Two-level Just-in-Time Compilation with One Interpreter and One Engine

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Abstract
Modern, powerful virtual machines such as those running Java or JavaScript support multi-tier JIT compilation and optimization features to achieve their high performance. However, implementing and maintaining several compilers/optimizers that interact with each other requires hard-working VM developers. In this paper, we propose a technique to realize two-level JIT compilation in RPython without implementing several interpreters or compilers from scratch. As a preliminary realization, we created adaptive RPython, which performs both baseline JIT compilation based on threaded code and tracing JIT compilation. We also implemented a small programming language with it. Furthermore, we preliminarily evaluated the performance of that small language, and our baseline JIT compilation ran 1.77x faster than the interpreter-only execution. Furthermore, we observed that when we apply an optimal JIT compilation for different target methods, the performance was mostly the same as the one optimizing JIT compilation strategy, saving about 40% of the compilation code size.

CCS Concepts: • Software and its engineering → Just-in-time compilers.

Keywords: JIT compiler, adaptive compilation, tracing compilation, RPython, language implementation framework

1 Introduction
Language implementation frameworks, e.g. RPython [6] and Truffle/Graal [24], are tools used to build a virtual machine (VM) with a highly efficient just-in-time (JIT) compiler which is done by providing an interpreter of the language. For example, PyPy [5], which is a fully compatible Python implementation, achieved 4.5x speedup from the original CPython 3.7 interpreter [23]. The other successful examples include Topaz [9], Hippy VM [8], TruffleRuby [20], and GraalPython [21].

One of the limitations of RPython and Truffle/Graal, which is differed from the current language-specific VMs such as Java or JavaScript, is that they don’t support a multtier JIT compilation strategy. One naïve approach for multtier compilation is to create compilers for each optimization level. However, this approach makes existing implementations more complex and requires more developing efforts to implement and maintain — we need to at least consider how to share components, along with how to exchange profiling information and compiled code between each compiler. To avoid this situation, we have to find another efficient and reasonable way to support multtier JIT compilation in a framework. Several works in RPython [2, 4, 14] found that specifying special annotations in an interpreter definition can influence how RPython’s meta-tracing JIT compiler works. In other words, we can view the interpreter definition as a specification of a compiler. We believe those approaches can be extended to achieve an adaptive optimization system at the meta-level.

As a proof of concept of language-agnostic multtier JIT compilation, we propose adaptive RPython. Adaptive RPython can generate a VM with two-level JIT compilation. We do not create two separated compilers in adaptive RPython but indeed generate two different interpreters — the one for the first level of compilation and another is for the second level. As first-level compilation, we support threaded code [3, 13] in a meta-tracing compiler (we call this technique threaded code generation [15]). The second one is RPython’s original tracing JIT compiler. We can switch those compilation tiers by moving between the two interpreters. In addition, adaptive RPython generates two interpreters from one definition. It will reduce the implementation costs that language developers should pay if they are in a traditional development way. In the future, we plan to extend this system to realize a nonstop compilation-tier changing mechanism in a language implementation framework — we can use an appropriate and efficient optimization level or a compilation strategy, depending on the executed program.

The contributions of the current paper can be summarized as follows:

• An approach to generate multiple interpreter implementations from one common interpreter definition to obtain JIT compilers with different optimization levels.

• The technical details of enabling threaded code generation as a first-level JIT compilation by driving an existing meta-tracing JIT compiler engine.

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Figure 1. An overview of adaptive RPython: two different interpreters are generated from a single generic interpreter by adaptive RPython at VM generation time. At run-time, the two interpreters that is, the baseline JIT and tracing JIT interpreters, behave as tier 1 and tier 2, respectively.

- The preliminary evaluation of our two-level JIT compilation on a simple programming language.

The rest of the current paper is organized as follows: Section 2 proposes an idea and technique to support two-level JIT compilation with one interpreter in RPython without crafting a compiler from scratch. We evaluate our preliminary implementation in Section 3. Section 4 discusses related work, and we conclude the paper and denote the future work in Section 5.

2 Two-level Just-in-Time Compilation with RPython

In this section, we propose a multitier meta-tracing JIT compiler framework called adaptive RPython along with its technique to support two different compilation levels with one interpreter and one engine. Section 2.1 introduces adaptive RPython. Then, Sections 2.2 and 2.3 explain the technical details to realize two-level JIT compilation in RPython. Sections 2.2 and 2.3 correspond to “one interpreter” and “one engine,” respectively.

2.1 Adaptive RPython

Adaptive RPython lets the existing meta-tracing engine to behave in two ways: as both a baseline JIT compiler and a tracing JIT compiler. To realize this behavior, the most obvious approach would be to implement two different compilers or interpreters. However, this approach increases the amount of implementation necessary. Thus, we do not craft compilers from scratch but derive two different compilation strategies by providing a specializing interpreter called the generic interpreter to Adaptive RPython. Figure 1 shows an overview of how Adaptive RPython and the generic interpreter work. At VM generation time (the upper half of Figure 1), the developer writes the generic interpreter. Adaptive RPython generates two different interpreters that support different JIT compilation tiers, e.g., baseline JIT and tracing JIT interpreters work as tier-1 and tier-2, respectively. At run-time (the bottom half of Figure 1), a generated baseline JIT interpreter firstly accepts and runs a base-program. While running the program, the execution switches to a generated tracing JIT interpreter if the hot spot is suitable for tracing JIT compilation.

2.2 Generic Interpreter

Adaptive RPython takes the generic interpreter as the input. The generic interpreter is converted into an interpreter that includes two definitions – one for baseline JIT compilation and another is for tracing JIT compilation. To remove the task of manually writing redundant definitions in the method-traversal interpreter [15], we internally generate both the method-traversal interpreter (for the baseline JIT compilation) and a normal interpreter (for tracing JIT compilation) from the generic interpreter definition.

Listing 1. A skeleton of the generic interpreter definition.
is shown in Listing 1. When developers write the generic interpreter, they first declare an instance of JitTierDriver class that has a field pc. It tells adaptive RPython fundamental information such as the variable name of the program counter. Furthermore, transforming hints should be defined in a specific handler. can_enter_tier1_branch, can_enter_tier1_jump, and can_enter_tier1_ret tell the adaptive RPython’s transformer the necessary information to generate the method-traversal interpreter. The method-traversal interpreter requires a particular kind of code in the JUMP_IF, JUMP, and RET bytecode handlers so that hints can be called in those handlers. The requisite information in each handler and hint is the following:

**can_enter_tier1_branch.** The method-traversal interpreter needs to drive the engine to trace both sides of a branch instruction. Thus, we have to pass the following variables/expressions to the transformer:

- the true and false paths of program counters: to manage them in the traverse stack
- the conditional expression: to generate the if expression

In the handler of JUMP_IF in Listing 1, we pass the following statements/expressions: target as true_path, pc+1 as a false_path and self.is_true as cond. We also remember and mark the cond to utilize at trace-stitching inside of adaptive RPython (details are explained in Section 2.3.1).

**can_enter_tier1_jump.** A jump instruction possibly placed at the end of a function/method. In this case, the engine does not follow the destination but takes out a program counter from the top of traverse_stack. Otherwise, the jump instruction performs as defined in the original interpreter. Thus, the method-traversal interpreter requires the program counter of a jump target to manage it in the traverse_stack. As shown in the handler of JUMP in Listing 1, we pass target to the transform_jump function.

**can_enter_tier1_ret.** A return instruction is invoked at the end of a function/method. The method-traversal interpreter requires a return value, so we have to pass w_x via transform_ret, as illustrated in the handler of RET in Listing 1.

**we_are_in_tier2.** This is a hint function to tell the area where a definition for the tracing JIT compilation is written to the transformer. One thing we need to do is to specify the type of handler function defined immediately above. For example, we add the keyword argument kind='branch' in the handler of JUMP_IF in Listing 1.

### 2.3 Just-in-Time Trace Stitching

The just-in-time trace stitching technique builds back up the original control of a trace yielded from the method-traversal interpreter to emit an executable JITted code. This is the essential component in the baseline JIT compilation of adaptive RPython.

To reconstruct the original control flow, we need to connect a correct guard operation and bridging trace. Therefore, we should treat the destination of a "false" branch in a special manner while doing trace-stitching. In tracing JIT compilers, at the branching instructions, guards are inserted. After a guard operation fails numerous times, a tracing JIT compiler will trace the destination path starting from the failing guard, that is, trace the other branch. The resulting trace from a guard failure is called a bridge, which will be connected to the loop body. On the other hand, in trace-stitching, we perform a sequence of generating and connecting a bridge in one go. For the sake of ease and reducing code size, we generate a trace that essentially consists of call operations by threaded code generation.²

The left-hand side of Figure 2 illustrates the process of traversing an example target method that has nested branches. In tracing a branch instruction, we record the other destination, for example, a program counter from B to D in node B, in the traverse stack. For example, when tracing B and C, we push each program counter from B to D and from C to F to the traverse stack. Then, we pop a program counter from the traverse stack and set it to E and F. After traversing all paths, we obtain a single trace that does not keep the structure of the target as shown in the right-hand side of Figure 2.

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¹Technically speaking, type-checking guards are inserted to optimize the obtained trace based on the observed run-time type information. However, we currently handle branching guards only and leave type optimization to the last JIT tier.

²Note that threaded code generation [15] yields call and guard operations. In contrast to normal tracing JIT compilation, it can reduce the code size and compilation time by 80% and 60%.
2.3.1 Resolving Guard Failures and Bridges. Intending to resolve the relations between guards and bridges, we utilize the nature of the method-traversal interpreter: it manages the base-program’s branches as a stack data structure, so the connections are first-in-last-out. Thus, we implement guard failure stack to manage each guard’s failure. The guard failure stack saves guard failures in each guard operation and pops them at the start of a bridge, that is, right after emit_jump or emit_ret operations that indicate a cut-here line.

Before explaining the details of the algorithm, we give a high-level overview of how we resolve the connections between guard failures and bridges by using Figure 3 as an example. First, the necessary information is which guard failure goes to which bridges. We resolve it by sequentially reading and utilizing the guard failure stack. When we start to stitch the trace shown in Figure 3, we sequentially read the operations from the trace. In node B, when it turns out that the guard operation is already marked as cond in the generic interpreter, we take its guard failure (g1) and push it to the guard failure stack. In node C, we do the same thing in the case of node B. Next, in node E, we finish tracing an operation and cut the current trace. In addition, we pop a guard failure and connect it to the bridge that we are going to retrieve, because the bridges are lined up below with a depth-first approach. In node F, we do the same thing in the case of node F. In node D, finally, we finish reading and produce one trace and two bridges. The connections are illustrated as red arrows in Figure 3.

2.3.2 The Mechanism of Just-in-Time Trace-Stitching. How JIT trace-stitching works is explained through Algorithm 1. First, the trace-stitcher DoTraceStitching prepares an associative array called token_map, and the (key, value) pair is (program counter, target_token). Next, it declares guard_failure_stack, trace, and result. guard_failure_stack is a key data structure to resolve the relation between guard failures and bridges. trace temporarily stores a handled operation, and result memorizes a pair of a trace and its corresponding guard_failure. After done this, it manipulates each operation in the given ops. We specifically handle the following operations: (1) a guard operation marked by the generic interpreter, (2) pseudo call operations CallOp(emit_ret) and CallOp(emit_jump), and (3) RPython’s return and jump operations. Note that almost all operations except guards are represented as a call operation because the resulting trace is produced from our threaded code generator.

Marked Guard Operation. To resolve the guard–bridge relation, we firstly collect the guard operations that we have marked in the generic interpreter. The reason we mark some guards is to distinguish between branching guards and others. When we encounter such a guard operation, we take its guard_failure and append it to the guard_failure_stack. Its algorithm is shown in the first branching block of Algorithm 1.

Pseudo call operations. Pseudo functions emit_jump and emit_ret are used as a sign of cutting the trace at this position and to start recording a bridge. They are represented as Call(emit_jump) and Call(emit_ret) in a trace.

In the case of CallOp(emit_jump):
1. look up a target_token from the token_map using the target program counter as a key
2. try to retrieve a guard_failure from the guard_failure_stack. If it the stack is empty, we do nothing because the current recording trace is a body (not a bridge). Otherwise, pop a guard failure from the guard_failure_stack.
3. create a jump operation with the inputargs and target_token and append to the trace.
4. append the pair of the trace and guard_failure to the result.

In the case of CallOp(emit_ret):
1. take a return value (retval) from the operation.
2. take a guard_failure if it is not the first time.
3. create a return operation with the retval and append to the trace.
4. append the pair of the trace and guard_failure.

RPython’s Jump and Return. These operations are placed at the end of a trace. When we read them, we append the pair of the operation and retrieve the guard failure to the result, and then, we have finished reading.

\footnote{target_token is an identifier for a trace/bridge. When we encounter emit_jump or emit_ret operations, we get the program counter (key) passed as an argument to emit_jump or emit_ret operations, hence creating a new target_token (value).}
3 Preliminary Evaluation

In this section, we evaluate our implementations of JIT trace-stitching and baseline JIT compilation can actually work. Because our work is not finished, these results can only be preliminary.

3.1 Implementation

We wrote a small interpreter called TLA in adaptive RPython and executed several micro benchmark programs on it. In the TLA language, we have both primitive and object types, and they are dynamically typed.

Simulating Multitier Compilation. To conduct this preliminary evaluation, we partially implemented two-level JIT compilation by separately defining interpreters for each execution tier – baseline JIT compilation (tier 1), and tracing JIT compilation (tier 2). In other words, to support multitier JIT compilation, we prepared two interpreters that have different jitdrivers in TLA: the one is for baseline JIT compilation while the other is for tracing JIT compilation. For example, during executing a base-program, we call separate interpreters for different JIT compilation tiers that are manually specified in a base-program.

Accessibility. The implementations of proof-of-concept adaptive RPython and TLA interpreter is hosted on Heptapod. Moreover, the generic interpreter implementations are hosted on our GitHub organization.

3.2 Targets

To verify that our JIT trace-stitching mechanism works on a program with some complex structure, we wrote a single loop program loop and nested loop program loopabit in TLA for the experiments.

Furthermore, to confirm the effectiveness of shifting different JIT compilation levels, we wrote callabit, which has two different methods and; each method has a single loop. According to the specified JIT compilation strategy, callabit has the following variants:

(a) callabit_baseline_interp: the main method is compiled by baseline JIT compilation, but the other is interpreted.
(b) callabit_baseline_only: the two methods are compiled by baseline JIT compilation.
(c) callabit_baseline_tracing: the main method is compiled by baseline JIT compilation, and the other is compiled by tracing JIT compilation.
(d) callabit_tracing_baseline: the main method is compiled by tracing JIT compilation, and the other is by baseline JIT compilation.

(e) callabit_tracing_only: all methods are compiled by tracing JIT compilation.

All bytecode programs used for this evaluation are shown in Appendix C.2.

3.3 Methodology

We took two kinds of data: the times of stable and startup speeds. When we measured the stable speed, we discarded the first iteration and accumulated the elapsed time of each 100 iterations. In contrast, we measured the startup speed; we iterated 100 times the spawning of an execution process. In addition, we took how many operations they emit and how much time they consumed in tracing and compiling in the case of callabit programs. Note that in every benchmark, we did not change the default threshold of the original RPython to enter JIT compilation.

We conducted the preliminary evaluation in the following environment: CPU: Ryzen 9 5950X, Mem: 32 GB DDR4-3200MHz, OS: Ubuntu 20.04.3 LTS with a 64-bit Linux kernel 5.11.0-34-generic.

3.4 Result

Compiling Single and Nested Loops. Figure 4 visualizes the resulting traces from loopabit.tla by baseline JIT compilation. We can initially confirm that our baseline JIT compilation works correctly when looking at this figure. Figure 5a and 5b show the results of stable and startup times in the loop and loopabit programs, respectively. In stable speed, on average, baseline JIT and tracing JIT are 1.7x and 3.25x faster than the interpreter-only execution. More specifically, baseline JIT compilation is about 2x slower than tracing JIT compilation. In startup time (Figure 5b), baseline JIT compilation is about 1.9x faster and tracing JIT compilation is about 5x faster. The loop and loopabit programs are much suitable for tracing JIT compilation, so we consider that tracing JIT compilation should be dominant in executing such programs. Furthermore, at applying the baseline JIT compilation for such a program, we should reduce the value of threshold to enter JIT compilation. Tuning the value is left for our future work.

Simulating Multitier JIT Compilation. Figure 6 shows how the simulated multitier JIT compilation works on a program with two different methods. The callabit has main method that repeatedly calls sub_loop that reduces the given number one by one. The call method is not implemented by using jump but by invoking an interpreter, so the effectiveness of inlining by tracing JIT compilation is limited in this case. In other words, main is relatively suitable for baseline JIT compilation and sub_loop works well for tracing JIT compilation.

In the stable and startup speeds (Figure 6a and 6b), callabit_baseline_interp is about 3% slower than the interpreter-only execution. This means that repeating back

\[ \text{https://foss.heptapod.net/pypy/pypy/-/tree/branch/threaded-code-generation/rpython/jit/tl/threadedcode} \]

\[ \text{https://github.com/prg-titech/mti_transformer} \]
and forth between native code and an interpreter execution leads to run-time overhead. Meanwhile, the combination of baseline JIT and tracing JIT compilations (callabit_baseline_tracing) is as fast as the tracing JIT compilation-only strategy (callabit_tracing_only). Additionally, when looking at the Figure 7, the baseline-tracing JIT strategy’s trace size is about 40 % smaller than the only tracing JIT strategy. In contrast, the trace sizes are the same between baseline-tracing JIT and tracing-baseline JIT strategies, but the tracing-baseline JIT strategy is about 45 % slower than baseline-tracing JIT strategy, and the baseline-only strategy is about 5 % faster than tracing-baseline JIT strategy. From these results, we can deduce that there is a ceiling to using only a single JIT strategy. Furthermore, to leverage different levels of JIT compilations, we have to apply an appropriate compilation according to the structure or nature of the target program.

In summary, our baseline JIT compilation is about 1.77x faster than the interpreter-only execution in both the stable and startup speeds. Moreover, our baseline JIT compilation is only about 43 % slower than the tracing JIT compilation, even though it has very few optimizations, such as inlining and type specialization. This means that our approach to enabling baseline JIT compilation alongside with tracing JIT compilation has enough potential to work as a startup compilation if we carefully adjust the threshold to enter a baseline JIT compilation. This is left as future work.

4 Related Work

Both well-developed VMs, such as Java VM or JavaScript VM, and research-oriented VMs of a certain size support multtier JIT compilation to balance among the startup speed, compilation time, and memory footprint. As far as the authors know, such VMs build at least two different compilers to realize multtier optimization. In contrast, our approach realizes it in one engine with a language implementation framework.

The Java HotSpot™ VM has the two different compilers, that is C1 [16] and C2 [22], and four optimization levels. The typical path is moving through the level 0, 3 to 4. Level 0 means interpreting. On level 3, C1 compiler compiles a target with profiling information gathered by the interpreter. If the C2’s compilation queue is not full and the target turns out to be hot, C2 starts to optimize the method aggressively (level 4). Level 1 and 2 are used when C2’s compilation queue is full, or level 3 optimization cannot work.

The Firefox JavaScript VM called SpiderMonkey [17] has several interpreters and compilers to enable multtier optimization. For interpreters, it has normal and baseline interpreters [18]. The baseline interpreter supports inline caches [7, 12] to improve its performance. The baseline JIT compiler uses the same inline caching mechanism, but it translates the entire bytecode into machine code. In addition, a full-fledged compiler WarpMonkey [19] compiles a hot spot into fast machine code. Besides such a JavaScript engine, the SpiderMonkey VM has an interpreter and compiler called WASM-Baseline and WASM-Ion.

Google’s JavaScript engine V8, which is included in the Chrome browser, also supports a multtier compilation mechanism [10]. V8 sees it as a problem that the JIT-compiled code can consume a large amount of memory, but it runs only once. The baseline interpreter/compiler is called Ignition, and it is so highly optimized to collaborate with V8’s JIT compiler engine Turbofan. It can reduce the code size up to 50 % by preserving the original.

Google’s V8 has another optimizing compiler called Liftoff [11]. The Liftoff compiler is designed for a startup compiler of WebAssembly and works alongside Turbofan. Turbofan is based on its intermediate representation (ir), so it needs to translate WebAssembly code into the ir, leading to a reduction in the startup performance of the Chrome browser. However, Liftoff instead directly compiles WebAssembly code into machine code. The liftoff compiler is tuned to quickly generate memory-efficient code to reduce the memory footprint at startup time.

The Jikes Java Research VM (originally called Jalapeño) [1], which was developed by IBM Research, is a research-oriented VM that is written in Java. It has baseline and optimizing JIT compilers and supports an optimization strategy in three-tier.

5 Conclusion and Future Work

In the current paper, we proposed the concept and initial stage implementation of adaptive RPython, which can generate a VM that supports two-tier compilation. In realizing adaptive RPython, we did not implement another compiler from scratch but drove the existing meta-tracing JIT compilation engine by a specially instrumented interpreter called the generic interpreter. The generic interpreter supports a fluent API that can be easily integrated with RPython’s original hint function. The adaptive RPython compiler generates different interpreters that support a different compilation tier. The JIT trace-stitching reconstructs the initial control flow of a generated trace from a baseline JIT interpreter to emit the executable native code. In our preliminary evaluation, when we manually applied a suitable compilation depending on the control flow of a target method, we confirmed that the baseline-tracing JIT compilation runs as fast as the tracing JIT-only compilation and reduces 50 % of the trace size. From this result, selecting an appropriate compilation strategy according to a target program’s control flow or nature is essential in the multtier compilation.

To implement an internal graph-to-graph conversion of the generic interpreter in RPython is something we plan.
to work on next. We currently implement the generic interpreter transformer as source to source because it is a proof-of-concept. For a smoother integration with RPython, we need to switch implementation strategies in the future.

To realize the technique to automatically shift JIT compilation tiers in Adaptive RPython, we also need to investigate a compilation scheme including of suitable heuristics regarding when to go from one tier to the next.

Finally, we would implement our Adaptive RPython techniques in the PyPy programming language because it brings many benefits. For example, we can obtain a lot of data by running our adaptive RPython on existing polished benchmark programs to determine a certain threshold to switch a JIT compilation. Furthermore, we could potentially bring our research results to many Python programmers.

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References

[1] Bowen Alpern, C. R. Attanasio, Anthony Cocchi, Derek Lieber, Stephen Smith, Ton Ngo, John J. Barton, Susan Flynn Hummel, Janice C. Sheperd, and Mark Mergen. 1999. Implementing Jalapeño in Java. In Proceedings of the 14th ACM SIGPLAN Conference on Object-Oriented Programming, Systems, Languages, and Applications (Denver, Colorado, USA) (OOPSLA ’99). Association for Computing Machinery, New York, NY, USA, 314–324. https://doi.org/10.1145/320384.320418

[2] Spenser Bauman, Carl Friedrich Bolz, Robert Hirschfeld, Vasily Kirilichev, Tobias Pape, Jeremy G. Siek, and Sam Tobin-Hochstadt. 2015. Pycket: A Tracing JIT for a Functional Language. In Proceedings of the 20th ACM SIGPLAN International Conference on Functional Programming (Vancouver, BC, Canada) (ICFP 2015). ACM, New York, NY, USA, 22–34. https://doi.org/10.1145/2784731.2784740

[3] James R. Bell. 1973. Threaded Code. Commun. ACM 16, 6 (June 1973), 370–372. https://doi.org/10.1145/362248.362270

[4] Carl Friedrich Bolz, Antonio Cuni, Maciej Fijalkowski, Michael Leuschel, Samuele Pedroni, and Armin Rigo. 2011. Runtime Feedback in a Meta-tracing JIT for Efficient Dynamic Languages. In Proceedings of the 6th Workshop on Implementation, Compilation, Optimization of Object-Oriented Languages, Programs and Systems (Lancaster, United Kingdom) (ECOOLPS ’11). ACM, New York, NY, USA, Article 9, 8 pages. https://doi.org/10.1145/2069172.2069181

[5] Carl Friedrich Bolz, Antonio Cuni, Maciej Fijalkowski, and Armin Rigo. 2009. Tracing the Meta-level: PyPy’s Tracing JIT Compiler. In Proceedings of the 4th Workshop on the Implementation, Compilation, Optimization of Object-Oriented Languages and Programming Systems (Genova, Italy). ACM, New York, NY, USA, 18–25. https://doi.org/10.1145/1565824.1565827

[6] Carl Friedrich Bolz and Laurence Tratt. 2015. The Impact of Meta-tracing on VM Design and Implementation. Science of Computer Programming 98 (2015), 408 – 421. https://doi.org/10.1016/j.scico.2013.02.001 Special Issue on Advances in Dynamic Languages.

[7] L. Peter Deutsch and Allan M. Schiffman. 1984. Efficient Implementation of the Smalltalk-80 System. In Proceedings of the 11th ACM SIGACT-SIGPLAN Symposium on Principles of Programming Languages (Salt Lake City, Utah, USA) (POPL ’84). Association for Computing Machinery, New York, NY, USA, 297–302. https://doi.org/10.1145/800178.800542

[8] Maciej Fijalkowski, Armin Rigo, Rafał Galczyński, Ronan Lamy, Sebastian Pawluś, Ashwini Oruganti, and Edd Barrett. 2014. HippynVM: an implementation of the PHP language in RPython. Retrieved 2021-10-07 from http://hippyvm.barquesoftware.com

[9] Alex Gaynor, Tim Felgentreff, Charles Nutter, Evan Phoenix, Brian Ford, and PyPy development team. 2013. A high performance ruby written in RPython. Retrieved 2021-10-07 from http://docs.topazruby.com/en/latest/

[10] Google. 2016. Firing up the Ignition interpreter. Retrieved 2021-10-07 from https://v8.dev/blog/ignition-compiler

[11] Google. 2018. Liftoff: a new baseline compiler for WebAssembly in V8. https://v8.dev/blog/liftoff

[12] Urs Hölzle, Craig Chambers, and David Ungar. 1991. Optimizing dynamically-typed object-oriented languages with polymorphic in-line caches. In ECOOP’91 European Conference on Object-Oriented Programming, Pierre America (Ed.). Springer Berlin Heidelberg, Berlin, Heidelberg, 21–38.

[13] P. Joseph Hong. 1992. Threaded Code Designs for Forth Interpreters. SIGFORTH NewsL. 4, 2 (Oct. 1992), 11–16. https://doi.org/10.1145/146559.146561

[14] Ruochen Huang, Hidehiko Masuhara, and Tomoyuki Aotani. 2016. Improving Sequential Performance of Erlang Based on a Meta-tracing Just-In-Time Compiler. In International Symposium on Trends in Functional Programming. Springer, 44–58.

[15] Yusuke Izawa, Hidehiko Masuhara, Carl Friedrich Bolz-Tereick, and Yoyou Cong. 2021. Threaded Code Generation with a Meta-tracing JIT Compiler. (Sept. 2021). arXiv:2106.12496 submitted for publication.

[16] Thomas Kotzmann, Christian Wimmer, Hanspeter Mössenböck, Thomas Rodriguez, Kenneth Russell, and David Cox. 2008. Design of the Java HotSpot™ Client Compiler for Java 6. ACM Trans. Archit. Code Optim. 5, 1, Article 7 (May 2008), 32 pages. https://doi.org/10.1145/1369396.1370017

[17] Mozilla. 2019. SpiderMonkey: Mozilla’s JavaScript and WebAssembly Engine. Retrieved 2021-10-07 from https://spidermonkey.dev

[18] Mozilla. 2019. SpiderMonkey’s JavaScript Interpreter and Compiler. Retrieved 2021-09-27 from https://firefox-source-docs.mozilla.org/js

[19] Mozilla. 2020. Warp: Improved JS performance in Firefox 83. Retrieved 2021-10-07 from https://blogs.mozilla.org/2020/11/warp-improved-js-performance-in-firefox-83/

[20] Oracle Lab. 2013. A high performance implementation of the Ruby programming language. https://github.com/oracle/truffleruby

[21] Oracle Labs. 2018. Graal/Truffle-based implementation of Python. Retrieved 2021-10-07 from https://github.com/graalvm/graalpython

[22] Michael Paleczny, Christopher Vick, and Cliff Click. 2001. The Java HotSpot™ Server Compiler. In Proceedings of the 2001 Symposium on JavaTM Virtual Machine Research and Technology Symposium - Volume 1 (Monterey, California) (JVM ’01). USENIX Association, USA, 1.

[23] PyPy development team. 2009. PyPy Speed Center. Retrieved 2021-09-27 from https://speed.pypy.org

[24] Thomas Würthinger, Christian Wimmer, Christian Humer, Andreas Wöß, Lukas Stadler, Chris Seaton, Gilles Duboscq, Doug Simon, and Matthias Grimmer. 2017. Practical Partial Evaluation for High-performance Dynamic Language Runtimes. In Proceedings of the 38th ACM SIGPLAN Conference on Programming Language Design and Implementation (Barcelona, Spain) (PLDI ’17). ACM, New York, NY, USA, 662–676. https://doi.org/10.1145/3062341.3062381
A The Algorithm of Just-in-Time Trace-Stitching

Algorithm 1: DoTraceStitching(inputargs, ops)

input : red variables inputargs of the given trace
input : a list of operations ops taken from the given trace
/* Note that token_map and guard_failure_stack are global variables */
token_map ← CreateTokenMap(ops);
guard_failure_stack, trace, result ← [], [], [];
for op in ops do
    if op is guard and marked then
        guard_failure ← GetGuardFailure(op);
        append guard_failure to guard_failure_stack;
    else if op is call then
        if op is CallOp(emit_jump) then
            trace, guard_failure ← HandleEmitJump(op, inputargs);
            append (trace, guard_failure) to result;
            trace ← [];
        else if op is CallOp(emit_ret) then
            trace, guard_failure ← HandleEmitRet(op);
            append (trace, guard_failure) to result;
            trace ← [];
        else
            append op to trace;
    else if op is JumpOp then
        append op to trace;
        guard_failure ← PopGuardFailure();
        append (trace, guard_failure) to result;
        break;
    else if op is RetOp then
        append op to trace;
        guard_failure ← PopGuardFailure();
        append (trace, guard_failure) to result;
        break;
    else
        append op to trace;

return result;

Function PopGuardFailure():
if first pop? then
    return None;
else
    failure ← pop the element from guard_failure_stack;
    return failure;

Function HandleEmitJump(op, inputargs):
target ← GetProgramCounter(op);
token ← token_map[target];
guard_failure ← PopGuardFailure();
append JumpOpt(args, token) to trace;
return trace, guard_failure;

Function HandleEmitRet(op):
retval ← GetRetVal(op);
guard_failure ← PopGuardFailure();
append RetOp(retval) to trace;
return trace, guard_failure;

Figure 4. The visualization of the resulting traces from loopabit.tla compiled by baseline JIT compilation. Note that each trace was joined at one compile time.

B Results of the Preliminary Evaluation

Figure 5. The results of loop and loopabit. Execution times are normalized to the interpreter-only execution. Higher is better.
C Programs

C.1 The Definition of Traverse Stack

```python
class TraverseStack:
    _immutable_fields_ = ['pc', 'next']

    def __init__(self, pc, next):
        self.pc = pc
        self.next = next

    def t_pop(self):
        return self.pc, self.next

    @elidable
def t_is_empty(self):
        return self.is _T_EMPTY

_T_EMPTY = None
```

Figure 6. The results of callabit programs with simulated multi-tier JIT compilation. Every data is normalized to the interpreter-only execution. Higher is better.

Figure 7. The trace sizes and compilation times in callabit programs. The program is so small that the compilation time is at most 3% of the total.

Listing 2. The definition of traverse_stack.

Listing 3. Definitions of Loop.

Listing 4. Definition of loopabit.
# callabit.tla

- `callabit_baseline_interp` replaces XXX with `tla.CALL_NORMAL`, 16
- `callabit_baseline_tracing` and `callabit_tracing_only` replace XXX with `tla.CALL_JIT`, 16

```
main (n)
  tla.DUP,
  tla.CALL , 16 ,  # XXX
  tla.POP,
  tla.CONST_INT , 1 ,
  tla.SUB,
  tla.DUP,
  tla.CONST_INT , 1 ,
  tla.LT ,
  tla.JUMP_IF , 15 ,
  tla.JUMP , 0 ,
  tla.EXIT ,
```

```
sub_loop (n)
  tla.CONST_INT , 1 ,
  tla.SUB ,
  tla.DUP ,
  tla.CONST_INT , 1 ,
  tla.LT ,
  tla.JUMP_IF , 27 ,
  tla.JUMP , 16 ,
  tla.RET , 1
```

Listing 5. The definition of `callabit`.