.23x faster | Significant (t=86.82)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlglot_optimize               | 75.3 ms    | 61.3 ms    | 1.23x faster | Significant (t=89.97)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlglot_parse                  | 2.33 ms    | 1.62 ms    | 1.44x faster | Significant (t=129.85) |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlglot_transpile              | 2.76 ms    | 1.95 ms    | 1.41x faster | Significant (t=83.09)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sqlite_synth                   | 3.68 us    | 3.07 us    | 1.20x faster | Significant (t=76.70)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sympy_expand                   | 622 ms     | 537 ms     | 1.16x faster | Significant (t=29.76)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sympy_integrate                | 27.0 ms    | 22.1 ms    | 1.22x faster | Significant (t=52.24)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sympy_str                      | 373 ms     | 324 ms     | 1.15x faster | Significant (t=29.39)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| sympy_sum                      | 209 ms     | 181 ms     | 1.15x faster | Significant (t=43.71)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| telco                          | 8.34 ms    | 7.67 ms    | 1.09x faster | Significant (t=22.23)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| tomli_loads                    | 3.29 sec   | 2.50 sec   | 1.32x faster | Significant (t=66.74)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| tornado_http                   | 168 ms     | 137 ms     | 1.23x faster | Significant (t=27.00)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| typing_runtime_protocols       | 607 us     | 512 us     | 1.18x faster | Significant (t=30.73)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| unpack_sequence                | 58.4 ns    | 44.8 ns    | 1.30x faster | Significant (t=5.12)   |
+--------------------------------+------------+------------+--------------+-----------------------+
| unpickle                       | 15.8 us    | 14.5 us    | 1.09x faster | Significant (t=18.21)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| unpickle_list                  | 5.39 us    | 5.20 us    | 1.04x faster | Significant (t=9.47)   |
+--------------------------------+------------+------------+--------------+-----------------------+
| unpickle_pure_python           | 360 us     | 277 us     | 1.30x faster | Significant (t=79.85)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| xml_etree_generate             | 109 ms     | 91.8 ms    | 1.19x faster | Significant (t=70.86)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| xml_etree_iterparse            | 119 ms     | 110 ms     | 1.08x faster | Significant (t=29.01)  |
+--------------------------------+------------+------------+--------------+-----------------------+
| xml_etree_parse                | 166 ms     | 165 ms     | 1.01x faster | Not significant       |
+--------------------------------+------------+------------+--------------+-----------------------+
| xml_etree_process              | 87.5 ms    | 64.5 ms    | 1.36x faster | Significant (t=144.92) |
+--------------------------------+------------+------------+--------------+-----------------------+

Skipped 8 benchmarks only in py311.json: async_tree_cpu_io_mixed_tg, async_tree_eager_cpu_io_mixed_tg,
  async_tree_eager_io_tg, async_tree_eager_memoization_tg, async_tree_eager_tg, async_tree_io_tg,
  async_tree_memoization_tg, async_tree_none_tg
```

Listing A.1: Comparison table of PyPerformance benchmark results between CPython versions 3.10.17 and 3.11.12.

```
 1   py311.json
 2   =========
 3
 4   Performance version: 1.11.0
 5   Report on Linux-6.8.0-1029-aws-x86_64-with-glibc2.39
 6   Number of logical CPUs: 16
 7   Start date: 2025-06-02 22:42:35.309501
 8   End date: 2025-06-02 23:09:34.936710
 9
10   py313.json
11   =========
12
13   Performance version: 1.11.0
14   Report on Linux-6.8.0-1029-aws-x86_64-with-glibc2.39
15   Number of logical CPUs: 16
16   Start date: 2025-06-02 22:07:57.491156
17   End date: 2025-06-02 22:31:36.629262
18
19   +--------------------------------+-----------+-----------+-------------+------------------------+
20   | Benchmark                      | py311.json | py313.json | Change      | Significance           |
21   +================================+===========+===========+=============+========================+
22   | async_generators               | 405 ms    | 460 ms    | 1.14x slower | Significant (t=-27.58) |
23   +--------------------------------+-----------+-----------+-------------+------------------------+
24   | async_tree_cpu_io_mixed        | 959 ms    | 677 ms    | 1.42x faster | Significant (t=106.37) |
25   +--------------------------------+-----------+-----------+-------------+------------------------+
26   | async_tree_cpu_io_mixed_tg     | 829 ms    | 742 ms    | 1.12x faster | Significant (t=20.80)  |
27   +--------------------------------+-----------+-----------+-------------+------------------------+
28   | async_tree_eager               | 607 ms    | 135 ms    | 4.51x faster | Significant (t=596.51) |
29   +--------------------------------+-----------+-----------+-------------+------------------------+
30   | async_tree_eager_cpu_io_mixed  | 959 ms    | 468 ms    | 2.05x faster | Significant (t=134.71) |
31   +--------------------------------+-----------+-----------+-------------+------------------------+
32   | async_tree_eager_cpu_io_mixed_tg | 827 ms  | 627 ms    | 1.32x faster | Significant (t=36.13)  |
33   +--------------------------------+-----------+-----------+-------------+------------------------+
34   | async_tree_eager_io            | 1.39 sec  | 1.00 sec  | 1.39x faster | Significant (t=32.35)  |
35   +--------------------------------+-----------+-----------+-------------+------------------------+
36   | async_tree_eager_io_tg         | 1.30 sec  | 1.10 sec  | 1.19x faster | Significant (t=11.67)  |
37   +--------------------------------+-----------+-----------+-------------+------------------------+
38   | async_tree_eager_memoization   | 753 ms    | 281 ms    | 2.68x faster | Significant (t=301.57) |
39   +--------------------------------+-----------+-----------+-------------+------------------------+
40   | async_tree_eager_memoization_tg | 694 ms   | 438 ms    | 1.58x faster | Significant (t=34.92)  |
41   +--------------------------------+-----------+-----------+-------------+------------------------+
42   | async_tree_eager_tg            | 528 ms    | 318 ms    | 1.66x faster | Significant (t=56.23)  |
43   +--------------------------------+-----------+-----------+-------------+------------------------+
44   | async_tree_io                  | 1.39 sec  | 966 ms    | 1.44x faster | Significant (t=36.45)  |
45   +--------------------------------+-----------+-----------+-------------+------------------------+
46   | async_tree_io_tg               | 1.30 sec  | 1.00 sec  | 1.30x faster | Significant (t=68.18)  |
47   +--------------------------------+-----------+-----------+-------------+------------------------+
48   | async_tree_memoization         | 754 ms    | 536 ms    | 1.41x faster | Significant (t=16.34)  |
49   +--------------------------------+-----------+-----------+-------------+------------------------+
50   | async_tree_memoization_tg      | 700 ms    | 533 ms    | 1.31x faster | Significant (t=24.40)  |
51   +--------------------------------+-----------+-----------+-------------+------------------------+
52   | async_tree_none                | 607 ms    | 412 ms    | 1.47x faster | Significant (t=144.13) |
53   +--------------------------------+-----------+-----------+-------------+------------------------+
54   | async_tree_none_tg             | 528 ms    | 381 ms    | 1.39x faster | Significant (t=105.89) |
55   +--------------------------------+-----------+-----------+-------------+------------------------+
56   | asyncio_tcp                    | 775 ms    | 476 ms    | 1.63x faster | Significant (t=124.10) |
57   +--------------------------------+-----------+-----------+-------------+------------------------+
58   | asyncio_tcp_ssl                | 3.63 sec  | 1.74 sec  | 2.08x faster | Significant (t=853.90) |
59   +--------------------------------+-----------+-----------+-------------+------------------------+
```

asyncio_websockets	633 ms	642 ms	1.01x slower	Not significant
bench_mp_pool	12.8 ms	12.7 ms	1.01x faster	Not significant
bench_thread_pool	1.69 ms	1.68 ms	1.01x faster	Not significant
chameleon	7.88 ms	8.15 ms	1.03x slower	Significant (t=-11.58)
chaos	81.1 ms	71.5 ms	1.13x faster	Significant (t=23.56)
comprehensions	25.5 us	20.2 us	1.26x faster	Significant (t=38.57)
coroutines	28.8 ms	26.9 ms	1.07x faster	Significant (t=27.12)
coverage	84.8 ms	108 ms	1.27x slower	Significant (t=-31.89)
create_gc_cycles	1.11 ms	1.23 ms	1.11x slower	Significant (t=-21.36)
crypto_pyaes	85.5 ms	78.7 ms	1.09x faster	Significant (t=26.47)
dask	454 ms	449 ms	1.01x faster	Not significant
deepcopy	407 us	449 us	1.11x slower	Significant (t=-49.99)
deepcopy_memo	45.5 us	49.4 us	1.08x slower	Significant (t=-38.52)
deepcopy_reduce	3.59 us	4.05 us	1.13x slower	Significant (t=-29.35)
deltablue	4.08 ms	3.55 ms	1.15x faster	Significant (t=57.73)
django_template	38.9 ms	40.9 ms	1.05x slower	Significant (t=-8.99)
docutils	2.70 sec	2.74 sec	1.01x slower	Not significant
dulwich_log	79.0 ms	79.3 ms	1.00x slower	Not significant
fannkuch	434 ms	470 ms	1.08x slower	Significant (t=-11.43)
float	86.2 ms	95.1 ms	1.10x slower	Significant (t=-31.15)
gc_traversal	3.56 ms	3.75 ms	1.05x slower	Significant (t=-4.61)
generators	55.7 ms	36.9 ms	1.51x faster	Significant (t=122.22)
genshi_text	25.6 ms	26.3 ms	1.03x slower	Significant (t=-4.97)
genshi_xml	61.1 ms	61.2 ms	1.00x slower	Not significant
go	166 ms	171 ms	1.03x slower	Significant (t=-8.53)
hexiom	7.43 ms	6.89 ms	1.08x faster	Significant (t=25.05)
html5lib	81.4 ms	85.1 ms	1.05x slower	Significant (t=-4.97)
json_dumps	13.6 ms	12.0 ms	1.14x faster	Significant (t=44.50)
json_loads	28.4 us	30.3 us	1.07x slower	Significant (t=-23.47)
logging_format	7.91 us	7.79 us	1.02x faster	Not significant
logging_silent	123 ns	137 ns	1.11x slower	Significant (t=-14.30)
logging_simple	7.10 us	6.75 us	1.05x faster	Significant (t=7.92)

Benchmark				
mako	11.7 ms	12.8 ms	1.09x slower	Significant (t=-30.48)
mdp	3.20 sec	3.02 sec	1.06x faster	Significant (t=9.91)
meteor_contest	109 ms	116 ms	1.07x slower	Significant (t=-19.41)
nbody	102 ms	106 ms	1.04x slower	Significant (t=-12.11)
nqueens	94.7 ms	92.6 ms	1.02x faster	Significant (t=4.58)
pathlib	27.6 ms	26.0 ms	1.06x faster	Significant (t=13.29)
pickle	11.8 us	14.9 us	1.27x slower	Significant (t=-54.21)
pickle_dict	29.5 us	33.3 us	1.13x slower	Significant (t=-43.03)
pickle_list	4.16 us	4.98 us	1.20x slower	Significant (t=-39.29)
pickle_pure_python	364 us	359 us	1.01x faster	Not significant
pidigits	208 ms	218 ms	1.05x slower	Significant (t=-34.21)
pprint_pformat	1.70 sec	1.82 sec	1.07x slower	Significant (t=-14.43)
pprint_safe_repr	825 ms	884 ms	1.07x slower	Significant (t=-22.24)
pyflate	463 ms	513 ms	1.11x slower	Significant (t=-25.73)
python_startup	10.2 ms	12.5 ms	1.22x slower	Significant (t=-292.44)
python_startup_no_site	7.62 ms	8.57 ms	1.12x slower	Significant (t=-136.29)
raytrace	355 ms	309 ms	1.15x faster	Significant (t=43.55)
regex_compile	161 ms	156 ms	1.03x faster	Significant (t=10.62)
regex_dna	182 ms	215 ms	1.18x slower	Significant (t=-38.47)
regex_effbot	3.23 ms	3.24 ms	1.00x slower	Not significant
regex_v8	24.7 ms	27.9 ms	1.13x slower	Significant (t=-27.49)
richards	56.0 ms	60.7 ms	1.08x slower	Significant (t=-12.87)
richards_super	67.5 ms	67.5 ms	1.00x slower	Not significant
scimark_fft	387 ms	419 ms	1.08x slower	Significant (t=-18.47)
scimark_lu	141 ms	137 ms	1.03x faster	Significant (t=8.59)
scimark_monte_carlo	77.1 ms	78.9 ms	1.02x slower	Significant (t=-8.31)
scimark_sor	140 ms	157 ms	1.12x slower	Significant (t=-62.46)
scimark_sparse_mat_mult	4.90 ms	5.50 ms	1.12x slower	Significant (t=-16.82)
spectral_norm	131 ms	128 ms	1.02x faster	Not significant
sqlglot_normalize	128 ms	129 ms	1.01x slower	Not significant
sqlglot_optimize	61.3 ms	62.6 ms	1.02x slower	Significant (t=-6.14)

```
186  | sqlglot_parse                   | 1.62 ms   | 1.49 ms   | 1.08x faster | Significant (t=43.70)   |
187  +---------------------------------+-----------+-----------+--------------+-------------------------+
188  | sqlglot_transpile               | 1.95 ms   | 1.82 ms   | 1.07x faster | Significant (t=24.15)   |
189  +---------------------------------+-----------+-----------+--------------+-------------------------+
190  | sqlite_synth                    | 3.07 us   | 3.37 us   | 1.10x slower | Significant (t=-34.84)  |
191  +---------------------------------+-----------+-----------+--------------+-------------------------+
192  | sympy_expand                    | 537 ms    | 523 ms    | 1.03x faster | Significant (t=6.58)    |
193  +---------------------------------+-----------+-----------+--------------+-------------------------+
194  | sympy_integrate                 | 22.1 ms   | 21.2 ms   | 1.04x faster | Significant (t=18.00)   |
195  +---------------------------------+-----------+-----------+--------------+-------------------------+
196  | sympy_str                       | 324 ms    | 307 ms    | 1.06x faster | Significant (t=13.82)   |
197  +---------------------------------+-----------+-----------+--------------+-------------------------+
198  | sympy_sum                       | 181 ms    | 162 ms    | 1.12x faster | Significant (t=31.73)   |
199  +---------------------------------+-----------+-----------+--------------+-------------------------+
200  | telco                           | 7.67 ms   | 9.23 ms   | 1.20x slower | Significant (t=-39.84)  |
201  +---------------------------------+-----------+-----------+--------------+-------------------------+
202  | tomli_loads                     | 2.50 sec  | 2.50 sec  | 1.00x slower | Not significant         |
203  +---------------------------------+-----------+-----------+--------------+-------------------------+
204  | tornado_http                    | 137 ms    | 134 ms    | 1.02x faster | Not significant         |
205  +---------------------------------+-----------+-----------+--------------+-------------------------+
206  | typing_runtime_protocols        | 512 us    | 189 us    | 2.71x faster | Significant (t=186.48)  |
207  +---------------------------------+-----------+-----------+--------------+-------------------------+
208  | unpack_sequence                 | 44.8 ns   | 52.9 ns   | 1.18x slower | Significant (t=-3.27)   |
209  +---------------------------------+-----------+-----------+--------------+-------------------------+
210  | unpickle                        | 14.5 us   | 16.0 us   | 1.10x slower | Significant (t=-19.09)  |
211  +---------------------------------+-----------+-----------+--------------+-------------------------+
212  | unpickle_list                   | 5.20 us   | 5.64 us   | 1.09x slower | Significant (t=-31.35)  |
213  +---------------------------------+-----------+-----------+--------------+-------------------------+
214  | unpickle_pure_python            | 277 us    | 262 us    | 1.05x faster | Significant (t=18.66)   |
215  +---------------------------------+-----------+-----------+--------------+-------------------------+
216  | xml_etree_generate              | 91.8 ms   | 99.3 ms   | 1.08x slower | Significant (t=-39.71)  |
217  +---------------------------------+-----------+-----------+--------------+-------------------------+
218  | xml_etree_iterparse             | 110 ms    | 112 ms    | 1.02x slower | Not significant         |
219  +---------------------------------+-----------+-----------+--------------+-------------------------+
220  | xml_etree_parse                 | 165 ms    | 164 ms    | 1.01x faster | Not significant         |
221  +---------------------------------+-----------+-----------+--------------+-------------------------+
222  | xml_etree_process               | 64.5 ms   | 68.7 ms   | 1.07x slower | Significant (t=-39.35)  |
223  +---------------------------------+-----------+-----------+--------------+-------------------------+
224
225  Skipped 2 benchmarks only in py311.json: sqlalchemy_declarative, sqlalchemy_imperative
226
227  Skipped 1 benchmarks only in py313.json: 2to3
```

Listing A.2: Comparison table of PyPerformance benchmark results between CPython versions 3.11.12 and 3.13.3.

```
 1  py313.json
 2  ==========
 3
 4  Performance version: 1.11.0
 5  Report on Linux-6.8.0-1029-aws-x86_64-with-glibc2.39
 6  Number of logical CPUs: 16
 7  Start date: 2025-06-02 22:07:57.491156
 8  End date: 2025-06-02 22:31:36.629262
 9
10  py313-jit.json
11  ==============
12
13  Performance version: 1.11.0
14  Report on Linux-6.8.0-1029-aws-x86_64-with-glibc2.39
15  Number of logical CPUs: 16
16  Start date: 2025-06-02 21:40:29.802724
17  End date: 2025-06-02 22:04:08.722964
18
```

Benchmark	py313.json	py313-jit.json	Change	Significance
====================================	============	================	==============	=========================
async_generators	460 ms	485 ms	1.05x slower	Significant (t=-8.31)
async_tree_cpu_io_mixed	677 ms	672 ms	1.01x faster	Not significant
async_tree_cpu_io_mixed_tg	742 ms	735 ms	1.01x faster	Not significant
async_tree_eager	135 ms	138 ms	1.03x slower	Significant (t=-5.82)
async_tree_eager_cpu_io_mixed	468 ms	465 ms	1.01x faster	Not significant
async_tree_eager_cpu_io_mixed_tg	627 ms	620 ms	1.01x faster	Not significant
async_tree_eager_io	1.00 sec	997 ms	1.00x faster	Not significant
async_tree_eager_io_tg	1.10 sec	1.12 sec	1.02x slower	Not significant
async_tree_eager_memoization	281 ms	289 ms	1.03x slower	Significant (t=-3.93)
async_tree_eager_memoization_tg	438 ms	439 ms	1.00x slower	Not significant
async_tree_eager_tg	318 ms	322 ms	1.01x slower	Not significant
async_tree_io	966 ms	960 ms	1.01x faster	Not significant
async_tree_io_tg	1.00 sec	990 ms	1.01x faster	Not significant
async_tree_memoization	536 ms	538 ms	1.00x slower	Not significant
async_tree_memoization_tg	533 ms	531 ms	1.00x faster	Not significant
async_tree_none	412 ms	414 ms	1.01x slower	Not significant
async_tree_none_tg	381 ms	383 ms	1.00x slower	Not significant
asyncio_tcp	476 ms	504 ms	1.06x slower	Significant (t=-10.55)
asyncio_tcp_ssl	1.74 sec	1.75 sec	1.00x slower	Not significant
asyncio_websockets	642 ms	647 ms	1.01x slower	Not significant
bench_mp_pool	12.7 ms	13.1 ms	1.03x slower	Not significant
bench_thread_pool	1.68 ms	1.74 ms	1.04x slower	Significant (t=-13.58)
chameleon	8.15 ms	8.22 ms	1.01x slower	Not significant
chaos	71.5 ms	71.2 ms	1.00x faster	Not significant
comprehensions	20.2 us	19.5 us	1.03x faster	Significant (t=4.31)
coroutines	26.9 ms	26.9 ms	1.00x faster	Not significant
coverage	108 ms	96.5 ms	1.12x faster	Significant (t=23.68)
create_gc_cycles	1.23 ms	1.24 ms	1.01x slower	Not significant
crypto_pyaes	78.7 ms	76.2 ms	1.03x faster	Significant (t=5.83)
dask	449 ms	455 ms	1.01x slower	Not significant

deepcopy	449 us	466 us	1.04x slower	Significant (t=-4.65)
deepcopy_memo	49.4 us	45.5 us	1.09x faster	Significant (t=40.04)
deepcopy_reduce	4.05 us	4.11 us	1.01x slower	Not significant
deltablue	3.55 ms	3.97 ms	1.12x slower	Significant (t=-55.41)
django_template	40.9 ms	43.3 ms	1.06x slower	Significant (t=-7.95)
docutils	2.74 sec	2.87 sec	1.05x slower	Significant (t=-8.39)
dulwich_log	79.3 ms	81.1 ms	1.02x slower	Significant (t=-2.44)
fannkuch	470 ms	423 ms	1.11x faster	Significant (t=24.08)
float	95.1 ms	82.4 ms	1.15x faster	Significant (t=37.45)
gc_traversal	3.75 ms	3.76 ms	1.00x slower	Not significant
generators	36.9 ms	37.1 ms	1.00x slower	Not significant
genshi_text	26.3 ms	30.2 ms	1.15x slower	Significant (t=-22.09)
genshi_xml	61.2 ms	68.5 ms	1.12x slower	Significant (t=-32.32)
go	171 ms	174 ms	1.02x slower	Significant (t=-5.09)
hexiom	6.89 ms	7.13 ms	1.04x slower	Significant (t=-8.44)
html5lib	85.1 ms	82.9 ms	1.03x faster	Significant (t=9.55)
json_dumps	12.0 ms	11.8 ms	1.01x faster	Not significant
json_loads	30.3 us	30.4 us	1.00x slower	Not significant
logging_format	7.79 us	7.25 us	1.07x faster	Significant (t=7.00)
logging_silent	137 ns	135 ns	1.01x faster	Not significant
logging_simple	6.75 us	6.65 us	1.02x faster	Not significant
mako	12.8 ms	11.6 ms	1.10x faster	Significant (t=12.42)
mdp	3.02 sec	3.06 sec	1.01x slower	Not significant
meteor_contest	116 ms	117 ms	1.00x slower	Not significant
nbody	106 ms	113 ms	1.06x slower	Significant (t=-14.11)
nqueens	92.6 ms	104 ms	1.12x slower	Significant (t=-18.68)
pathlib	26.0 ms	26.1 ms	1.00x slower	Not significant
pickle	14.9 us	14.7 us	1.01x faster	Not significant
pickle_dict	33.3 us	32.6 us	1.02x faster	Significant (t=4.89)
pickle_list	4.98 us	4.97 us	1.00x faster	Not significant
pickle_pure_python	359 us	367 us	1.02x slower	Significant (t=-10.93)
pidigits	218 ms	212 ms	1.03x faster	Significant (t=32.66)

pprint_pformat	1.82 sec	1.81 sec	1.00x faster	Not significant
pprint_safe_repr	884 ms	886 ms	1.00x slower	Not significant
pyflate	513 ms	482 ms	1.06x faster	Significant (t=13.39)
python_startup	12.5 ms	14.3 ms	1.15x slower	Significant (t=-169.42)
python_startup_no_site	8.57 ms	10.4 ms	1.22x slower	Significant (t=-303.79)
raytrace	309 ms	318 ms	1.03x slower	Significant (t=-9.91)
regex_compile	156 ms	153 ms	1.02x faster	Significant (t=7.49)
regex_dna	215 ms	199 ms	1.08x faster	Significant (t=20.71)
regex_effbot	3.24 ms	3.13 ms	1.04x faster	Significant (t=4.77)
regex_v8	27.9 ms	28.0 ms	1.00x slower	Not significant
richards	60.7 ms	47.6 ms	1.27x faster	Significant (t=46.32)
richards_super	67.5 ms	55.4 ms	1.22x faster	Significant (t=40.93)
scimark_fft	419 ms	359 ms	1.17x faster	Significant (t=32.96)
scimark_lu	137 ms	157 ms	1.14x slower	Significant (t=-46.95)
scimark_monte_carlo	78.9 ms	80.7 ms	1.02x slower	Significant (t=-7.75)
scimark_sor	157 ms	162 ms	1.03x slower	Significant (t=-15.13)
scimark_sparse_mat_mult	5.50 ms	4.64 ms	1.19x faster	Significant (t=23.43)
spectral_norm	128 ms	107 ms	1.20x faster	Significant (t=41.15)
sqlglot_normalize	129 ms	132 ms	1.03x slower	Significant (t=-4.35)
sqlglot_optimize	62.6 ms	65.2 ms	1.04x slower	Significant (t=-9.74)
sqlglot_parse	1.49 ms	1.46 ms	1.02x faster	Not significant
sqlglot_transpile	1.82 ms	1.81 ms	1.01x faster	Not significant
sqlite_synth	3.37 us	3.27 us	1.03x faster	Significant (t=8.77)
sympy_expand	523 ms	574 ms	1.10x slower	Significant (t=-19.84)
sympy_integrate	21.2 ms	22.8 ms	1.07x slower	Significant (t=-31.11)
sympy_str	307 ms	327 ms	1.06x slower	Significant (t=-16.63)
sympy_sum	162 ms	175 ms	1.08x slower	Significant (t=-22.14)
telco	9.23 ms	9.47 ms	1.03x slower	Significant (t=-6.64)
tomli_loads	2.50 sec	2.27 sec	1.10x faster	Significant (t=28.24)
tornado_http	134 ms	139 ms	1.04x slower	Significant (t=-4.64)
typing_runtime_protocols	189 us	199 us	1.05x slower	Significant (t=-6.47)

```
208  | unpack_sequence                | 52.9 ns  | 197 ns        | 3.73x slower | Significant (t=-366.64) |
209  +-------------------------------+----------+--------------+-------------+------------------------+
210  | unpickle                       | 16.0 us  | 15.9 us       | 1.01x faster | Not significant         |
211  +-------------------------------+----------+--------------+-------------+------------------------+
212  | unpickle_list                  | 5.64 us  | 5.36 us       | 1.05x faster | Significant (t=12.69)   |
213  +-------------------------------+----------+--------------+-------------+------------------------+
214  | unpickle_pure_python           | 262 us   | 260 us        | 1.01x faster | Not significant         |
215  +-------------------------------+----------+--------------+-------------+------------------------+
216  | xml_etree_generate             | 99.3 ms  | 96.7 ms       | 1.03x faster | Significant (t=11.44)   |
217  +-------------------------------+----------+--------------+-------------+------------------------+
218  | xml_etree_iterparse            | 112 ms   | 108 ms        | 1.03x faster | Significant (t=13.58)   |
219  +-------------------------------+----------+--------------+-------------+------------------------+
220  | xml_etree_parse                | 164 ms   | 164 ms        | 1.00x faster | Not significant         |
221  +-------------------------------+----------+--------------+-------------+------------------------+
222  | xml_etree_process              | 68.7 ms  | 68.6 ms       | 1.00x faster | Not significant         |
223  +-------------------------------+----------+--------------+-------------+------------------------+
224
225  Skipped 1 benchmarks only in py313.json: 2to3
```

Listing A.3: Comparison table of PyPerformance benchmark results between CPython 3.13.3 with and without the JIT enabled.

Appendix B

MLIR workloads

B.1 Constant folding

```python
1  def constant_folding_module(size: int) -> ModuleOp:
2      """Generate a constant folding workload of a given size.
3
4      The output of running the command
5      `print(WorkloadBuilder().constant_folding_module(size=5))` is shown
6      below:
7
8      ```mlir
9      "builtin.module"() ({
10         %0 = "arith.constant"() {"value" = 865 : i32} : () -> i32
11         %1 = "arith.constant"() {"value" = 395 : i32} : () -> i32
12         %2 = "arith.addi"(%1, %0) : (i32, i32) -> i32
13         %3 = "arith.constant"() {"value" = 777 : i32} : () -> i32
14         %4 = "arith.addi"(%3, %2) : (i32, i32) -> i32
15         %5 = "arith.constant"() {"value" = 912 : i32} : () -> i32
16         "test.op"(%4) : (i32) -> ()
17     }) : () -> ()
18     ```
19     """
20     assert size >= 0
21     random.seed(RANDOM_SEED)
22     ops: list[Operation] = []
23     ops.append(ConstantOp(IntegerAttr(random.randint(1, 1000), i32)))
24     for i in range(1, size + 1):
25         if i % 2 == 0:
26             ops.append(AddiOp(ops[i - 1], ops[i - 2]))
27         else:
28             ops.append(ConstantOp(IntegerAttr(random.randint(1, 1000), i32)))
29     ops.append(TestOp([ops[(size // 2) * 2]]))
30     return ModuleOp(ops)
```

Listing B.1: Python implementation of a parameterised generator for constant folding over integers in xDSL.

Appendix C

MLIR benchmark results

C.1 Pipeline phase micro-benchmark results

C.2 How Slow is MLIR micro-benchmark results

The following section describes the procedure and provides the raw results from "How Slow is MLIR's" micro-benchmarks.

```
1  cmake -G Ninja ../llvm \
2      -DLLVM_ENABLE_PROJECTS=mlir \
3      -DLLVM_TARGETS_TO_BUILD="host" \
4      -DLLVM_ENABLE_BENCHMARKS=ON \
5      -DCMAKE_BUILD_TYPE=Release \
6      -DCMAKE_C_COMPILER=clang-18 -DCMAKE_CXX_COMPILER=clang++-18
7  ./tools/mlir/unittests/Benchmarks/MLIR_IR_Benchmark
```

Listing C.1: Bash commands to downloads, compiler, and run the benchmarks from "How Slow is MLIR".

```
1   2025-05-14T12:19:17+00:00
2   Running ./tools/mlir/unittests/Benchmarks/MLIR_IR_Benchmark
3   Run on (16 X 2799.99 MHz CPU s)
4   CPU Caches:
5     L1 Data 32 KiB (x8)
6     L1 Instruction 32 KiB (x8)
7     L2 Unified 512 KiB (x8)
8     L3 Unified 16384 KiB (x2)
9   Load Average: 0.02, 0.06, 0.02
10  -------------------------------------------------------------------------------
11  Benchmark                                    Time           CPU   Iterations
12  -------------------------------------------------------------------------------
13  Analysis/symbolTable/10                       258 ns        258 ns      2695939
14  Analysis/symbolTable/64                      1280 ns       1280 ns       543255
15  Analysis/symbolTable/512                    11790 ns      11788 ns        60690
16  Analysis/symbolTable/4096                  224244 ns     224225 ns         3104
17  Analysis/symbolTable/32768                2313859 ns    2313755 ns          301
18  Analysis/symbolTable/262144              20582734 ns   20580290 ns           34
```

19	Analysis/symbolTable/2097152	207555204 ns	207544488 ns	3
20	Analysis/symbolTable/10000000	1111381830 ns	1111329506 ns	1
21	Analysis/symbolTable_BigO	110.60 N	110.60 N	
22	Analysis/symbolTable_RMS	6 %	6 %	
23	AttributesBench/sameString/10	25400 ns	25395 ns	27578
24	AttributesBench/sameString/64	29777 ns	29770 ns	23165
25	AttributesBench/sameString/512	67519 ns	67508 ns	10391
26	AttributesBench/sameString/4096	368952 ns	368882 ns	1901
27	AttributesBench/sameString/32768	2616887 ns	2616441 ns	268
28	AttributesBench/sameString/262144	20386755 ns	20382261 ns	35
29	AttributesBench/sameString/2097152	160800051 ns	160770866 ns	4
30	AttributesBench/sameString/10000000	789746984 ns	789711748 ns	1
31	AttributesBench/sameString_BigO	78.88 N	78.87 N	
32	AttributesBench/sameString_RMS	1 %	1 %	
33	AttributesBench/newString/10	26939 ns	26938 ns	26077
34	AttributesBench/newString/64	38844 ns	38835 ns	18031
35	AttributesBench/newString/512	176931 ns	176919 ns	3973
36	AttributesBench/newString/4096	1362397 ns	1362302 ns	509
37	AttributesBench/newString/32768	11228015 ns	11227408 ns	62
38	AttributesBench/newString/262144	111172923 ns	111167549 ns	6
39	AttributesBench/newString/2097152	1591535825 ns	1591347447 ns	1
40	AttributesBench/newString/10000000	8887091339 ns	8886357582 ns	1
41	AttributesBench/newString_BigO	882.93 N	882.86 N	
42	AttributesBench/newString_RMS	8 %	8 %	
43	AttributesBench/sameStringNoThreading/10	25093 ns	25091 ns	27714
44	AttributesBench/sameStringNoThreading/64	29761 ns	29759 ns	23732
45	AttributesBench/sameStringNoThreading/512	67391 ns	67385 ns	10772
46	AttributesBench/sameStringNoThreading/4096	362256 ns	362239 ns	1985
47	AttributesBench/sameStringNoThreading/32768	2653860 ns	2653773 ns	263
48	AttributesBench/sameStringNoThreading/262144	20414147 ns	20412688 ns	34
49	AttributesBench/sameStringNoThreading/2097152	161449035 ns	161410387 ns	4
50	AttributesBench/sameStringNoThreading/10000000	812195579 ns	812055621 ns	1
51	AttributesBench/sameStringNoThreading_BigO	81.04 N	81.02 N	
52	AttributesBench/sameStringNoThreading_RMS	2 %	2 %	
53	AttributesBench/newStringNoThreading/10	25899 ns	25894 ns	26880
54	AttributesBench/newStringNoThreading/64	33426 ns	33420 ns	20941
55	AttributesBench/newStringNoThreading/512	111491 ns	111464 ns	6322
56	AttributesBench/newStringNoThreading/4096	799421 ns	799274 ns	871
57	AttributesBench/newStringNoThreading/32768	6615350 ns	6615040 ns	107
58	AttributesBench/newStringNoThreading/262144	60571886 ns	60568929 ns	10
59	AttributesBench/newStringNoThreading/2097152	1011572721 ns	1011488998 ns	1
60	AttributesBench/newStringNoThreading/10000000	5860333524 ns	5859865437 ns	1
61	AttributesBench/newStringNoThreading_BigO	581.43 N	581.38 N	
62	AttributesBench/newStringNoThreading_RMS	9 %	9 %	
63	AttributesBench/sameStringMultithreaded/1	177082 ns	132487 ns	5349
64	AttributesBench/sameStringMultithreaded/8	188428 ns	138520 ns	4991
65	AttributesBench/sameStringMultithreaded/64	217087 ns	158959 ns	4453
66	AttributesBench/sameStringMultithreaded/512	401011 ns	186276 ns	3759
67	AttributesBench/sameStringMultithreaded/4096	1692038 ns	197919 ns	3654
68	AttributesBench/sameStringMultithreaded/10000	3872841 ns	204502 ns	1000
69	AttributesBench/sameStringMultithreaded_BigO	391.99 N	25.31 N	
70	AttributesBench/sameStringMultithreaded_RMS	15 %	77 %	
71	AttributesBench/newStringMultithreaded/1	176590 ns	131450 ns	5397
72	AttributesBench/newStringMultithreaded/8	225039 ns	158980 ns	4537
73	AttributesBench/newStringMultithreaded/64	270241 ns	185683 ns	3781
74	AttributesBench/newStringMultithreaded/512	1787474 ns	206312 ns	3342
75	AttributesBench/newStringMultithreaded/4096	13267092 ns	219467 ns	1000
76	AttributesBench/newStringMultithreaded/10000	31691415 ns	228920 ns	100
77	AttributesBench/newStringMultithreaded_BigO	3179.93 N	28.25 N	
78	AttributesBench/newStringMultithreaded_RMS	2 %	77 %	
79	AttributesBench/newStringEachMultithreaded/1	181078 ns	134121 ns	5180
80	AttributesBench/newStringEachMultithreaded/8	217968 ns	159165 ns	4343
81	AttributesBench/newStringEachMultithreaded/64	393130 ns	197247 ns	3421

82	AttributesBench/newStringEachMultithreaded/512	2220815 ns	212651 ns	3259
83	AttributesBench/newStringEachMultithreaded/4096	15542558 ns	238015 ns	1000
84	AttributesBench/newStringEachMultithreaded/10000	37028639 ns	262253 ns	100
85	AttributesBench/newStringEachMultithreaded_BigO	3717.53 N	31.79 N	
86	AttributesBench/newStringEachMultithreaded_RMS	2 %	75 %	
87	AttributesBench/setAttrRaw/1	352 ns	352 ns	1894864
88	AttributesBench/setAttrRaw/8	1935 ns	1934 ns	362435
89	AttributesBench/setAttrRaw/64	14422 ns	14422 ns	48335
90	AttributesBench/setAttrRaw/512	114092 ns	114079 ns	6155
91	AttributesBench/setAttrRaw/4096	917976 ns	917885 ns	768
92	AttributesBench/setAttrRaw/32768	7267919 ns	7267427 ns	96
93	AttributesBench/setAttrRaw/100000	22257550 ns	22255369 ns	31
94	AttributesBench/setAttrRaw_BigO	222.50 N	222.48 N	
95	AttributesBench/setAttrRaw_RMS	0 %	0 %	
96	AttributesBench/setAttrProp/1	1.27 ns	1.27 ns	552856899
97	AttributesBench/setAttrProp/8	5.57 ns	5.57 ns	125431956
98	AttributesBench/setAttrProp/64	40.4 ns	40.3 ns	17349876
99	AttributesBench/setAttrProp/512	326 ns	326 ns	2139325
100	AttributesBench/setAttrProp/4096	2589 ns	2588 ns	270117
101	AttributesBench/setAttrProp/32768	20657 ns	20655 ns	33859
102	AttributesBench/setAttrProp/100000	62989 ns	62984 ns	11150
103	AttributesBench/setAttrProp_BigO	0.63 N	0.63 N	
104	AttributesBench/setAttrProp_RMS	0 %	0 %	
105	AttributesBench/setProp/1	1.27 ns	1.27 ns	527999624
106	AttributesBench/setProp/8	6.43 ns	6.43 ns	106786484
107	AttributesBench/setProp/64	41.7 ns	41.7 ns	16801887
108	AttributesBench/setProp/512	332 ns	332 ns	2105804
109	AttributesBench/setProp/4096	2591 ns	2591 ns	270559
110	AttributesBench/setProp/32768	20664 ns	20663 ns	33868
111	AttributesBench/setProp/262144	165411 ns	165400 ns	4230
112	AttributesBench/setProp/1000000	631175 ns	631128 ns	1109
113	AttributesBench/setProp_BigO	0.63 N	0.63 N	
114	AttributesBench/setProp_RMS	0 %	0 %	
115	AttributesBench/setPropHoist/1	0.947 ns	0.947 ns	740202993
116	AttributesBench/setPropHoist/8	5.05 ns	5.05 ns	138881195
117	AttributesBench/setPropHoist/64	40.3 ns	40.3 ns	17345436
118	AttributesBench/setPropHoist/512	325 ns	325 ns	2153624
119	AttributesBench/setPropHoist/4096	2586 ns	2585 ns	270515
120	AttributesBench/setPropHoist/32768	20703 ns	20702 ns	33857
121	AttributesBench/setPropHoist/262144	165570 ns	165564 ns	4225
122	AttributesBench/setPropHoist/1000000	631529 ns	631485 ns	1112
123	AttributesBench/setPropHoist_BigO	0.63 N	0.63 N	
124	AttributesBench/setPropHoist_RMS	0 %	0 %	
125	ConstantFolding/folding/1	3895 ns	3832 ns	182475
126	ConstantFolding/folding/8	15109 ns	15069 ns	46046
127	ConstantFolding/folding/64	114518 ns	114466 ns	6091
128	ConstantFolding/folding/512	508223 ns	508155 ns	1390
129	ConstantFolding/folding/4096	3223717 ns	3223398 ns	214
130	ConstantFolding/folding/10000	7825265 ns	7824889 ns	90
131	ConstantFolding/folding_BigO	783.68 N	783.64 N	
132	ConstantFolding/folding_RMS	3 %	3 %	
133	ConstantFolding/opFolder/1	5910 ns	5866 ns	119213
134	ConstantFolding/opFolder/8	20958 ns	20932 ns	33807
135	ConstantFolding/opFolder/64	153989 ns	153958 ns	4553
136	ConstantFolding/opFolder/512	742573 ns	742498 ns	953
137	ConstantFolding/opFolder/4096	4734908 ns	4734590 ns	145
138	ConstantFolding/opFolder/10000	11462842 ns	11462018 ns	63
139	ConstantFolding/opFolder_BigO	1148.40 N	1148.32 N	
140	ConstantFolding/opFolder_RMS	3 %	3 %	
141	ConstantFolding/llvm_folding/1	1456 ns	1381 ns	507760
142	ConstantFolding/llvm_folding/8	4257 ns	4180 ns	168245
143	ConstantFolding/llvm_folding/64	26929 ns	26840 ns	26297
144	ConstantFolding/llvm_folding/512	156498 ns	156342 ns	4432

145	ConstantFolding/llvm_folding/1000	289457 ns	289321 ns	2429
146	ConstantFolding/llvm_folding_BigO	293.25 N	293.07 N	
147	ConstantFolding/llvm_folding_RMS	5 %	5 %	
148	Cloning/cloneOps/10	2220 ns	2220 ns	318436
149	Cloning/cloneOps/64	14691 ns	14690 ns	46549
150	Cloning/cloneOps/512	136508 ns	136502 ns	5122
151	Cloning/cloneOps/4096	1242184 ns	1242098 ns	565
152	Cloning/cloneOps/32768	10503352 ns	10502102 ns	66
153	Cloning/cloneOps/262144	108813716 ns	108810122 ns	5
154	Cloning/cloneOps/2097152	1521077252 ns	1521011265 ns	1
155	Cloning/cloneOps/10000000	7660330775 ns	7659616760 ns	1
156	Cloning/cloneOps_BigO	764.08 N	764.01 N	
157	Cloning/cloneOps_RMS	4 %	4 %	
158	CreateOps/simple/10	1536 ns	1536 ns	460046
159	CreateOps/simple/64	9646 ns	9644 ns	72357
160	CreateOps/simple/512	78018 ns	78000 ns	9087
161	CreateOps/simple/4096	633086 ns	633009 ns	1105
162	CreateOps/simple/32768	5075687 ns	5074757 ns	141
163	CreateOps/simple/262144	39982401 ns	39974803 ns	17
164	CreateOps/simple/2097152	360437464 ns	360353166 ns	2
165	CreateOps/simple/10000000	2086232311 ns	2086075480 ns	1
166	CreateOps/simple_BigO	207.04 N	207.02 N	
167	CreateOps/simple_RMS	9 %	9 %	
168	CreateOps/hoistedOpState/10	1428 ns	1428 ns	493202
169	CreateOps/hoistedOpState/64	9086 ns	9086 ns	76665
170	CreateOps/hoistedOpState/512	72140 ns	72131 ns	9599
171	CreateOps/hoistedOpState/4096	578253 ns	578227 ns	1203
172	CreateOps/hoistedOpState/32768	4646163 ns	4645889 ns	152
173	CreateOps/hoistedOpState/262144	37132617 ns	37129104 ns	19
174	CreateOps/hoistedOpState/2097152	294337820 ns	294303042 ns	2
175	CreateOps/hoistedOpState/10000000	1415526483 ns	1415445417 ns	1
176	CreateOps/hoistedOpState_BigO	141.50 N	141.49 N	
177	CreateOps/hoistedOpState_RMS	0 %	0 %	
178	CreateOps/withInsert/10	1438 ns	1438 ns	457959
179	CreateOps/withInsert/64	7362 ns	7362 ns	109665
180	CreateOps/withInsert/512	48655 ns	48653 ns	13639
181	CreateOps/withInsert/4096	399650 ns	399628 ns	1781
182	CreateOps/withInsert/32768	3183901 ns	3183579 ns	220
183	CreateOps/withInsert/262144	25701754 ns	25699965 ns	28
184	CreateOps/withInsert/2097152	203392387 ns	203380240 ns	3
185	CreateOps/withInsert/10000000	1091894863 ns	1091801688 ns	1
186	CreateOps/withInsert_BigO	108.67 N	108.66 N	
187	CreateOps/withInsert_RMS	5 %	5 %	
188	CreateOps/simpleRegistered/10	1071 ns	1070 ns	637199
189	CreateOps/simpleRegistered/64	7944 ns	7943 ns	100889
190	CreateOps/simpleRegistered/512	75907 ns	75901 ns	9140
191	CreateOps/simpleRegistered/4096	602203 ns	602160 ns	1171
192	CreateOps/simpleRegistered/32768	5002004 ns	5001232 ns	100
193	CreateOps/simpleRegistered/262144	38527344 ns	38525541 ns	18
194	CreateOps/simpleRegistered/2097152	314170408 ns	314147116 ns	2
195	CreateOps/simpleRegistered/10000000	1486016787 ns	1485892910 ns	1
196	CreateOps/simpleRegistered_BigO	148.65 N	148.64 N	
197	CreateOps/simpleRegistered_RMS	0 %	0 %	
198	CreateOps/withInsertRegistered/10	1529 ns	1529 ns	446050
199	CreateOps/withInsertRegistered/64	8186 ns	8186 ns	92710
200	CreateOps/withInsertRegistered/512	60538 ns	60532 ns	11322
201	CreateOps/withInsertRegistered/4096	469575 ns	469520 ns	1447
202	CreateOps/withInsertRegistered/32768	3768329 ns	3768200 ns	183
203	CreateOps/withInsertRegistered/262144	30147703 ns	30146259 ns	23
204	CreateOps/withInsertRegistered/2097152	240048733 ns	240016824 ns	3
205	CreateOps/withInsertRegistered/10000000	1287778683 ns	1287710159 ns	1
206	CreateOps/withInsertRegistered_BigO	128.17 N	128.16 N	
207	CreateOps/withInsertRegistered_RMS	5 %	5 %	

208	CreateOps/llvm_withInsertRegistered/10	621 ns	621 ns	1310205
209	CreateOps/llvm_withInsertRegistered/64	3399 ns	3399 ns	208887
210	CreateOps/llvm_withInsertRegistered/512	26754 ns	26751 ns	26019
211	CreateOps/llvm_withInsertRegistered/4096	214032 ns	214024 ns	3267
212	CreateOps/llvm_withInsertRegistered/32768	1740016 ns	1739836 ns	409
213	CreateOps/llvm_withInsertRegistered/262144	13703840 ns	13703383 ns	51
214	CreateOps/llvm_withInsertRegistered/2097152	116423890 ns	116413778 ns	7
215	CreateOps/llvm_withInsertRegistered/10000000	508718534 ns	508690844 ns	1
216	CreateOps/llvm_withInsertRegistered_BigO	51.07 N	51.07 N	
217	CreateOps/llvm_withInsertRegistered_RMS	4 %	4 %	
218	CreateOps/simpleConstant/10	4259 ns	4259 ns	166102
219	CreateOps/simpleConstant/64	27216 ns	27212 ns	25925
220	CreateOps/simpleConstant/512	215266 ns	215255 ns	3259
221	CreateOps/simpleConstant/4096	1706406 ns	1706316 ns	407
222	CreateOps/simpleConstant/32768	13536332 ns	13535658 ns	51
223	CreateOps/simpleConstant/262144	109289148 ns	109280023 ns	6
224	CreateOps/simpleConstant/2097152	872710808 ns	872649757 ns	1
225	CreateOps/simpleConstant/10000000	4174540562 ns	4174213028 ns	1
226	CreateOps/simpleConstant_BigO	417.40 N	417.37 N	
227	CreateOps/simpleConstant_RMS	0 %	0 %	
228	CreateOps/simpleRegisteredConstant/10	3584 ns	3583 ns	195947
229	CreateOps/simpleRegisteredConstant/64	22858 ns	22857 ns	30869
230	CreateOps/simpleRegisteredConstant/512	179839 ns	179822 ns	3900
231	CreateOps/simpleRegisteredConstant/4096	1436457 ns	1436281 ns	495
232	CreateOps/simpleRegisteredConstant/32768	11687039 ns	11686423 ns	61
233	CreateOps/simpleRegisteredConstant/262144	93986445 ns	93981382 ns	8
234	CreateOps/simpleRegisteredConstant/2097152	734716294 ns	734631856 ns	1
235	CreateOps/simpleRegisteredConstant/10000000	3516873944 ns	3516440595 ns	1
236	CreateOps/simpleRegisteredConstant_BigO	351.64 N	351.59 N	
237	CreateOps/simpleRegisteredConstant_RMS	0 %	0 %	
238	DialectConversion/noPatterns/1	2114 ns	2058 ns	341049
239	DialectConversion/noPatterns/8	3206 ns	3144 ns	223480
240	DialectConversion/noPatterns/64	10719 ns	10667 ns	67748
241	DialectConversion/noPatterns/512	67336 ns	67225 ns	10457
242	DialectConversion/noPatterns/4096	522999 ns	522861 ns	1337
243	DialectConversion/noPatterns/32768	4157336 ns	4156524 ns	168
244	DialectConversion/noPatterns/262144	34530702 ns	34527365 ns	20
245	DialectConversion/noPatterns/1000000	141217638 ns	141213232 ns	5
246	DialectConversion/noPatterns_BigO	140.59 N	140.59 N	
247	DialectConversion/noPatterns_RMS	4 %	4 %	
248	DialectConversion/toLLVM/1	26222 ns	26240 ns	26347
249	DialectConversion/toLLVM/8	52543 ns	52546 ns	13238
250	DialectConversion/toLLVM/64	270734 ns	270727 ns	2555
251	DialectConversion/toLLVM/512	1942653 ns	1942429 ns	355
252	DialectConversion/toLLVM/4096	15547873 ns	15547373 ns	45
253	DialectConversion/toLLVM/32768	135306178 ns	135301871 ns	5
254	DialectConversion/toLLVM/262144	1349905322 ns	1349700436 ns	1
255	DialectConversion/toLLVM/1000000	6221941548 ns	6221300959 ns	1
256	DialectConversion/toLLVM_BigO	6150.91 N	6150.26 N	
257	DialectConversion/toLLVM_RMS	10 %	10 %	
258	GreedyRewriter/empty/1	160 ns	160 ns	4317770
259	GreedyRewriter/empty/8	310 ns	310 ns	2242470
260	GreedyRewriter/empty/64	1999 ns	1998 ns	344037
261	GreedyRewriter/empty/512	18588 ns	18584 ns	37692
262	GreedyRewriter/empty/4096	196155 ns	196116 ns	3571
263	GreedyRewriter/empty/32768	1562059 ns	1561765 ns	453
264	GreedyRewriter/empty/262144	14990618 ns	14987106 ns	47
265	GreedyRewriter/empty/2097152	161013784 ns	160978620 ns	4
266	GreedyRewriter/empty/10000000	1160105739 ns	1159997571 ns	1
267	GreedyRewriter/empty_BigO	114.32 N	114.31 N	
268	GreedyRewriter/empty_RMS	18 %	18 %	
269	GreedyRewriter/withCanonicalizationPatterns/10	40997 ns	40995 ns	16619
270	GreedyRewriter/withCanonicalizationPatterns/64	43101 ns	43100 ns	16070

271	GreedyRewriter/withCanonicalizationPatterns/512	61193 ns	61189 ns	11507
272	GreedyRewriter/withCanonicalizationPatterns/4096	229037 ns	229017 ns	2960
273	GreedyRewriter/withCanonicalizationPatterns/32768	1687291 ns	1686925 ns	430
274	GreedyRewriter/withCanonicalizationPatterns/262144	15046323 ns	15042271 ns	47
275	GreedyRewriter/withCanonicalizationPatterns/2097152	166651302 ns	166609746 ns	4
276	GreedyRewriter/withCanonicalizationPatterns/10000000	1205316641 ns	1205235646 ns	1
277	GreedyRewriter/withCanonicalizationPatterns_BigO	118.76 N	118.75 N	
278	GreedyRewriter/withCanonicalizationPatterns_RMS	17 %	17 %	
279	GreedyRewriter/withPatterns/100	48255 ns	48244 ns	14615
280	GreedyRewriter/withPatterns/512	86790 ns	86771 ns	7815
281	GreedyRewriter/withPatterns/4096	630096 ns	630079 ns	1172
282	GreedyRewriter/withPatterns/10000	1454875 ns	1454797 ns	480
283	GreedyRewriter/withPatterns_BigO	146.77 N	146.76 N	
284	GreedyRewriter/withPatterns_RMS	4 %	4 %	
285	InterfaceBench/vectorTraveralCallInterfaceMethod/10	99.8 ns	99.8 ns	7047449
286	InterfaceBench/vectorTraveralCallInterfaceMethod/64	591 ns	591 ns	1183230
287	InterfaceBench/vectorTraveralCallInterfaceMethod/512	4638 ns	4638 ns	150472
288	InterfaceBench/vectorTraveralCallInterfaceMethod/4096	37237 ns	37229 ns	18789
289	InterfaceBench/vectorTraveralCallInterfaceMethod/32768	300670 ns	300651 ns	2333
290	InterfaceBench/vectorTraveralCallInterfaceMethod/262144	2643092 ns	2642860 ns	263
291	InterfaceBench/vectorTraveralCallInterfaceMethod/2097152	20712952 ns	20708857 ns	34
292	InterfaceBench/vectorTraveralCallInterfaceMethod/10000000	98550537 ns	98542763 ns	7
293	InterfaceBench/vectorTraveralCallInterfaceMethod_BigO	9.86 N	9.86 N	
294	InterfaceBench/vectorTraveralCallInterfaceMethod_RMS	0 %	0 %	
295	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod/10	15.0 ns	15.0 ns	46612990
296	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod/64	93.3 ns	93.3 ns	7470909
297	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod/512	699 ns	699 ns	995669
298	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod/4096	5522 ns	5521 ns	126964
299	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod/10000	15494 ns	15493 ns	45167
300	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod_BigO	1.52 N	1.52 N	
301	InterfaceBench/llvm_vectorTraveralCallInterfaceMethod_RMS	8 %	8 %	
302	LoopUnrolling/unroll/1	4502 ns	4410 ns	158967
303	LoopUnrolling/unroll/8	23767 ns	23618 ns	29563
304	LoopUnrolling/unroll/64	172746 ns	172507 ns	4052
305	LoopUnrolling/unroll/512	1322454 ns	1321995 ns	534
306	LoopUnrolling/unroll/1000	2545860 ns	2545325 ns	276
307	LoopUnrolling/unroll_BigO	2554.05 N	2553.43 N	
308	LoopUnrolling/unroll_RMS	1 %	1 %	
309	LoopUnrolling/llvm_unroll/1	36144 ns	36123 ns	19441
310	LoopUnrolling/llvm_unroll/8	255243 ns	255368 ns	2735
311	LoopUnrolling/llvm_unroll/64	2700037 ns	2700070 ns	259
312	LoopUnrolling/llvm_unroll/512	73407469 ns	73402333 ns	10
313	LoopUnrolling/llvm_unroll/1000	260718746 ns	260696177 ns	3
314	LoopUnrolling/llvm_unroll_BigO	235708.03 N	235688.13 N	
315	LoopUnrolling/llvm_unroll_RMS	36 %	36 %	
316	ParserPrinter/parseTextualIR/10	61549 ns	61546 ns	11338
317	ParserPrinter/parseTextualIR/64	179556 ns	179544 ns	3894
318	ParserPrinter/parseTextualIR/512	1220245 ns	1220158 ns	573
319	ParserPrinter/parseTextualIR/4096	9856960 ns	9855832 ns	71
320	ParserPrinter/parseTextualIR/32768	82664124 ns	82658142 ns	8
321	ParserPrinter/parseTextualIR/262144	995924502 ns	995851929 ns	1
322	ParserPrinter/parseTextualIR/1000000	4324001717 ns	4323683749 ns	1
323	ParserPrinter/parseTextualIR_BigO	4288.45 N	4288.13 N	
324	ParserPrinter/parseTextualIR_RMS	7 %	7 %	
325	ParserPrinter/parseBytecodeIR/10	47988 ns	47984 ns	14588
326	ParserPrinter/parseBytecodeIR/64	100307 ns	100281 ns	6952
327	ParserPrinter/parseBytecodeIR/512	573133 ns	573025 ns	1218
328	ParserPrinter/parseBytecodeIR/4096	4586582 ns	4585625 ns	153
329	ParserPrinter/parseBytecodeIR/32768	37373868 ns	37371286 ns	19
330	ParserPrinter/parseBytecodeIR/262144	420982484 ns	420959945 ns	2
331	ParserPrinter/parseBytecodeIR/1000000	2034472944 ns	2034323491 ns	1
332	ParserPrinter/parseBytecodeIR_BigO	2006.03 N	2005.89 N	
333	ParserPrinter/parseBytecodeIR_RMS	12 %	12 %	

334	ParserPrinter/printTextualIR/10	14484 ns	14482 ns	48128
335	ParserPrinter/printTextualIR/64	62662 ns	62660 ns	11078
336	ParserPrinter/printTextualIR/512	463614 ns	463600 ns	1507
337	ParserPrinter/printTextualIR/4096	3802635 ns	3802384 ns	184
338	ParserPrinter/printTextualIR/32768	31159720 ns	31152274 ns	22
339	ParserPrinter/printTextualIR/262144	298570499 ns	298498153 ns	2
340	ParserPrinter/printTextualIR/1000000	1246963499 ns	1246833554 ns	1
341	ParserPrinter/printTextualIR_BigO	1239.72 N	1239.58 N	
342	ParserPrinter/printTextualIR_RMS	5 %	5 %	
343	ParserPrinter/printBytecodeIR/10	12809 ns	12805 ns	53762
344	ParserPrinter/printBytecodeIR/64	49801 ns	49790 ns	13943
345	ParserPrinter/printBytecodeIR/512	408265 ns	408185 ns	1735
346	ParserPrinter/printBytecodeIR/4096	3312854 ns	3312253 ns	209
347	ParserPrinter/printBytecodeIR/32768	28967742 ns	28958923 ns	23
348	ParserPrinter/printBytecodeIR/262144	299572774 ns	299555963 ns	2
349	ParserPrinter/printBytecodeIR/1000000	1386730152 ns	1386637183 ns	1
350	ParserPrinter/printBytecodeIR_BigO	1370.55 N	1370.45 N	
351	ParserPrinter/printBytecodeIR_RMS	10 %	10 %	
352	IRWalk/blockTraveral/10	17.5 ns	17.5 ns	39881680
353	IRWalk/blockTraveral/64	110 ns	110 ns	6379697
354	IRWalk/blockTraveral/512	1596 ns	1595 ns	439735
355	IRWalk/blockTraveral/4096	10195 ns	10194 ns	68860
356	IRWalk/blockTraveral/32768	81073 ns	81055 ns	8650
357	IRWalk/blockTraveral/262144	1841230 ns	1840690 ns	381
358	IRWalk/blockTraveral/2097152	16323138 ns	16319776 ns	43
359	IRWalk/blockTraveral/10000000	80215734 ns	80210678 ns	9
360	IRWalk/blockTraveral_BigO	8.01 N	8.01 N	
361	IRWalk/blockTraveral_RMS	2 %	2 %	
362	IRWalk/vectorTraveral/10	4.06 ns	4.06 ns	171981038
363	IRWalk/vectorTraveral/64	26.4 ns	26.4 ns	26457066
364	IRWalk/vectorTraveral/512	232 ns	232 ns	3020721
365	IRWalk/vectorTraveral/4096	1849 ns	1849 ns	379201
366	IRWalk/vectorTraveral/32768	14762 ns	14759 ns	47414
367	IRWalk/vectorTraveral/262144	114403 ns	114397 ns	6116
368	IRWalk/vectorTraveral/2097152	1028901 ns	1028851 ns	685
369	IRWalk/vectorTraveral/10000000	6133232 ns	6132622 ns	114
370	IRWalk/vectorTraveral_BigO	0.61 N	0.61 N	
371	IRWalk/vectorTraveral_RMS	10 %	10 %	
372	IRWalk/simpleWalk/10	62.6 ns	62.6 ns	11116850
373	IRWalk/simpleWalk/64	350 ns	350 ns	1999507
374	IRWalk/simpleWalk/512	2729 ns	2729 ns	256518
375	IRWalk/simpleWalk/4096	21833 ns	21831 ns	32038
376	IRWalk/simpleWalk/32768	176236 ns	176223 ns	3985
377	IRWalk/simpleWalk/262144	1742919 ns	1742834 ns	404
378	IRWalk/simpleWalk/2097152	14132705 ns	14131555 ns	49
379	IRWalk/simpleWalk/10000000	67449778 ns	67445037 ns	10
380	IRWalk/simpleWalk_BigO	6.74 N	6.74 N	
381	IRWalk/simpleWalk_RMS	0 %	0 %	
382	IRWalk/filteredOps/10	17.1 ns	17.1 ns	40873782
383	IRWalk/filteredOps/64	113 ns	113 ns	6174719
384	IRWalk/filteredOps/512	1603 ns	1603 ns	431125
385	IRWalk/filteredOps/4096	9621 ns	9620 ns	72549
386	IRWalk/filteredOps/32768	76871 ns	76866 ns	9082
387	IRWalk/filteredOps/262144	1558707 ns	1558516 ns	452
388	IRWalk/filteredOps/2097152	13222558 ns	13221336 ns	53
389	IRWalk/filteredOps/10000000	62731864 ns	62725928 ns	11
390	IRWalk/filteredOps_BigO	6.27 N	6.27 N	
391	IRWalk/filteredOps_RMS	1 %	1 %	
392	IRWalk/nestedRegion/10	84.7 ns	84.7 ns	8264952
393	IRWalk/nestedRegion/16	125 ns	125 ns	5587643
394	IRWalk/nestedRegion/64	454 ns	454 ns	1531392
395	IRWalk/nestedRegion/256	1828 ns	1828 ns	384758
396	IRWalk/nestedRegion/1024	7129 ns	7129 ns	91981

397	IRWalk/nestedRegion/4096	30161 ns	30159 ns	23193
398	IRWalk/nestedRegion/8000	57663 ns	57658 ns	12012
399	IRWalk/nestedRegion_BigO	7.24 N	7.24 N	
400	IRWalk/nestedRegion_RMS	2 %	2 %	
401	IRWalk/llvm_blockTraversal/10	7.48 ns	7.48 ns	93670794
402	IRWalk/llvm_blockTraversal/64	69.4 ns	69.4 ns	10072389
403	IRWalk/llvm_blockTraversal/512	1476 ns	1476 ns	469258
404	IRWalk/llvm_blockTraversal/4096	9975 ns	9975 ns	70587
405	IRWalk/llvm_blockTraversal/32768	80465 ns	80459 ns	8673
406	IRWalk/llvm_blockTraversal/262144	1803648 ns	1803592 ns	390
407	IRWalk/llvm_blockTraversal/2097152	16225756 ns	16225254 ns	43
408	IRWalk/llvm_blockTraversal/10000000	78978276 ns	78975659 ns	9
409	IRWalk/llvm_blockTraversal_BigO	7.89 N	7.89 N	
410	IRWalk/llvm_blockTraversal_RMS	1 %	1 %	
411	IRWalk/vectorTraveralOpCastFail/10	7.36 ns	7.36 ns	95088104
412	IRWalk/vectorTraveralOpCastFail/64	45.7 ns	45.7 ns	15317168
413	IRWalk/vectorTraveralOpCastFail/512	476 ns	476 ns	1450136
414	IRWalk/vectorTraveralOpCastFail/4096	3790 ns	3790 ns	184584
415	IRWalk/vectorTraveralOpCastFail/32768	39812 ns	39809 ns	17634
416	IRWalk/vectorTraveralOpCastFail/262144	975434 ns	975405 ns	720
417	IRWalk/vectorTraveralOpCastFail/2097152	8580938 ns	8580456 ns	81
418	IRWalk/vectorTraveralOpCastFail/10000000	40768999 ns	40764746 ns	17
419	IRWalk/vectorTraveralOpCastFail_BigO	4.08 N	4.08 N	
420	IRWalk/vectorTraveralOpCastFail_RMS	1 %	1 %	
421	IRWalk/vectorTraveralOpCastSuccess/10	7.39 ns	7.39 ns	93692158
422	IRWalk/vectorTraveralOpCastSuccess/64	45.7 ns	45.7 ns	15323919
423	IRWalk/vectorTraveralOpCastSuccess/512	523 ns	523 ns	1294067
424	IRWalk/vectorTraveralOpCastSuccess/4096	3785 ns	3785 ns	186404
425	IRWalk/vectorTraveralOpCastSuccess/32768	39972 ns	39970 ns	17502
426	IRWalk/vectorTraveralOpCastSuccess/262144	977336 ns	977306 ns	720
427	IRWalk/vectorTraveralOpCastSuccess/2097152	8450122 ns	8447973 ns	81
428	IRWalk/vectorTraveralOpCastSuccess/10000000	40680953 ns	40678330 ns	17
429	IRWalk/vectorTraveralOpCastSuccess_BigO	4.07 N	4.07 N	
430	IRWalk/vectorTraveralOpCastSuccess_RMS	1 %	1 %	
431	IRWalk/vectorTraveralOpIsaSuccess/10	7.02 ns	7.02 ns	99761463
432	IRWalk/vectorTraveralOpIsaSuccess/64	47.6 ns	47.6 ns	14778467
433	IRWalk/vectorTraveralOpIsaSuccess/512	420 ns	420 ns	1628629
434	IRWalk/vectorTraveralOpIsaSuccess/4096	4313 ns	4313 ns	161931
435	IRWalk/vectorTraveralOpIsaSuccess/32768	38468 ns	38465 ns	17969
436	IRWalk/vectorTraveralOpIsaSuccess/262144	983971 ns	983943 ns	708
437	IRWalk/vectorTraveralOpIsaSuccess/2097152	8727375 ns	8726866 ns	79
438	IRWalk/vectorTraveralOpIsaSuccess/10000000	41350491 ns	41343429 ns	17
439	IRWalk/vectorTraveralOpIsaSuccess_BigO	4.14 N	4.14 N	
440	IRWalk/vectorTraveralOpIsaSuccess_RMS	1 %	1 %	
441	IRWalk/vectorTraveralWithoutInterfaceCastFail/10	39.2 ns	39.2 ns	17857367
442	IRWalk/vectorTraveralWithoutInterfaceCastFail/64	254 ns	254 ns	2761824
443	IRWalk/vectorTraveralWithoutInterfaceCastFail/512	2132 ns	2131 ns	328156
444	IRWalk/vectorTraveralWithoutInterfaceCastFail/4096	16273 ns	16272 ns	42906
445	IRWalk/vectorTraveralWithoutInterfaceCastFail/32768	131320 ns	131283 ns	5341
446	IRWalk/vectorTraveralWithoutInterfaceCastFail/262144	1665353 ns	1664450 ns	422
447	IRWalk/vectorTraveralWithoutInterfaceCastFail/2097152	13372446 ns	13369410 ns	52
448	IRWalk/vectorTraveralWithoutInterfaceCastFail/10000000	63311417 ns	63307361 ns	11
449	IRWalk/vectorTraveralWithoutInterfaceCastFail_BigO	6.33 N	6.33 N	
450	IRWalk/vectorTraveralWithoutInterfaceCastFail_RMS	0 %	0 %	
451	IRWalk/vectorTraveralWithInterfaceCastFail/10	47.3 ns	47.3 ns	14787937
452	IRWalk/vectorTraveralWithInterfaceCastFail/64	308 ns	308 ns	2278677
453	IRWalk/vectorTraveralWithInterfaceCastFail/512	2458 ns	2458 ns	285080
454	IRWalk/vectorTraveralWithInterfaceCastFail/4096	19516 ns	19515 ns	35921
455	IRWalk/vectorTraveralWithInterfaceCastFail/32768	156901 ns	156861 ns	4470
456	IRWalk/vectorTraveralWithInterfaceCastFail/262144	2045579 ns	2045320 ns	338
457	IRWalk/vectorTraveralWithInterfaceCastFail/2097152	16461268 ns	16455022 ns	43
458	IRWalk/vectorTraveralWithInterfaceCastFail/10000000	78230340 ns	78221750 ns	9
459	IRWalk/vectorTraveralWithInterfaceCastFail_BigO	7.82 N	7.82 N	

460	IRWalk/vectorTraveralWithInterfaceCastFail_RMS	0 %	0 %	
461	IRWalk/vectorTraveralWithInterfaceCastSuccess/10	85.7 ns	85.7 ns	8214303
462	IRWalk/vectorTraveralWithInterfaceCastSuccess/64	489 ns	489 ns	1431791
463	IRWalk/vectorTraveralWithInterfaceCastSuccess/512	3933 ns	3933 ns	179271
464	IRWalk/vectorTraveralWithInterfaceCastSuccess/4096	30951 ns	30949 ns	22630
465	IRWalk/vectorTraveralWithInterfaceCastSuccess/32768	248877 ns	248870 ns	2805
466	IRWalk/vectorTraveralWithInterfaceCastSuccess/262144	2338713 ns	2337678 ns	300
467	IRWalk/vectorTraveralWithInterfaceCastSuccess/2097152	18149006 ns	18146236 ns	38
468	IRWalk/vectorTraveralWithInterfaceCastSuccess/10000000	88021965 ns	88009654 ns	8
469	IRWalk/vectorTraveralWithInterfaceCastSuccess_BigO	8.80 N	8.79 N	
470	IRWalk/vectorTraveralWithInterfaceCastSuccess_RMS	1 %	1 %	
471	IRWalk/vectorTraveralOpTraitFail/10	83.6 ns	83.6 ns	8404678
472	IRWalk/vectorTraveralOpTraitFail/64	543 ns	543 ns	1292619
473	IRWalk/vectorTraveralOpTraitFail/512	4284 ns	4284 ns	163011
474	IRWalk/vectorTraveralOpTraitFail/4096	34317 ns	34315 ns	20364
475	IRWalk/vectorTraveralOpTraitFail/32768	278203 ns	278124 ns	2511
476	IRWalk/vectorTraveralOpTraitFail/262144	2520282 ns	2519074 ns	281
477	IRWalk/vectorTraveralOpTraitFail/2097152	19620514 ns	19610789 ns	36
478	IRWalk/vectorTraveralOpTraitFail/10000000	93801856 ns	93792653 ns	7
479	IRWalk/vectorTraveralOpTraitFail_BigO	9.38 N	9.38 N	
480	IRWalk/vectorTraveralOpTraitFail_RMS	0 %	0 %	
481	IRWalk/vectorTraveralOpTraitSuccess/10	117 ns	117 ns	5977891
482	IRWalk/vectorTraveralOpTraitSuccess/64	749 ns	749 ns	935541
483	IRWalk/vectorTraveralOpTraitSuccess/512	5927 ns	5927 ns	118265
484	IRWalk/vectorTraveralOpTraitSuccess/4096	47596 ns	47592 ns	14704
485	IRWalk/vectorTraveralOpTraitSuccess/32768	383662 ns	383566 ns	1826
486	IRWalk/vectorTraveralOpTraitSuccess/262144	3441962 ns	3440234 ns	202
487	IRWalk/vectorTraveralOpTraitSuccess/2097152	27770850 ns	27769434 ns	25
488	IRWalk/vectorTraveralOpTraitSuccess/10000000	133148747 ns	133141848 ns	5
489	IRWalk/vectorTraveralOpTraitSuccess_BigO	13.31 N	13.31 N	
490	IRWalk/vectorTraveralOpTraitSuccess_RMS	0 %	0 %	
491	SimpleConstantFolding/folding/1	10112 ns	10070 ns	70189
492	SimpleConstantFolding/folding/8	81970 ns	81663 ns	8557
493	SimpleConstantFolding/folding/64	640847 ns	638256 ns	1074
494	SimpleConstantFolding/folding/512	5222675 ns	5202763 ns	135
495	SimpleConstantFolding/folding/4096	42047737 ns	41843492 ns	17
496	SimpleConstantFolding/folding/10000	100531426 ns	100120405 ns	7
497	SimpleConstantFolding/folding_BigO	10083.92 N	10041.57 N	
498	SimpleConstantFolding/folding_RMS	1 %	1 %	
499	Dynamism/noCall/10	6.14 ns	6.14 ns	113553610
500	Dynamism/noCall/64	39.4 ns	39.4 ns	17745295
501	Dynamism/noCall/512	325 ns	325 ns	2157076
502	Dynamism/noCall/4096	2532 ns	2532 ns	277616
503	Dynamism/noCall/32768	20200 ns	20199 ns	34687
504	Dynamism/noCall/262144	161503 ns	161477 ns	4331
505	Dynamism/noCall/2097152	1321702 ns	1321604 ns	541
506	Dynamism/noCall/10000000	6161264 ns	6160970 ns	113
507	Dynamism/noCall_BigO	0.62 N	0.62 N	
508	Dynamism/noCall_RMS	1 %	1 %	
509	Dynamism/regularCall/10	7.38 ns	7.38 ns	94848237
510	Dynamism/regularCall/64	40.7 ns	40.7 ns	17091447
511	Dynamism/regularCall/512	333 ns	333 ns	2155774
512	Dynamism/regularCall/4096	2537 ns	2537 ns	275792
513	Dynamism/regularCall/32768	20152 ns	20151 ns	34725
514	Dynamism/regularCall/262144	161299 ns	161295 ns	4337
515	Dynamism/regularCall/2097152	1290940 ns	1290854 ns	541
516	Dynamism/regularCall/10000000	6153182 ns	6152711 ns	114
517	Dynamism/regularCall_BigO	0.62 N	0.62 N	
518	Dynamism/regularCall_RMS	0 %	0 %	
519	Dynamism/regularCallNoinline/10	16.9 ns	16.9 ns	41368407
520	Dynamism/regularCallNoinline/64	112 ns	112 ns	6255407
521	Dynamism/regularCallNoinline/512	799 ns	799 ns	873954
522	Dynamism/regularCallNoinline/4096	6299 ns	6298 ns	110858

```
523   Dynamism/regularCallNoinline/32768                         50360 ns         50347 ns         13933
524   Dynamism/regularCallNoinline/262144                       402420 ns        402348 ns          1741
525   Dynamism/regularCallNoinline/2097152                     3215942 ns       3215367 ns           217
526   Dynamism/regularCallNoinline/10000000                   15373396 ns      15372190 ns            46
527   Dynamism/regularCallNoinline_BigO                           1.54 N           1.54 N
528   Dynamism/regularCallNoinline_RMS                              0 %              0 %
529   Dynamism/regularPointerCall/10                             6.81 ns          6.80 ns     102257870
530   Dynamism/regularPointerCall/64                             40.7 ns          40.7 ns      16965482
531   Dynamism/regularPointerCall/512                             324 ns           324 ns       2163497
532   Dynamism/regularPointerCall/4096                           2530 ns          2530 ns        276256
533   Dynamism/regularPointerCall/32768                         20109 ns         20107 ns         34720
534   Dynamism/regularPointerCall/262144                       160961 ns        160944 ns          4351
535   Dynamism/regularPointerCall/2097152                     1288637 ns       1288545 ns           543
536   Dynamism/regularPointerCall/10000000                    6164348 ns       6164179 ns           114
537   Dynamism/regularPointerCall_BigO                           0.62 N           0.62 N
538   Dynamism/regularPointerCall_RMS                               0 %              0 %
539   Dynamism/runtimePolymorphicPointerCall/10                  19.2 ns          19.2 ns      36665574
540   Dynamism/runtimePolymorphicPointerCall/64                   129 ns           129 ns       5411307
541   Dynamism/runtimePolymorphicPointerCall/512                  958 ns           958 ns        730546
542   Dynamism/runtimePolymorphicPointerCall/4096                7582 ns          7581 ns         92110
543   Dynamism/runtimePolymorphicPointerCall/32768             60403 ns         60399 ns         11566
544   Dynamism/runtimePolymorphicPointerCall/262144           483774 ns        483742 ns          1451
545   Dynamism/runtimePolymorphicPointerCall/2097152         3859047 ns       3858720 ns           181
546   Dynamism/runtimePolymorphicPointerCall/10000000       18391560 ns      18390115 ns            38
547   Dynamism/runtimePolymorphicPointerCall_BigO                1.84 N           1.84 N
548   Dynamism/runtimePolymorphicPointerCall_RMS                   0 %              0 %
```

Listing C.2: Results for the "How Slow is MLIR?" micro-benchmarks.

Appendix D

xDSL benchmark results

D.1   Pipeline phase micro-benchmark results

D.2   Micro-benchmark results

The following section describes the procedure and provides the raw results from the xDSL micro-benchmarks derived from "How Slow is MLIR's".

```
1   git clone https://github.com/xdslproject/xdsl
2   make venv
3   python3 benchmarks/microbenchmarks all timeit
```

Listing D.1: Bash commands to download, setup the environment for, and run the benchmarks for xDSL derived from from "How Slow is MLIR".

```
1   Test IRTraversal.iterate_ops ran in: 0.000326 ± 5.92e-06s // ÷ 32768
2   Test IRTraversal.iterate_block_ops ran in: 0.00675 ± 4.5e-05s // ÷ 32768
3   Test IRTraversal.walk_block_ops ran in: 0.0172 ± 9.31e-05s // ÷ 32768
4   Test Extensibility.interface_check_trait ran in: 3.87e-08 ± 2.79e-07s
5   Test Extensibility.interface_cast_trait ran in: 1.02e-07 ± 4.67e-07s
6   Test Extensibility.interface_check ran in: 3.71e-08 ± 2.72e-07s
7   Test Extensibility.trait_check ran in: 1.92e-06 ± 6.95e-07s
8   Test Extensibility.trait_check_optimised ran in: 2.39e-07 ± 3.51e-08s
9   Test Extensibility.trait_check_single ran in: 1.73e-06 ± 7.03e-07s
10  Test Extensibility.trait_check_neg ran in: 2.83e-06 ± 7.76e-07s
11  Test OpCreation.operation_create ran in: 3.77e-06 ± 9.16e-07s
12  Test OpCreation.operation_build ran in: 1.27e-05 ± 1.81e-06s
13  Test OpCreation.operation_create_optimised ran in: 3.78e-07 ± 4.42e-08s
14  Test OpCreation.operation_clone ran in: 0.000962 ± 1.15e-05s
15  Test OpCreation.operation_clone_single ran in: 6.96e-06 ± 1.55e-06s
16  Test OpCreation.operation_constant_init ran in: 3.34e-05 ± 3.68e-06s
17  Test OpCreation.operation_constant_create ran in: 1.83e-06 ± 7.74e-07s
18  Test ConstantFoldingSimple.20 ran in: 0.00114 ± 3.79e-05s
19  Test ConstantFoldingSimpleInlined.20 ran in: 0.000135 ± 2.68e-05s
```

Listing D.2: Results for the xDSL micro-benchmarks derived from "How Slow is MLIR?", for CPython version 3.10.17.

```
1   Test IRTraversal.iterate_ops ran in: 0.00036 ± 8.27e-06s
2   Test IRTraversal.iterate_block_ops ran in: 0.00401 ± 2.31e-05s
3   Test IRTraversal.walk_block_ops ran in: 0.0141 ± 0.000126s
4   Test Extensibility.interface_check_trait ran in: 2.8e-08 ± 3e-07s
5   Test Extensibility.interface_check ran in: 3.02e-08 ± 2.6e-07s
6   Test Extensibility.trait_check ran in: 1.71e-06 ± 7.53e-07s
7   Test Extensibility.trait_check_optimised ran in: 1.91e-07 ± 3.34e-08s
8   Test Extensibility.trait_check_single ran in: 1.48e-06 ± 7.36e-07s
9   Test Extensibility.trait_check_neg ran in: 2.53e-06 ± 9.22e-07s
10  Test OpCreation.operation_create ran in: 2.84e-06 ± 8.83e-07s
11  Test OpCreation.operation_build ran in: 1.06e-05 ± 1.94e-06s
12  Test OpCreation.operation_create_optimised ran in: 2.65e-07 ± 3.72e-08s
13  Test OpCreation.operation_clone ran in: 0.00074 ± 1.09e-05s
14  Test OpCreation.operation_clone_single ran in: 5.27e-06 ± 1.1e-06s
15  Test OpCreation.operation_constant_init ran in: 2.77e-05 ± 3.64e-06s
16  Test OpCreation.operation_constant_create ran in: 1.7e-06 ± 1.24e-06s
17  Test ConstantFoldingSimple.20 ran in: 0.00086 ± 2.68e-05s
18  Test ConstantFoldingSimpleInlined.20 ran in: 9.24e-05 ± 2.15e-05s
```

Listing D.3: Results for the xDSL micro-benchmarks derived from "How Slow is MLIR?", for CPython version 3.11.12.

```
1   Test IRTraversal.iterate_ops ran in: 0.000318 ± 6.61e-06s
2   Test IRTraversal.iterate_block_ops ran in: 0.00487 ± 2.48e-05s
3   Test IRTraversal.walk_block_ops ran in: 0.0129 ± 7.65e-05s
4   Test Extensibility.interface_check_trait ran in: 3.94e-08 ± 3.1e-07s
5   Test Extensibility.interface_cast_trait ran in: 8.47e-08 ± 4.25e-07s
6   Test Extensibility.interface_check ran in: 3.97e-08 ± 2.3e-07s
7   Test Extensibility.trait_check ran in: 1.19e-06 ± 5.53e-07s
8   Test Extensibility.trait_check_optimised ran in: 2.21e-07 ± 3.09e-08s
9   Test Extensibility.trait_check_single ran in: 1e-06 ± 5.2e-07s
10  Test Extensibility.trait_check_neg ran in: 2.09e-06 ± 6.81e-07s
11  Test OpCreation.operation_create ran in: 2.99e-06 ± 8.08e-07s
12  Test OpCreation.operation_build ran in: 1.17e-05 ± 1.59e-06s
13  Test OpCreation.operation_create_optimised ran in: 3.65e-07 ± 3.25e-08s
14  Test OpCreation.operation_clone ran in: 0.000746 ± 1.11e-05s
15  Test OpCreation.operation_clone_single ran in: 5.2e-06 ± 1.56e-06s
16  Test OpCreation.operation_constant_init ran in: 2.85e-05 ± 3.54e-06s
17  Test OpCreation.operation_constant_create ran in: 1.91e-06 ± 1.25e-06s
18  Test ConstantFoldingSimple.20 ran in: 0.000892 ± 2.66e-05s
19  Test ConstantFoldingSimpleInlined.20 ran in: 0.000108 ± 2.51e-05s
```

Listing D.4: Results for the xDSL micro-benchmarks derived from "How Slow is MLIR?", for CPython version 3.13.3.

```
1   Test IRTraversal.iterate_ops ran in: 0.000152 ± 9.27e-06s
2   Test IRTraversal.iterate_block_ops ran in: 0.0036 ± 2.78e-05s
3   Test IRTraversal.walk_block_ops ran in: 0.014 ± 5.28e-05s
4   Test Extensibility.interface_check_trait ran in: 2.53e-08 ± 3.66e-07s
5   Test Extensibility.interface_check ran in: 5.38e-08 ± 3.16e-07s
6   Test Extensibility.trait_check ran in: 1.22e-06 ± 5.73e-07s
7   Test Extensibility.trait_check_optimised ran in: 2.24e-07 ± 3.03e-08s
8   Test Extensibility.trait_check_single ran in: 1.04e-06 ± 5.17e-07s
9   Test Extensibility.trait_check_neg ran in: 2.11e-06 ± 6.1e-07s
10  Test OpCreation.operation_create ran in: 2.98e-06 ± 7.59e-07s
11  Test OpCreation.operation_build ran in: 1.16e-05 ± 1.56e-06s
12  Test OpCreation.operation_create_optimised ran in: 3.91e-07 ± 3.57e-08s
13  Test OpCreation.operation_clone ran in: 0.000741 ± 1.11e-05s
14  Test OpCreation.operation_clone_single ran in: 5.08e-06 ± 1.23e-06s
15  Test OpCreation.operation_constant_init ran in: 2.85e-05 ± 3.76e-06s
16  Test OpCreation.operation_constant_create ran in: 1.95e-06 ± 1.31e-06s
17  Test ConstantFoldingSimple.20 ran in: 0.00094 ± 2.9e-05s
18  Test ConstantFoldingSimpleInlined.20 ran in: 0.000105 ± 2.55e-05s
```

Listing D.5: Results for the xDSL micro-benchmarks derived from "How Slow is MLIR?", for CPython version 3.13.3 with the experimental JIT enabled.

Appendix E

Bytecode profiles

```
1  //// Trace of `OpCreation.time_operation_build` :
2
3  // == microbenchmarks:278 `time_operation_build` ==
4  // >>> EmptyOp.build()
5  295       0   LOAD_GLOBAL       0   (EmptyOp)                                          // 8    ns
6             2   LOAD_METHOD       1   (build)                                            // 10   ns
7             4   CALL_METHOD       0   ()                                                 // 38   ns
8
9      // ========== operations:160 `build` ===========
10     // >>> op = cls.__new__(cls)
11     184       0   LOAD_FAST         0   (cls)                                          // 15   ns
12               2   LOAD_METHOD       0   (__new__)                                      // 15   ns
13               4   LOAD_FAST         0   (cls)                                          // 15   ns
14               6   CALL_METHOD       1   ()                                             // 18   ns
15               8   STORE_FAST        7   (op)                                           // 15   ns
16     // >>> IRDLOperation.__init__(
17     185       10  LOAD_GLOBAL       1   (IRDLOperation)                                // 13   ns
18               12  LOAD_ATTR         2   (__init__)                                     // 14   ns
19     // >>> op,
20     186       14  LOAD_FAST         7   (op)                                           // 12   ns
21     // >>> operands=operands,
22     187       16  LOAD_FAST         1   (operands)                                     // 12   ns
23     // >>> result_types=result_types,
24     188       18  LOAD_FAST         2   (result_types)                                 // 12   ns
25     // >>> properties=properties,
26     189       20  LOAD_FAST         4   (properties)                                   // 12   ns
27     // >>> attributes=attributes,
28     190       22  LOAD_FAST         3   (attributes)                                   // 12   ns
29     // >>> successors=successors,
30     191       24  LOAD_FAST         5   (successors)                                   // 12   ns
31     // >>> regions=regions,
32     192       26  LOAD_FAST         6   (regions)                                      // 12   ns
33     // >>> IRDLOperation.__init__(
34     185       28  LOAD_CONST        1   (('operands', 'result_types', 'properties', 'attributes',
       ↪  'successors', 'regions'))  // 13   ns
35               30  CALL_FUNCTION_KW  7   ()                                             // 33   ns
36
37         // ========= operations:93 `__init__` ==========
38         // >>> if operands is None:
39         115       0   LOAD_FAST         1   (operands)                                 // 12   ns
40                   2   LOAD_CONST        0   (None)                                     // 12   ns
41                   4   IS_OP             0   ()                                         // 11   ns
```

```
              6  POP_JUMP_IF_FALSE     6  (to 12)                    // 12   ns
// >>> operands = []
116       8  BUILD_LIST            0  ()                         // 12   ns
         10  STORE_FAST            1  (operands)                 // 12   ns
// >>> if result_types is None:
117   >> 12  LOAD_FAST             2  (result_types)             // 12   ns
         14  LOAD_CONST            0  (None)                     // 11   ns
         16  IS_OP                 0  ()                         // 12   ns
         18  POP_JUMP_IF_FALSE    12  (to 24)                    // 12   ns
// >>> result_types = []
118      20  BUILD_LIST            0  ()                         // 12   ns
         22  STORE_FAST            2  (result_types)             // 12   ns
// >>> if properties is None:
119   >> 24  LOAD_FAST             3  (properties)               // 11   ns
         26  LOAD_CONST            0  (None)                     // 12   ns
         28  IS_OP                 0  ()                         // 11   ns
         30  POP_JUMP_IF_FALSE    18  (to 36)                    // 12   ns
// >>> properties = {}
120      32  BUILD_MAP             0  ()                         // 12   ns
         34  STORE_FAST            3  (properties)               // 12   ns
// >>> if attributes is None:
121   >> 36  LOAD_FAST             4  (attributes)               // 11   ns
         38  LOAD_CONST            0  (None)                     // 11   ns
         40  IS_OP                 0  ()                         // 12   ns
         42  POP_JUMP_IF_FALSE    24  (to 48)                    // 12   ns
// >>> attributes = {}
122      44  BUILD_MAP             0  ()                         // 12   ns
         46  STORE_FAST            4  (attributes)               // 12   ns
// >>> if successors is None:
123   >> 48  LOAD_FAST             5  (successors)               // 12   ns
         50  LOAD_CONST            0  (None)                     // 11   ns
         52  IS_OP                 0  ()                         // 12   ns
         54  POP_JUMP_IF_FALSE    30  (to 60)                    // 12   ns
// >>> successors = []
124      56  BUILD_LIST            0  ()                         // 12   ns
         58  STORE_FAST            5  (successors)               // 12   ns
// >>> if regions is None:
125   >> 60  LOAD_FAST             6  (regions)                  // 12   ns
         62  LOAD_CONST            0  (None)                     // 11   ns
         64  IS_OP                 0  ()                         // 12   ns
         66  POP_JUMP_IF_FALSE    36  (to 72)                    // 12   ns
// >>> regions = []
126      68  BUILD_LIST            0  ()                         // 12   ns
         70  STORE_FAST            6  (regions)                  // 12   ns
// >>> irdl_op_init(
127   >> 72  LOAD_GLOBAL           0  (irdl_op_init)             // 12   ns
// >>> self,
128      74  LOAD_FAST             0  (self)                     // 12   ns
// >>> type(self).get_irdl_definition(),
129      76  LOAD_GLOBAL           1  (type)                     // 12   ns
         78  LOAD_FAST             0  (self)                     // 11   ns
         80  CALL_FUNCTION         1  ()                         // 12   ns
         82  LOAD_METHOD           2  (get_irdl_definition)      // 14   ns
         84  CALL_METHOD           0  ()                         // 24   ns

    // === operations:2004 `get_irdl_definition` ===
    // >>> return op_def
    2006        0  LOAD_DEREF            0  (op_def)              // 10   ns
                2  RETURN_VALUE             ()                   // 24   ns
    // ===============================================

// >>> operands=operands,
130      86  LOAD_FAST             1  (operands)                 // 12   ns
```

```
105         // >>> result_types=result_types,
106         131       88 LOAD_FAST          2 (result_types)                        // 12   ns
107         // >>> properties=properties,
108         132       90 LOAD_FAST          3 (properties)                          // 11   ns
109         // >>> attributes=attributes,
110         133       92 LOAD_FAST          4 (attributes)                          // 11   ns
111         // >>> successors=successors,
112         134       94 LOAD_FAST          5 (successors)                          // 11   ns
113         // >>> regions=regions,
114         135       96 LOAD_FAST          6 (regions)                             // 11   ns
115         // >>> irdl_op_init(
116         127       98 LOAD_CONST         1 (('operands', 'result_types', 'properties', 'attributes',
    ↪ 'successors', 'regions'))  // 11   ns
117                  100 CALL_FUNCTION_KW   8 ()                                    // 127  ns
118
119         // ====== operations:1738 `irdl_op_init` ======
120         // >>> from xdsl.dialects.builtin import DenseArrayBase, i32
121         1760       0 LOAD_CONST         1 (0)                                   // 71   ns
122                    2 LOAD_CONST         2 (('DenseArrayBase', 'i32'))           // 69   ns
123                    4 IMPORT_NAME        0 (xdsl.dialects.builtin)               // 100  ns
124                    6 IMPORT_FROM        1 (DenseArrayBase)                      // 69   ns
125                    8 STORE_FAST         8 (DenseArrayBase)                      // 68   ns
126                   10 IMPORT_FROM        2 (i32)                                 // 67   ns
127                   12 STORE_FAST         9 (i32)                                 // 66   ns
128                   14 POP_TOP              ()                                    // 65   ns
129         // >>> error_prefix = f"Error in {op_def.name} builder: "
130         1762      16 LOAD_CONST         3 ('Error in ')                         // 64   ns
131                   18 LOAD_FAST          1 (op_def)                             // 63   ns
132                   20 LOAD_ATTR          3 (name)                               // 64   ns
133                   22 FORMAT_VALUE       0 ()                                    // 63   ns
134                   24 LOAD_CONST         4 (' builder: ')                        // 62   ns
135                   26 BUILD_STRING       3 ()                                    // 65   ns
136                   28 STORE_FAST        10 (error_prefix)                        // 67   ns
137         // >>> operands_arg = [irdl_build_operations_arg(operand) for operand in operands]
138         1764      30 LOAD_CONST         5 (<code object <listcomp> at 0x70c199c29dc0, file
    ↪ "/home/ubuntu/Desktop/xdsl/xdsl/irdl/operations.py", line 1764>)  // 65   ns
139                   32 LOAD_CONST         6 ('irdl_op_init.<locals>.<listcomp>')  // 62   ns
140                   34 MAKE_FUNCTION      0 ()                                    // 64   ns
141                   36 LOAD_FAST          2 (operands)                           // 60   ns
142                   38 GET_ITER             ()                                    // 61   ns
143                   40 CALL_FUNCTION      1 ()                                    // 48   ns
144
145         // ======= operations:1764 `<listcomp>` ========
146         // >>> operands_arg = [irdl_build_operations_arg(operand) for operand in operands]
147         1764       0 BUILD_LIST         0 ()                                    // 10   ns
148                    2 LOAD_FAST          0 (.0)                                  // 11   ns
149              >>    4 FOR_ITER           6 (to 18)                               // 11   ns
150              >>   18 RETURN_VALUE         ()                                    // 51   ns
151         // ==============================================
152
153                   42 STORE_FAST        11 (operands_arg)                        // 61   ns
154         // >>> regions_arg = [irdl_build_regions_arg(region) for region in regions]
155         1766      44 LOAD_CONST         7 (<code object <listcomp> at 0x70c199c29e70, file
    ↪ "/home/ubuntu/Desktop/xdsl/xdsl/irdl/operations.py", line 1766>)  // 59   ns
156                   46 LOAD_CONST         6 ('irdl_op_init.<locals>.<listcomp>')  // 58   ns
157                   48 MAKE_FUNCTION      0 ()                                    // 60   ns
158                   50 LOAD_FAST          7 (regions)                            // 58   ns
159                   52 GET_ITER             ()                                    // 58   ns
160                   54 CALL_FUNCTION      1 ()                                    // 48   ns
161
162         // ======= operations:1766 `<listcomp>` ========
163         // >>> regions_arg = [irdl_build_regions_arg(region) for region in regions]
164         1766       0 BUILD_LIST         0 ()                                    // 11   ns
```

```
165                      2   LOAD_FAST          0   (.0)                     // 11   ns
166              >>  4   FOR_ITER           6   (to 18)                  // 11   ns
167              >> 18   RETURN_VALUE           ()                       // 50   ns
168           // ============================================

170                     56   STORE_FAST        12   (regions_arg)            // 60   ns
171     // >>> built_operands, operand_sizes = irdl_build_arg_list(
172     1769           58   LOAD_GLOBAL        4   (irdl_build_arg_list)    // 60   ns
173     // >>> VarIRConstruct.OPERAND, operands_arg, op_def.operands, error_prefix
174     1770           60   LOAD_GLOBAL        5   (VarIRConstruct)         // 59   ns
175                    62   LOAD_ATTR          6   (OPERAND)                // 65   ns
176                    64   LOAD_FAST         11   (operands_arg)           // 58   ns
177                    66   LOAD_FAST          1   (op_def)                 // 57   ns
178                    68   LOAD_ATTR          7   (operands)               // 57   ns
179                    70   LOAD_FAST         10   (error_prefix)           // 57   ns
180     // >>> built_operands, operand_sizes = irdl_build_arg_list(
181     1769           72   CALL_FUNCTION      4   ()                       // 70   ns

183           // === operations:1637 `irdl_build_arg_list` ===
184           // >>> if len(args) != len(arg_defs):
185     1645            0   LOAD_GLOBAL        0   (len)                    // 27   ns
186                     2   LOAD_FAST          1   (args)                   // 25   ns
187                     4   CALL_FUNCTION      1   ()                       // 26   ns
188                     6   LOAD_GLOBAL        0   (len)                    // 24   ns
189                     8   LOAD_FAST          2   (arg_defs)               // 23   ns
190                    10   CALL_FUNCTION      1   ()                       // 24   ns
191                    12   COMPARE_OP         3   (!=)                     // 24   ns
192                    14   POP_JUMP_IF_FALSE  27   (to 54)                  // 24   ns
193           // >>> res = list[_T]()
194     1651      >> 54   LOAD_GLOBAL        3   (list)                   // 23   ns
195                    56   LOAD_GLOBAL        4   (_T)                     // 23   ns
196                    58   BINARY_SUBSCR          ()                       // 28   ns
197                    60   CALL_FUNCTION      0   ()                       // 37   ns
198                    62   STORE_FAST         4   (res)                    // 25   ns
199           // >>> arg_sizes = list[int]()
200     1652           64   LOAD_GLOBAL        3   (list)                   // 23   ns
201                    66   LOAD_GLOBAL        5   (int)                    // 22   ns
202                    68   BINARY_SUBSCR          ()                       // 26   ns
203                    70   CALL_FUNCTION      0   ()                       // 33   ns
204                    72   STORE_FAST         5   (arg_sizes)              // 26   ns
205           // >>> for arg_idx, ((arg_name, arg_def), arg) in enumerate(zip(arg_defs, args)):
206     1654           74   LOAD_GLOBAL        6   (enumerate)              // 25   ns
207                    76   LOAD_GLOBAL        7   (zip)                    // 23   ns
208                    78   LOAD_FAST          2   (arg_defs)               // 23   ns
209                    80   LOAD_FAST          1   (args)                   // 21   ns
210                    82   CALL_FUNCTION      2   ()                       // 24   ns
211                    84   CALL_FUNCTION      1   ()                       // 23   ns
212                    86   GET_ITER               ()                       // 21   ns
213              >> 88   FOR_ITER         126   (to 342)                 // 26   ns
214           // >>> return res, arg_sizes
215     1683      >> 342   LOAD_FAST          4   (res)                    // 20   ns
216                   344   LOAD_FAST          5   (arg_sizes)              // 20   ns
217                   346   BUILD_TUPLE        2   ()                       // 20   ns
218                   348   RETURN_VALUE           ()                       // 65   ns
219           // ============================================

221                    74   UNPACK_SEQUENCE    2   ()                       // 60   ns
222                    76   STORE_FAST        13   (built_operands)         // 59   ns
223                    78   STORE_FAST        14   (operand_sizes)          // 58   ns
224     // >>> built_res_types, result_sizes = irdl_build_arg_list(
225     1774           80   LOAD_GLOBAL        4   (irdl_build_arg_list)    // 57   ns
226     // >>> VarIRConstruct.RESULT, result_types, op_def.results, error_prefix
227     1775           82   LOAD_GLOBAL        5   (VarIRConstruct)         // 55   ns
```

```
228                    84  LOAD_ATTR          8   (RESULT)                        // 59  ns
229                    86  LOAD_FAST          3   (result_types)                  // 54  ns
230                    88  LOAD_FAST          1   (op_def)                        // 53  ns
231                    90  LOAD_ATTR          9   (results)                       // 53  ns
232                    92  LOAD_FAST          10  (error_prefix)                  // 53  ns
233       // >>> built_res_types, result_sizes = irdl_build_arg_list(
234       1774          94  CALL_FUNCTION      4   ()                              // 69  ns
235
236          // === operations:1637 `irdl_build_arg_list` ===
237          // >>> if len(args) != len(arg_defs):
238       1645           0  LOAD_GLOBAL        0   (len)                           // 26  ns
239                      2  LOAD_FAST          1   (args)                          // 26  ns
240                      4  CALL_FUNCTION      1   ()                              // 26  ns
241                      6  LOAD_GLOBAL        0   (len)                           // 24  ns
242                      8  LOAD_FAST          2   (arg_defs)                      // 23  ns
243                     10  CALL_FUNCTION      1   ()                              // 24  ns
244                     12  COMPARE_OP         3   (!=)                            // 24  ns
245                     14  POP_JUMP_IF_FALSE  27  (to 54)                         // 24  ns
246          // >>> res = list[_T]()
247       1651      >>  54  LOAD_GLOBAL        3   (list)                          // 23  ns
248                     56  LOAD_GLOBAL        4   (_T)                            // 23  ns
249                     58  BINARY_SUBSCR          ()                              // 27  ns
250                     60  CALL_FUNCTION      0   ()                              // 35  ns
251                     62  STORE_FAST         4   (res)                           // 25  ns
252          // >>> arg_sizes = list[int]()
253       1652          64  LOAD_GLOBAL        3   (list)                          // 23  ns
254                     66  LOAD_GLOBAL        5   (int)                           // 23  ns
255                     68  BINARY_SUBSCR          ()                              // 26  ns
256                     70  CALL_FUNCTION      0   ()                              // 33  ns
257                     72  STORE_FAST         5   (arg_sizes)                     // 25  ns
258          // >>> for arg_idx, ((arg_name, arg_def), arg) in enumerate(zip(arg_defs, args)):
259       1654          74  LOAD_GLOBAL        6   (enumerate)                     // 23  ns
260                     76  LOAD_GLOBAL        7   (zip)                           // 22  ns
261                     78  LOAD_FAST          2   (arg_defs)                      // 22  ns
262                     80  LOAD_FAST          1   (args)                          // 20  ns
263                     82  CALL_FUNCTION      2   ()                              // 24  ns
264                     84  CALL_FUNCTION      1   ()                              // 23  ns
265                     86  GET_ITER               ()                              // 21  ns
266                 >>  88  FOR_ITER           126 (to 342)                        // 25  ns
267          // >>> return res, arg_sizes
268       1683      >> 342  LOAD_FAST         4   (res)                            // 20  ns
269                    344 LOAD_FAST          5   (arg_sizes)                      // 20  ns
270                    346 BUILD_TUPLE        2   ()                               // 20  ns
271                    348 RETURN_VALUE           ()                               // 63  ns
272             // ===============================================
273
274                    96  UNPACK_SEQUENCE    2   ()                              // 56  ns
275                    98  STORE_FAST         15  (built_res_types)               // 56  ns
276                    100 STORE_FAST         16  (result_sizes)                  // 54  ns
277       // >>> built_regions, region_sizes = irdl_build_arg_list(
278       1779         102 LOAD_GLOBAL        4   (irdl_build_arg_list)           // 53  ns
279       // >>> VarIRConstruct.REGION, regions_arg, op_def.regions, error_prefix
280       1780         104 LOAD_GLOBAL        5   (VarIRConstruct)                // 51  ns
281                    106 LOAD_ATTR          10  (REGION)                        // 55  ns
282                    108 LOAD_FAST          12  (regions_arg)                   // 51  ns
283                    110 LOAD_FAST          1   (op_def)                        // 49  ns
284                    112 LOAD_ATTR          11  (regions)                       // 50  ns
285                    114 LOAD_FAST          10  (error_prefix)                  // 49  ns
286       // >>> built_regions, region_sizes = irdl_build_arg_list(
287       1779         116 CALL_FUNCTION      4   ()                              // 67  ns
288
289          // === operations:1637 `irdl_build_arg_list` ===
290          // >>> if len(args) != len(arg_defs):
```

```
1645        0   LOAD_GLOBAL       0   (len)                    // 26   ns
            2   LOAD_FAST         1   (args)                   // 26   ns
            4   CALL_FUNCTION     1   ()                       // 26   ns
            6   LOAD_GLOBAL       0   (len)                    // 23   ns
            8   LOAD_FAST         2   (arg_defs)               // 24   ns
           10   CALL_FUNCTION     1   ()                       // 24   ns
           12   COMPARE_OP        3   (!=)                     // 24   ns
           14   POP_JUMP_IF_FALSE 27  (to 54)                  // 24   ns
     // >>> res = list[_T]()
1651    >> 54   LOAD_GLOBAL       3   (list)                   // 23   ns
           56   LOAD_GLOBAL       4   (_T)                     // 23   ns
           58   BINARY_SUBSCR         ()                       // 27   ns
           60   CALL_FUNCTION     0   ()                       // 35   ns
           62   STORE_FAST        4   (res)                    // 25   ns
     // >>> arg_sizes = list[int]()
1652       64   LOAD_GLOBAL       3   (list)                   // 24   ns
           66   LOAD_GLOBAL       5   (int)                    // 23   ns
           68   BINARY_SUBSCR         ()                       // 26   ns
           70   CALL_FUNCTION     0   ()                       // 33   ns
           72   STORE_FAST        5   (arg_sizes)              // 25   ns
     // >>> for arg_idx, ((arg_name, arg_def), arg) in enumerate(zip(arg_defs, args)):
1654       74   LOAD_GLOBAL       6   (enumerate)              // 23   ns
           76   LOAD_GLOBAL       7   (zip)                    // 22   ns
           78   LOAD_FAST         2   (arg_defs)               // 21   ns
           80   LOAD_FAST         1   (args)                   // 20   ns
           82   CALL_FUNCTION     2   ()                       // 24   ns
           84   CALL_FUNCTION     1   ()                       // 23   ns
           86   GET_ITER              ()                       // 21   ns
        >> 88   FOR_ITER         126  (to 342)                 // 25   ns
     // >>> return res, arg_sizes
1683    >> 342  LOAD_FAST         4   (res)                    // 20   ns
           344  LOAD_FAST         5   (arg_sizes)              // 20   ns
           346  BUILD_TUPLE       2   ()                       // 20   ns
           348  RETURN_VALUE          ()                       // 61   ns
        // =============================================

           118  UNPACK_SEQUENCE   2   ()                       // 52   ns
           120  STORE_FAST        17  (built_regions)          // 51   ns
           122  STORE_FAST        18  (region_sizes)           // 50   ns
     // >>> built_successors, successor_sizes = irdl_build_arg_list(
1784       124  LOAD_GLOBAL       4   (irdl_build_arg_list)    // 50   ns
     // >>> VarIRConstruct.SUCCESSOR, successors, op_def.successors, error_prefix
1785       126  LOAD_GLOBAL       5   (VarIRConstruct)         // 48   ns
           128  LOAD_ATTR         12  (SUCCESSOR)              // 52   ns
           130  LOAD_FAST         6   (successors)             // 47   ns
           132  LOAD_FAST         1   (op_def)                 // 46   ns
           134  LOAD_ATTR         13  (successors)             // 47   ns
           136  LOAD_FAST         10  (error_prefix)           // 46   ns
     // >>> built_successors, successor_sizes = irdl_build_arg_list(
1784       138  CALL_FUNCTION     4   ()                       // 65   ns

     // === operations:1637 `irdl_build_arg_list` ===
     // >>> if len(args) != len(arg_defs):
1645        0   LOAD_GLOBAL       0   (len)                    // 26   ns
            2   LOAD_FAST         1   (args)                   // 26   ns
            4   CALL_FUNCTION     1   ()                       // 26   ns
            6   LOAD_GLOBAL       0   (len)                    // 24   ns
            8   LOAD_FAST         2   (arg_defs)               // 24   ns
           10   CALL_FUNCTION     1   ()                       // 24   ns
           12   COMPARE_OP        3   (!=)                     // 23   ns
           14   POP_JUMP_IF_FALSE 27  (to 54)                  // 23   ns
     // >>> res = list[_T]()
1651    >> 54   LOAD_GLOBAL       3   (list)                   // 23   ns
```

```
 354                               56 LOAD_GLOBAL          4   (_T)                    // 23  ns
 355                               58 BINARY_SUBSCR            ()                      // 27  ns
 356                               60 CALL_FUNCTION        0   ()                      // 35  ns
 357                               62 STORE_FAST           4   (res)                   // 25  ns
 358              // >>> arg_sizes = list[int]()
 359            1652           64 LOAD_GLOBAL          3   (list)                  // 23  ns
 360                               66 LOAD_GLOBAL          5   (int)                   // 23  ns
 361                               68 BINARY_SUBSCR            ()                      // 26  ns
 362                               70 CALL_FUNCTION        0   ()                      // 33  ns
 363                               72 STORE_FAST           5   (arg_sizes)             // 25  ns
 364              // >>> for arg_idx, ((arg_name, arg_def), arg) in enumerate(zip(arg_defs, args)):
 365            1654           74 LOAD_GLOBAL          6   (enumerate)             // 23  ns
 366                               76 LOAD_GLOBAL          7   (zip)                   // 22  ns
 367                               78 LOAD_FAST            2   (arg_defs)              // 21  ns
 368                               80 LOAD_FAST            1   (args)                  // 20  ns
 369                               82 CALL_FUNCTION        2   ()                      // 23  ns
 370                               84 CALL_FUNCTION        1   ()                      // 23  ns
 371                               86 GET_ITER                 ()                      // 21  ns
 372                      >>   88 FOR_ITER            126 (to 342)                // 25  ns
 373              // >>> return res, arg_sizes
 374            1683     >>  342 LOAD_FAST            4   (res)                   // 20  ns
 375                              344 LOAD_FAST            5   (arg_sizes)             // 20  ns
 376                              346 BUILD_TUPLE          2   ()                      // 20  ns
 377                              348 RETURN_VALUE             ()                      // 59  ns
 378                   // ============================================
 379
 380                              140 UNPACK_SEQUENCE      2   ()                      // 49  ns
 381                              142 STORE_FAST          19   (built_successors)      // 48  ns
 382                              144 STORE_FAST          20   (successor_sizes)       // 46  ns
 383          // >>> built_properties = dict[str, Attribute]()
 384            1789          146 LOAD_GLOBAL         14   (dict)                  // 45  ns
 385                              148 LOAD_GLOBAL         15   (str)                   // 43  ns
 386                              150 LOAD_GLOBAL         16   (Attribute)             // 42  ns
 387                              152 BUILD_TUPLE          2   ()                      // 43  ns
 388                              154 BINARY_SUBSCR            ()                      // 46  ns
 389                              156 CALL_FUNCTION        0   ()                      // 54  ns
 390                              158 STORE_FAST          21   (built_properties)      // 49  ns
 391          // >>> for attr_name, attr in properties.items():
 392            1790          160 LOAD_FAST            4   (properties)            // 45  ns
 393                              162 LOAD_METHOD         17   (items)                 // 44  ns
 394                              164 CALL_METHOD          0   ()                      // 45  ns
 395                              166 GET_ITER                 ()                      // 43  ns
 396                     >>  168 FOR_ITER            13   (to 196)                // 42  ns
 397          // >>> built_attributes = dict[str, Attribute]()
 398            1796     >>  196 LOAD_GLOBAL         14   (dict)                  // 40  ns
 399                              198 LOAD_GLOBAL         15   (str)                   // 39  ns
 400                              200 LOAD_GLOBAL         16   (Attribute)             // 40  ns
 401                              202 BUILD_TUPLE          2   ()                      // 41  ns
 402                              204 BINARY_SUBSCR            ()                      // 43  ns
 403                              206 CALL_FUNCTION        0   ()                      // 51  ns
 404                              208 STORE_FAST          24   (built_attributes)      // 41  ns
 405          // >>> for attr_name, attr in attributes.items():
 406            1797          210 LOAD_FAST            5   (attributes)            // 39  ns
 407                              212 LOAD_METHOD         17   (items)                 // 39  ns
 408                              214 CALL_METHOD          0   ()                      // 40  ns
 409                              216 GET_ITER                 ()                      // 39  ns
 410                     >>  218 FOR_ITER            13   (to 246)                // 39  ns
 411          // >>> for option in op_def.options:
 412            1803     >>  246 LOAD_FAST            1   (op_def)                // 38  ns
 413                              248 LOAD_ATTR           18   (options)               // 38  ns
 414                              250 GET_ITER                 ()                      // 38  ns
 415                     >>  252 FOR_ITER            223 (to 700)                // 43  ns
 416          // >>> Operation.__init__(
```

```
417          1863    >>  700 LOAD_GLOBAL          37 (Operation)                          // 38   ns
418                      702 LOAD_ATTR            38 (__init__)                           // 40   ns
419          // >>> self,
420          1864        704 LOAD_FAST             0 (self)                               // 38   ns
421          // >>> operands=built_operands,
422          1865        706 LOAD_FAST            13 (built_operands)                     // 37   ns
423          // >>> result_types=built_res_types,
424          1866        708 LOAD_FAST            15 (built_res_types)                    // 37   ns
425          // >>> properties=built_properties,
426          1867        710 LOAD_FAST            21 (built_properties)                   // 37   ns
427          // >>> attributes=built_attributes,
428          1868        712 LOAD_FAST            24 (built_attributes)                   // 37   ns
429          // >>> successors=built_successors,
430          1869        714 LOAD_FAST            19 (built_successors)                   // 37   ns
431          // >>> regions=built_regions,
432          1870        716 LOAD_FAST            17 (built_regions)                      // 37   ns
433          // >>> Operation.__init__(
434          1863        718 LOAD_CONST           19 (('operands', 'result_types', 'properties',
      ↪ 'attributes', 'successors', 'regions'))  // 37   ns
435                      720 CALL_FUNCTION_KW      7 ()                                   // 55   ns
436
437          // ============ core:914 `__init__` ============
438          // >>> super().__init__()
439          924           0 LOAD_GLOBAL           0 (super)                              // 18   ns
440                        2 CALL_FUNCTION         0 ()                                   // 21   ns
441                        4 LOAD_METHOD           1 (__init__)                           // 22   ns
442                        6 CALL_METHOD           0 ()                                   // 20   ns
443                        8 POP_TOP                 ()                                   // 17   ns
444          // >>> self.operands = operands
445          927          10 LOAD_FAST             1 (operands)                           // 16   ns
446                       12 LOAD_DEREF            0 (self)                               // 16   ns
447                       14 STORE_ATTR            2 (operands)                           // 36   ns
448
449          // ============ core:888 `operands` ============
450          // >>> new = tuple(new)
451          890           0 LOAD_GLOBAL           0 (tuple)                              // 15   ns
452                        2 LOAD_FAST             1 (new)                                // 14   ns
453                        4 CALL_FUNCTION         1 ()                                   // 15   ns
454                        6 STORE_FAST            1 (new)                                // 14   ns
455          // >>> for idx, operand in enumerate(self._operands):
456          891           8 LOAD_GLOBAL           1 (enumerate)                          // 13   ns
457                       10 LOAD_FAST             0 (self)                               // 13   ns
458                       12 LOAD_ATTR            2 (_operands)                           // 13   ns
459                       14 CALL_FUNCTION         1 ()                                   // 16   ns
460                       16 GET_ITER                ()                                   // 14   ns
461                  >>   18 FOR_ITER             12 (to 44)                              // 15   ns
462          // >>> for idx, operand in enumerate(new):
463          893     >>   44 LOAD_GLOBAL           1 (enumerate)                          // 13   ns
464                       46 LOAD_FAST             1 (new)                                // 14   ns
465                       48 CALL_FUNCTION         1 ()                                   // 15   ns
466                       50 GET_ITER                ()                                   // 13   ns
467                  >>   52 FOR_ITER             12 (to 78)                              // 15   ns
468          // >>> self._operands = new
469          895     >>   78 LOAD_FAST             1 (new)                                // 13   ns
470                       80 LOAD_FAST             0 (self)                               // 13   ns
471                       82 STORE_ATTR            2 (_operands)                          // 15   ns
472                       84 LOAD_CONST            0 (None)                               // 13   ns
473                       86 RETURN_VALUE            ()                                   // 32   ns
474          // ===========================================
475
476          // >>> self.results = tuple(
477          929          16 LOAD_GLOBAL           3 (tuple)                              // 17   ns
478                       18 LOAD_CLOSURE          0 (self)                               // 17   ns
```

```
479              20  BUILD_TUPLE        1   ()                                    // 17   ns
480              22  LOAD_CONST         1   (<code object <genexpr> at 0x70c199e02b80, file
                 ↪   "/home/ubuntu/Desktop/xdsl/xdsl/ir/core.py", line 929>)  // 17   ns
481              24  LOAD_CONST         2   ('Operation.__init__.<locals>.<genexpr>')  // 16
                 ↪   ns
482              26  MAKE_FUNCTION      8   (closure)                             // 18   ns
483     // >>> for (idx, result_type) in enumerate(result_types)
484     931      28  LOAD_GLOBAL        4   (enumerate)                           // 17   ns
485              30  LOAD_FAST          2   (result_types)                        // 16   ns
486              32  CALL_FUNCTION      1   ()                                    // 20   ns
487     // >>> self.results = tuple(
488     929      34  GET_ITER               ()                                    // 17   ns
489              36  CALL_FUNCTION      1   ()                                    // 20   ns
490              38  CALL_FUNCTION      1   ()                                    // 36   ns
491
492          // =========== core:929 `<genexpr>` ============
493              0   GEN_START          0   ()                                    // 15   ns
494          // >>> self.results = tuple(
495     929      2   LOAD_FAST          0   (.0)                                  // 15   ns
496          >>  4   FOR_ITER          11   (to 28)                               // 15   ns
497          >>  28  LOAD_CONST         0   (None)                                // 14   ns
498              30  RETURN_VALUE           ()                                    // 38   ns
499          // =============================================
500
501              40  LOAD_DEREF         0   (self)                                // 17   ns
502              42  STORE_ATTR         5   (results)                             // 18   ns
503     // >>> self.properties = dict(properties)
504     933      44  LOAD_GLOBAL        6   (dict)                                // 17   ns
505              46  LOAD_FAST          3   (properties)                          // 17   ns
506              48  CALL_FUNCTION      1   ()                                    // 19   ns
507              50  LOAD_DEREF         0   (self)                                // 17   ns
508              52  STORE_ATTR         7   (properties)                          // 18   ns
509     // >>> self.attributes = dict(attributes)
510     934      54  LOAD_GLOBAL        6   (dict)                                // 16   ns
511              56  LOAD_FAST          4   (attributes)                          // 16   ns
512              58  CALL_FUNCTION      1   ()                                    // 18   ns
513              60  LOAD_DEREF         0   (self)                                // 17   ns
514              62  STORE_ATTR         8   (attributes)                          // 17   ns
515     // >>> self.successors = list(successors)
516     935      64  LOAD_GLOBAL        9   (list)                                // 16   ns
517              66  LOAD_FAST          5   (successors)                          // 16   ns
518              68  CALL_FUNCTION      1   ()                                    // 18   ns
519              70  LOAD_DEREF         0   (self)                                // 17   ns
520              72  STORE_ATTR        10   (successors)                          // 33   ns
521
522          // =========== core:901 `successors` ===========
523          // >>> new = tuple(new)
524     903      0   LOAD_GLOBAL        0   (tuple)                               // 14   ns
525              2   LOAD_FAST          1   (new)                                 // 13   ns
526              4   CALL_FUNCTION      1   ()                                    // 15   ns
527              6   STORE_FAST         1   (new)                                 // 13   ns
528          // >>> for idx, successor in enumerate(self._successors):
529     904      8   LOAD_GLOBAL        1   (enumerate)                           // 13   ns
530              10  LOAD_FAST          0   (self)                                // 13   ns
531              12  LOAD_ATTR          2   (_successors)                         // 14   ns
532              14  CALL_FUNCTION      1   ()                                    // 16   ns
533              16  GET_ITER               ()                                    // 14   ns
534          >>  18  FOR_ITER          12   (to 44)                               // 15   ns
535          // >>> for idx, successor in enumerate(new):
536     906  >>  44  LOAD_GLOBAL        1   (enumerate)                           // 13   ns
537              46  LOAD_FAST          1   (new)                                 // 13   ns
538              48  CALL_FUNCTION      1   ()                                    // 15   ns
539              50  GET_ITER               ()                                    // 13   ns
```

```
        >> 52 FOR_ITER            12 (to 78)                    // 15   ns
    // >>> self._successors = new
908     >> 78 LOAD_FAST            1  (new)                      // 13   ns
        80 LOAD_FAST              0  (self)                     // 13   ns
        82 STORE_ATTR             2  (_successors)              // 14   ns
        84 LOAD_CONST             0  (None)                     // 13   ns
        86 RETURN_VALUE              ()                         // 32   ns
    // ===============================================


// >>> self.regions = ()
936     74 LOAD_CONST             3  (())                       // 17   ns
        76 LOAD_DEREF             0  (self)                     // 16   ns
        78 STORE_ATTR            11  (regions)                  // 20   ns
// >>> for region in regions:
937     80 LOAD_FAST              6  (regions)                  // 17   ns
        82 GET_ITER                 ()                         // 17   ns
     >> 84 FOR_ITER               7  (to 100)                  // 17   ns
// >>> self.__post_init__()
940  >> 100 LOAD_DEREF            0  (self)                     // 17   ns
       102 LOAD_METHOD           13  (__post_init__)            // 17   ns
       104 CALL_METHOD            0  ()                         // 45   ns


    // ====== operations:138 `__post_init__` ======
    // >>> op_def = self.get_irdl_definition()
139       0 LOAD_FAST             0  (self)                     // 22   ns
          2 LOAD_METHOD           0  (get_irdl_definition)      // 24   ns
          4 CALL_METHOD           0  ()                         // 28   ns


    // === operations:2004 `get_irdl_definition` ===
    // >>> return op_def
2006      0 LOAD_DEREF            0  (op_def)                   // 10   ns
          2 RETURN_VALUE             ()                         // 28   ns
        // ===============================================


          6 STORE_FAST            1  (op_def)                   // 21   ns
    // >>> for prop_name, prop_def in op_def.properties.items():
141       8 LOAD_FAST             1  (op_def)                   // 21   ns
         10 LOAD_ATTR             1  (properties)               // 21   ns
         12 LOAD_METHOD           2  (items)                    // 20   ns
         14 CALL_METHOD           0  ()                         // 22   ns
         16 GET_ITER                 ()                         // 21   ns
      >> 18 FOR_ITER             25  (to 70)                    // 21   ns
    // >>> for attr_name, attr_def in op_def.attributes.items():
150    >> 70 LOAD_FAST            1  (op_def)                   // 20   ns
         72 LOAD_ATTR             6  (attributes)               // 19   ns
         74 LOAD_METHOD           2  (items)                    // 19   ns
         76 CALL_METHOD           0  ()                         // 21   ns
         78 GET_ITER                 ()                         // 20   ns
      >> 80 FOR_ITER             25  (to 132)                   // 20   ns
    // >>> return super().__post_init__()
158    >> 132 LOAD_GLOBAL         7  (super)                    // 20   ns
        134 CALL_FUNCTION         0  ()                         // 22   ns
        136 LOAD_METHOD           8  (__post_init__)            // 22   ns
        138 CALL_METHOD           0  ()                         // 27   ns


    // ========= builder:343 `new_post_init` ========
    // >>> old_post_init(self)
344       0 LOAD_DEREF            0  (old_post_init)            // 9    ns
          2 LOAD_FAST             0  (self)                     // 9    ns
          4 CALL_FUNCTION         1  ()                         // 20   ns


    // ========= core:910 `__post_init__` ==========
    // >>> assert self.name != ""
```

```
603                911       0   LOAD_FAST          0    (self)                 // 8    ns
604                          2   LOAD_ATTR          0    (name)                 // 9    ns
605                          4   LOAD_CONST         1    ('')                   // 8    ns
606                          6   COMPARE_OP         3    (!=)                   // 8    ns
607                          8   POP_JUMP_IF_TRUE   7    (to 14)                // 8    ns
608          // >>> assert isinstance(self.name, str)
609                912   >>  14  LOAD_GLOBAL        1    (isinstance)           // 7    ns
610                          16  LOAD_FAST          0    (self)                 // 7    ns
611                          18  LOAD_ATTR          0    (name)                 // 8    ns
612                          20  LOAD_GLOBAL        2    (str)                  // 7    ns
613                          22  CALL_FUNCTION      2    ()                     // 9    ns
614                          24  POP_JUMP_IF_TRUE   15   (to 30)                // 8    ns
615                      >>  30  LOAD_CONST         0    (None)                 // 7    ns
616                          32  RETURN_VALUE            ()                     // 18   ns
617            // ==========================================
618
619                          6   POP_TOP                 ()                     // 10   ns
620          // >>> _op_init_callback(self)
621                345       8   LOAD_GLOBAL        0    (_op_init_callback)    // 9    ns
622                          10  LOAD_FAST          0    (self)                 // 9    ns
623                          12  CALL_FUNCTION      1    ()                     // 24   ns
624
625            // ====== builder:335 `_op_init_callback` ======
626            // >>> if (b := ImplicitBuilder.get()) is not None:
627                336       0   LOAD_GLOBAL        0    (ImplicitBuilder)      // 11   ns
628                          2   LOAD_METHOD        1    (get)                  // 13   ns
629                          4   CALL_METHOD        0    ()                     // 21   ns
630
631              // ============= builder:321 `get` =============
632              // >>> return cls._stack.get()
633                326       0   LOAD_FAST          0    (cls)                  // 7    ns
634                          2   LOAD_ATTR          0    (_stack)               // 9    ns
635                          4   LOAD_METHOD        1    (get)                  // 12   ns
636                          6   CALL_METHOD        0    ()                     // 18   ns
637
638                // ============= builder:261 `get` =============
639                // >>> if len(self.stack):
640                262       0   LOAD_GLOBAL        0    (len)                  // 8    ns
641                          2   LOAD_FAST          0    (self)                 // 7    ns
642                          4   LOAD_ATTR          1    (stack)                // 10   ns
643                          6   CALL_FUNCTION      1    ()                     // 9    ns
644                          8   POP_JUMP_IF_FALSE  10   (to 20)                // 9    ns
645                262   >>  20  LOAD_CONST         0    (None)                 // 8    ns
646                          22  RETURN_VALUE            ()                     // 18   ns
647                  // ==========================================
648
649                          8   RETURN_VALUE            ()                     // 19   ns
650              // ==========================================
651
652                          6   DUP_TOP                 ()                     // 11   ns
653                          8   STORE_FAST         1    (b)                    // 10   ns
654                          10  LOAD_CONST         0    (None)                 // 9    ns
655                          12  IS_OP              1    ()                     // 9    ns
656                          14  POP_JUMP_IF_FALSE  15   (to 30)                // 9    ns
657                336   >>  30  LOAD_CONST         0    (None)                 // 8    ns
658                          32  RETURN_VALUE            ()                     // 20   ns
659              // ==========================================
660
661                          14  POP_TOP                 ()                     // 10   ns
662                          16  LOAD_CONST         0    (None)                 // 9    ns
663                          18  RETURN_VALUE            ()                     // 27   ns
664            // ==========================================
665
```

```
666                         140 RETURN_VALUE              ()                        // 42  ns
667           // ==========================================
668
669                   106 POP_TOP                  ()                               // 18  ns
670                   108 LOAD_CONST           0   (None)                           // 17  ns
671                   110 RETURN_VALUE            ()                                // 51  ns
672           // ==========================================
673
674               722 POP_TOP                    ()                                 // 39  ns
675               724 LOAD_CONST           8   (None)                               // 38  ns
676               726 RETURN_VALUE            ()                                    // 76  ns
677         // ==========================================
678
679               102 POP_TOP                  ()                                   // 14  ns
680               104 LOAD_CONST           0   (None)                               // 13  ns
681               106 RETURN_VALUE            ()                                    // 34  ns
682       // ==========================================
683
684             32  POP_TOP                  ()                                     // 14  ns
685   // >>> return op
686   194        34  LOAD_FAST            7   (op)                                  // 13  ns
687             36  RETURN_VALUE            ()                                      // 29  ns
688       // ==========================================
689
690           6   POP_TOP                  ()                                       // 12  ns
691           8   LOAD_CONST           1   (None)                                   // 8   ns
692           10  RETURN_VALUE            ()                                        // 20  ns
693   // ==========================================
```

Listing E.1: Bytecode profile trace of the original implementation of instantiation of an empty operation.

```
1    //// Trace of `OpCreation.time_operation_create_optimised` :
2
3    // == microbenchmarks:297 `time_operation_create_optimised` ==
4    // >>> empty_op = EmptyOp.__new__(EmptyOp)
5    299        0   LOAD_GLOBAL          0   (EmptyOp)                              // 23  ns
6              2   LOAD_METHOD          1   (__new__)                              // 24  ns
7              4   LOAD_GLOBAL          0   (EmptyOp)                              // 22  ns
8              6   CALL_METHOD          1   ()                                     // 26  ns
9              8   STORE_FAST           1   (empty_op)                             // 20  ns
10   // >>> empty_op._operands = tuple()   # pyright: ignore[reportPrivateUsage]
11   300        10  LOAD_GLOBAL          2   (tuple)                                // 19  ns
12              12  CALL_FUNCTION        0   ()                                     // 20  ns
13              14  LOAD_FAST            1   (empty_op)                             // 19  ns
14              16  STORE_ATTR           3   (_operands)                            // 22  ns
15   // >>> empty_op.results = tuple()
16   301        18  LOAD_GLOBAL          2   (tuple)                                // 19  ns
17              20  CALL_FUNCTION        0   ()                                     // 20  ns
18              22  LOAD_FAST            1   (empty_op)                             // 18  ns
19              24  STORE_ATTR           4   (results)                              // 21  ns
20   // >>> empty_op.properties = {}
21   302        26  BUILD_MAP            0   ()                                     // 19  ns
22              28  LOAD_FAST            1   (empty_op)                             // 17  ns
23              30  STORE_ATTR           5   (properties)                           // 21  ns
24   // >>> empty_op.attributes = {}
25   303        32  BUILD_MAP            0   ()                                     // 19  ns
26              34  LOAD_FAST            1   (empty_op)                             // 18  ns
27              36  STORE_ATTR           6   (attributes)                           // 22  ns
28   // >>> empty_op._successors = tuple()  # pyright: ignore[reportPrivateUsage]
29   304        38  LOAD_GLOBAL          2   (tuple)                                // 18  ns
30              40  CALL_FUNCTION        0   ()                                     // 20  ns
```

```
31              42  LOAD_FAST        1   (empty_op)                              // 18   ns
32              44  STORE_ATTR       7   (_successors)                           // 21   ns
33  // >>> empty_op.regions = tuple()
34  305         46  LOAD_GLOBAL      2   (tuple)                                 // 18   ns
35              48  CALL_FUNCTION    0   ()                                      // 20   ns
36              50  LOAD_FAST        1   (empty_op)                              // 19   ns
37              52  STORE_ATTR       8   (regions)                               // 23   ns
38              54  LOAD_CONST       1   (None)                                  // 18   ns
39              56  RETURN_VALUE         ()                                      // 44   ns
40  // ============================================
```

Listing E.2: Bytecode profile trace of the optimised implementation of instantiation an empty operation.

```
1   //// Trace of `Extensibility.time_trait_check` :
2
3   // == microbenchmarks:176 `time_trait_check` ===
4   // >>> assert Extensibility.OP_WITH_REGION.has_trait(Extensibility.TRAIT_4)
5   204         0   LOAD_GLOBAL      0   (Extensibility)                         // 17   ns
6               2   LOAD_ATTR        1   (OP_WITH_REGION)                        // 18   ns
7               4   LOAD_METHOD      2   (has_trait)                             // 18   ns
8               6   LOAD_GLOBAL      0   (Extensibility)                         // 17   ns
9               8   LOAD_ATTR        3   (TRAIT_4)                               // 18   ns
10              10  CALL_METHOD      1   ()                                      // 54   ns
11
12      // =========== core:1192 `has_trait` ===========
13      // >>> from xdsl.dialects.builtin import UnregisteredOp
14      1204        0   LOAD_CONST       1   (0)                                 // 26   ns
15                  2   LOAD_CONST       2   (('UnregisteredOp',))               // 25   ns
16                  4   IMPORT_NAME      0   (xdsl.dialects.builtin)             // 72   ns
17                  6   IMPORT_FROM      1   (UnregisteredOp)                    // 28   ns
18                  8   STORE_FAST       3   (UnregisteredOp)                    // 23   ns
19                  10  POP_TOP              ()                                 // 21   ns
20      // >>> if issubclass(cls, UnregisteredOp):
21      1206        12  LOAD_GLOBAL      2   (issubclass)                        // 21   ns
22                  14  LOAD_FAST        0   (cls)                               // 21   ns
23                  16  LOAD_FAST        3   (UnregisteredOp)                    // 19   ns
24                  18  CALL_FUNCTION    2   ()                                 // 46   ns
25
26          // ======== abc:121 `__subclasscheck__` ========
27          // >>> return _abc_subclasscheck(cls, subclass)
28          123         0   LOAD_GLOBAL      0   (_abc_subclasscheck)            // 19   ns
29                      2   LOAD_FAST        0   (cls)                           // 18   ns
30                      4   LOAD_FAST        1   (subclass)                      // 17   ns
31                      6   CALL_FUNCTION    2   ()                             // 26   ns
32                      8   RETURN_VALUE         ()                             // 44   ns
33          // ============================================
34
35                  20  POP_JUMP_IF_FALSE  13  (to 26)                          // 22   ns
36      // >>> return cls.get_trait(trait) is not None
37      1209    >>  26  LOAD_FAST        0   (cls)                               // 21   ns
38                  28  LOAD_METHOD      3   (get_trait)                         // 23   ns
39                  30  LOAD_FAST        1   (trait)                             // 21   ns
40                  32  CALL_METHOD      1   ()                                 // 52   ns
41
42          // =========== core:1211 `get_trait` ===========
43          // >>> if isinstance(trait, type):
44          1216        0   LOAD_GLOBAL      0   (isinstance)                    // 24   ns
45                      2   LOAD_FAST        1   (trait)                         // 23   ns
46                      4   LOAD_GLOBAL      1   (type)                          // 25   ns
47                      6   CALL_FUNCTION    2   ()                             // 25   ns
48                      8   POP_JUMP_IF_FALSE  27  (to 54)                      // 23   ns
49          // >>> for t in cls.traits:
50          1217        10  LOAD_FAST        0   (cls)                           // 22   ns
```

```
 51              12  LOAD_ATTR              2   (traits)                              // 24   ns
 52              14  GET_ITER                   ()                                    // 43   ns
 53
 54          // ============ core:758 `__iter__` ============
 55          // >>> return iter(self.traits)
 56          759         0  LOAD_GLOBAL           0   (iter)                          // 17   ns
 57                      2  LOAD_FAST             0   (self)                          // 16   ns
 58                      4  LOAD_ATTR             1   (traits)                        // 38   ns
 59
 60              // ============ core:747 `traits` ============
 61              // >>> if callable(self._traits):
 62              750         0  LOAD_GLOBAL           0   (callable)                  // 17   ns
 63                          2  LOAD_FAST             0   (self)                      // 15   ns
 64                          4  LOAD_ATTR             1   (_traits)                   // 17   ns
 65                          6  CALL_FUNCTION         1   ()                          // 18   ns
 66                          8  POP_JUMP_IF_FALSE    12   (to 24)                     // 17   ns
 67              // >>> return self._traits
 68              752    >>  24  LOAD_FAST             0   (self)                      // 16   ns
 69                         26  LOAD_ATTR             1   (_traits)                   // 16   ns
 70                         28  RETURN_VALUE              ()                          // 38   ns
 71              // ===========================================
 72
 73                      6  CALL_FUNCTION         1   ()                              // 22   ns
 74                      8  RETURN_VALUE              ()                              // 42   ns
 75          // ===========================================
 76
 77              >>  16  FOR_ITER             16   (to 50)                            // 25   ns
 78                  18  STORE_FAST            2   (t)                                // 22   ns
 79      // >>> if isinstance(t, cast(type[OpTraitInvT], trait)):
 80      1218        20  LOAD_GLOBAL           0   (isinstance)                       // 21   ns
 81                  22  LOAD_FAST             2   (t)                                // 21   ns
 82                  24  LOAD_GLOBAL           3   (cast)                             // 21   ns
 83                  26  LOAD_GLOBAL           1   (type)                             // 19   ns
 84                  28  LOAD_GLOBAL           4   (OpTraitInvT)                      // 18   ns
 85                  30  BINARY_SUBSCR             ()                                 // 22   ns
 86                  32  LOAD_FAST             1   (trait)                            // 19   ns
 87                  34  CALL_FUNCTION         2   ()                                 // 41   ns
 88
 89          // ============ typing:1737 `cast` ============
 90          // >>> return val
 91          1745        0  LOAD_FAST             1   (val)                           // 18   ns
 92                      2  RETURN_VALUE             ()                               // 43   ns
 93          // ===========================================
 94
 95                  36  CALL_FUNCTION         2   ()                                 // 23   ns
 96                  38  POP_JUMP_IF_FALSE    24   (to 48)                            // 20   ns
 97      1218    >>  48  JUMP_ABSOLUTE         8   (to 16)                            // 20   ns
 98      // >>> for t in cls.traits:
 99              >>  16  FOR_ITER             16   (to 50)                            // 19   ns
100                  18  STORE_FAST            2   (t)                                // 19   ns
101      // >>> if isinstance(t, cast(type[OpTraitInvT], trait)):
102      1218        20  LOAD_GLOBAL           0   (isinstance)                       // 19   ns
103                  22  LOAD_FAST             2   (t)                                // 19   ns
104                  24  LOAD_GLOBAL           3   (cast)                             // 19   ns
105                  26  LOAD_GLOBAL           1   (type)                             // 18   ns
106                  28  LOAD_GLOBAL           4   (OpTraitInvT)                      // 18   ns
107                  30  BINARY_SUBSCR             ()                                 // 21   ns
108                  32  LOAD_FAST             1   (trait)                            // 19   ns
109                  34  CALL_FUNCTION         2   ()                                 // 40   ns
110
111          // ============ typing:1737 `cast` ============
112          // >>> return val
113      1745        0  LOAD_FAST             1   (val)                              // 18   ns
```

```
114                        2  RETURN_VALUE                    ()                              // 43   ns
115        // ============================================
116
117              36  CALL_FUNCTION        2   ()                              // 21   ns
118              38  POP_JUMP_IF_FALSE   24  (to 48)                          // 20   ns
119      // >>> return t
120      1219     40  LOAD_FAST            2   (t)                             // 19   ns
121              42  ROT_TWO                  ()                              // 19   ns
122              44  POP_TOP                  ()                              // 20   ns
123              46  RETURN_VALUE             ()                              // 47   ns
124        // ============================================
125
126          34  LOAD_CONST          3   (None)                              // 21   ns
127          36  IS_OP               1   ()                                  // 21   ns
128          38  RETURN_VALUE            ()                                  // 47   ns
129      // ==========================================
130
131          12  POP_JUMP_IF_TRUE     9   (to 18)                            // 16   ns
132      >>  18  LOAD_CONST          1   (None)                              // 16   ns
133          20  RETURN_VALUE           ()                                   // 39   ns
134  // ============================================
```

Listing E.3: Bytecode profile trace of the original implementation of `has_trait`.

```
1   //// Trace of `Extensibility.time_trait_check_optimised` :
2
3   // == microbenchmarks:206 `time_trait_check_optimised` ==
4   // >>> has_trait = False
5   208      0  LOAD_CONST          1   (False)                             // 14   ns
6            2  STORE_FAST          1   (has_trait)                         // 14   ns
7   // >>> for t in Extensibility.OP_WITH_REGION.traits._traits:
8   209      4  LOAD_GLOBAL         0   (Extensibility)                     // 13   ns
9            6  LOAD_ATTR           1   (OP_WITH_REGION)                    // 13   ns
10           8  LOAD_ATTR           2   (traits)                            // 13   ns
11          10  LOAD_ATTR           3   (_traits)                           // 13   ns
12          12  GET_ITER                ()                                  // 13   ns
13      >>  14  FOR_ITER           12   (to 40)                             // 13   ns
14          16  STORE_FAST          2   (t)                                 // 11   ns
15   // >>> if isinstance(t, Extensibility.TRAIT_4):
16   210     18  LOAD_GLOBAL         4   (isinstance)                        // 11   ns
17          20  LOAD_FAST           2   (t)                                 // 11   ns
18          22  LOAD_GLOBAL         0   (Extensibility)                     // 11   ns
19          24  LOAD_ATTR           5   (TRAIT_4)                           // 11   ns
20          26  CALL_FUNCTION       2   ()                                  // 12   ns
21          28  POP_JUMP_IF_FALSE  19   (to 38)                             // 11   ns
22   210 >>  38  JUMP_ABSOLUTE       7   (to 14)                            // 11   ns
23   // >>> for t in Extensibility.OP_WITH_REGION.traits._traits:
24      >>  14  FOR_ITER           12   (to 40)                             // 11   ns
25          16  STORE_FAST          2   (t)                                 // 11   ns
26   // >>> if isinstance(t, Extensibility.TRAIT_4):
27   210     18  LOAD_GLOBAL         4   (isinstance)                        // 11   ns
28          20  LOAD_FAST           2   (t)                                 // 10   ns
29          22  LOAD_GLOBAL         0   (Extensibility)                     // 11   ns
30          24  LOAD_ATTR           5   (TRAIT_4)                           // 11   ns
31          26  CALL_FUNCTION       2   ()                                  // 11   ns
32          28  POP_JUMP_IF_FALSE  19   (to 38)                             // 11   ns
33   // >>> has_trait = True
34   211     30  LOAD_CONST          2   (True)                             // 11   ns
35          32  STORE_FAST          1   (has_trait)                         // 11   ns
36   // >>> break
37   212     34  POP_TOP                 ()                                 // 11   ns
```

```
38                36  JUMP_FORWARD           1    (to 40)                                // 11   ns
39   // >>> assert has_trait
40   213     >>  40  LOAD_FAST              1    (has_trait)                            // 11   ns
41                42  POP_JUMP_IF_TRUE      24    (to 48)                                // 11   ns
42           >>  48  LOAD_CONST             3    (None)                                 // 11   ns
43                50  RETURN_VALUE               ()                                     // 23   ns
44   // ===========================================
```

Listing E.4: Bytecode profile trace of the optimised implementation of `has_trait`.

Appendix F

Disassembly of dynamic dispatch experiments

```
1   main:
2    stp        x29, x30, [sp, #-32]!
3    str        x19, [sp, #16]
4    mov        x29, sp
5    ldr        x0, [x1, #8]
6    mov        x19, x1
7    mov        x1, xzr
8    mov        w2, #0xa                      // #10
9    bl         0 <strtol>
10       R_AARCH64_CALL26 strtol
11   ldr        x8, [x19, #16]
12   mov        x19, x0
13   mov        x1, xzr
14   mov        w2, #0xa                      // #10
15   mov        x0, x8
16   bl         0 <strtol>
17       R_AARCH64_CALL26 strtol
18   // ===== Start of function invocation ===== //
19    sub        w0, w19, w0
20   // ====== End of function invocation ====== //
21    ldr        x19, [sp, #16]
22    ldp        x29, x30, [sp], #32
23    ret
```
Listing F.1: Disassembly of inlined function invocation (Listing 7.1a ❶).

```
1   main:
2    stp        x29, x30, [sp, #-32]!
3    str        x19, [sp, #16]
4    mov        x29, sp
5    ldr        x0, [x1, #8]
6    mov        x19, x1
7    mov        x1, xzr
8    mov        w2, #0xa                      // #10
9    bl         0 <strtol>
10       R_AARCH64_CALL26 strtol
11   ldr        x8, [x19, #16]
12   mov        x19, x0
```

```
13    mov      x1, xzr
14    mov      w2, #0xa                        // #10
15    mov      x0, x8
16    bl       0 <strtol>
17       R_AARCH64_CALL26 strtol
18  // ===== Start of function invocation ===== //
19    mov      x2, x0
20    add      x0, x29, #0x1f
21    mov      w1, w19
22    bl       0 <main>
23       R_AARCH64_CALL26 Base::uninlinedFunc(int, int)
24  // ====== End of function invocation ====== //
25    ldr      x19, [sp, #16]
26    ldp      x29, x30, [sp], #32
27    ret
28  Base::uninlinedFunc(int, int):
29    sub      w0, w1, w2
30    ret
```

Listing F.2: Disassembly of uninlined function invocation (Listing 7.1a ②).

```
1   main:
2    sub      sp, sp, #0x30
3    stp      x29, x30, [sp, #16]
4    stp      x20, x19, [sp, #32]
5    add      x29, sp, #0x10
6    ldr      x0, [x1, #8]
7    mov      x19, x1
8    mov      x1, xzr
9    mov      w2, #0xa                        // #10
10   bl       0 <strtol>
11      R_AARCH64_CALL26 strtol
12   ldr      x8, [x19, #16]
13   mov      x20, x0
14   mov      x1, xzr
15   mov      w2, #0xa                        // #10
16   mov      x0, x8
17   bl       0 <strtol>
18      R_AARCH64_CALL26 strtol
19   ldr      x8, [x19, #24]
20   mov      x19, x0
21   mov      x1, xzr
22   mov      w2, #0xa                        // #10
23   mov      x0, x8
24   bl       0 <strtol>
25      R_AARCH64_CALL26 strtol
26  // ===== Start of function invocation ===== //
27   adrp     x8, 0 <main>
28      R_AARCH64_ADR_PREL_PG_HI21 vtable for Base+0x10
29   add      x11, x8, #0x0
30      R_AARCH64_ADD_ABS_LO12_NC vtable for Base+0x10
31   cmp      w0, #0x0
32   adrp     x8, 0 <main>
33      R_AARCH64_ADR_PREL_PG_HI21 vtable for Derived+0x10
34   add      x8, x8, #0x0
35      R_AARCH64_ADD_ABS_LO12_NC vtable for Derived+0x10
36   mov      x9, sp
37   add      x10, sp, #0x8
38   stp      x8, x11, [sp]
39   mov      w1, w20
40   csel     x0, x10, x9, gt
41   mov      w2, w19
```

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```
42    ldr       x8, [x0]
43    ldr       x8, [x8]
44    blr       x8
45    // ====== End of function invocation ====== //
46    ldp       x20, x19, [sp, #32]
47    ldp       x29, x30, [sp, #16]
48    add       sp, sp, #0x30
49    ret
50  Base::virtualFunc(int, int):
51    sub       w0, w1, w2
52    ret
53  Derived::virtualFunc(int, int):
54    sub       w0, w2, w1
55    ret
```

Listing F.3: Disassembly of polymorphic function invocation (Listing 7.1a ③).

```
1   //// Trace of `Extensibility.time_invoke_method_baseline` :
2   // == microbenchmarks:152 `time_invoke_method_baseline` ==
3   // >>> a = 5
4   154         0   LOAD_CONST          1   (5)
5               2   STORE_FAST          1   (a)
6   // >>> b = 6
7   155         4   LOAD_CONST          2   (6)
8               6   STORE_FAST          2   (b)
9   // >>> _ = None  # Simulate passing arguments
10  156         8   LOAD_CONST          3   (None)
11              10  STORE_FAST          3   (_)
12  // >>> Extensibility.EXAMPLE.regularFunction
13  157         12  LOAD_GLOBAL         0   (Extensibility)
14              14  LOAD_ATTR           1   (EXAMPLE)
15              16  LOAD_ATTR           2   (regularFunction)
16              18  POP_TOP                 ()
17  // >>> return a - b
18  158         20  LOAD_FAST           1   (a)
19              22  LOAD_FAST           2   (b)
20              24  BINARY_SUBTRACT         ()
21              26  RETURN_VALUE            ()
22  // ============================================
23
24  // == microbenchmarks:160 `time_invoke_method` ==
25  // >>> a = 5
26  162         0   LOAD_CONST          1   (5)
27              2   STORE_FAST          1   (a)
28  // >>> b = 6
29  163         4   LOAD_CONST          2   (6)
30              6   STORE_FAST          2   (b)
31  // >>> return Extensibility.EXAMPLE.regularFunction(a, b)
32  164         8   LOAD_GLOBAL         0   (Extensibility)
33              10  LOAD_ATTR           1   (EXAMPLE)
34              12  LOAD_METHOD         2   (regularFunction)
35              14  LOAD_FAST           1   (a)
36              16  LOAD_FAST           2   (b)
37              18  CALL_METHOD         2   ()
38
39     // === microbenchmarks:16 `regularFunction` ====
40     // >>> return a - b
41      17         0   LOAD_FAST           1   (a)
42                 2   LOAD_FAST           2   (b)
43                 4   BINARY_SUBTRACT         ()
44                 6   RETURN_VALUE            ()
```

```
45      // ============================================
46              20   RETURN_VALUE              ()
47  // ==============================================
```

Listing F.4: Bytecode trace of Python method invocation, with the CALL_METHOD and RETURN_VALUE opcodes being the target of the measurement by subtracting the elapsed time from that of the baseline inlined implementation.