Multi-Level Quickening: Ten Years Later

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This paper presents important performance improvements for interpreters, exemplified by speedups of up to 5.5× for CPython. Although the original version of this paper was rejected multiple times, the reported speedups have not been achieved by any other interpreter optimization technique since. In addition, the paper uses a sound evaluation methodology based on a corollary on Amdahl’s law to quantify the speedup potential of benchmarks, which also has not been used in any other paper since.

This paper documents my best efforts, and includes all of the reviews the paper received, plus some more commentary on my side on what has changed since and what purpose the archived document could serve.

Contents

Abstract 1  
Contents 1  
1 Preliminary Remarks 2  
1.1 History 2  
1.2 Other Versions 2  
1.3 Related Work 2  
2 Original Paper 3  
3 Reviews 19  
3.1 PLDI’13 19  
3.2 PLDI’14 24  
3.3 TACO’14 28  
4 Reviewer Feedback 42  
4.1 Incorrect Paper Citation 42  
4.2 Indirect Branch Prediction Analysis 42  
4.3 Missing Data on Implementation Efficiency 43  
5 Conclusions 45  
5.1 Contributions 45  
5.2 Personal Conclusions 47

Outline. Section 2 contains the original paper, submitted to the ACM Transactions on Architecture and Code Optimizations, TACO, in 2014. The prior versions submitted to PLDI’13 (i.e., in November 2012) and PLDI’14 (i.e., in November 2013) were similar in content, but contained fewer material. These versions are available from the author upon request.

Section 3 contains all reviews received from PLDI 2013, PLDI 2014, and TACO 2014 in their entirety, with only some markup added to reflect the structure of the reviewing system.

Section 5 contains some comments regarding specific review information.
1 PRELIMINARY REMARKS

1.1 History
The research documented by this paper was carried out in 2011, after relocating from Vienna, Austria, to Irvine, CA, USA in March of 2011. The gist of the technique, was already mentioned on the last page of my PhD thesis, which postulates the interesting nature of combining two separate techniques of my thesis, namely the use of inline caching through quickening—i.e., the rewriting of interpreter instructions at run-time—with simple static analysis that was implemented to eliminate redundant reference count operations (DLS’12).

As a result of the substantial speedups, the author gave a series of talks about this research in the following universities:

- October 8th, 2012; Johannes Kepler Universität Linz, Institut für System Software, Prof. Dr. Mössenböck. http://informatik.jku.at/kolloquium/listTalk.jsp?talkId=284
- October 11th, 2012; TU Wien, Institut für Computersprachen, Prof. Dr. Knoop. http://www.complang.tuwien.ac.at/talks/Brunthaler2012-10-11
- October 11th, 2012; Institute of Science and Technology, Austria, Prof. Dr. Henzinger.

These talks coincided with the first submission to the ACM conference on programming languages and implementation (PLDI) 2012.

On April 3rd, 2013, the author was invited to give a talk at Mozilla Research, which was also recorded, broadcast online, and subsequently made available through the Mozilla Research website. Though the video is not available anymore, the following URL contains the announcement: https://bugzilla.mozilla.org/show_bug.cgi?id=857381.

1.2 Other Versions
At PLDI 2013 in Seattle, in personal conversation Zach Tatlock suggested to formalize the relevant parts and submit to POPL. After initially doubts, the author began work on formalizing the technique, which led to subsequent submissions to POPL’14, POPL’15, ECOOP’17, and finally to CPP’21, where the paper was finally accepted.

1.3 Related Work
In February of 2014, a competing system, ORBIT, was presented at CGO’14. The author was not aware about this system, but was kindly notified by Christian Wimmer, who attended the conference. Since there was a surprising amount of overlap between my original paper and the ORBIT paper, the author decided to resubmit quickly to the TACO journal, to establish the independent nature of these discoveries. This latter step seemed to be particularly pertinent, since a subsequent submission to either PLDI or CGO was impossible with such closely related work.

Many of the ideas presented in this paper resemble parts of the Truffle/Graal ecosystem, but predate the Truffle work by about a year. An important difference is that multi-level quickening does not require a just-in-time compiler, and sidesteps the whole problem of dynamic code-generation altogether.
2 ORIGINAL PAPER

The original paper starts on the following page, no. 4. The following changes have been made:

- changed from SIGPLAN to acmart Latex template,
- removed ACM copyright information;
- removed ACM subject classification information.
Multi-level Quickening: The Key to Interpreter Performance

Stefan Brunthaler

ABSTRACT

Interpreters have a bad reputation for having lower performance than just-in-time compilers. We present a new way of building high performance interpreters that is particularly effective for executing dynamically typed languages. The idea is that an interpreter incrementally and iteratively removes overhead by repeatedly replacing instructions with increasingly more specialized ones.

While the technique is general in nature and applies to all interpreters, our concrete implementation optimizes the Python 3 interpreter. In our optimized interpreter, we first gather type feedback by replacing dynamically typed Python instructions with type-specialized instructions. Then, we use an abstract interpreter to propagate the captured type information across sequences of instructions. Next, we replace all instructions belonging to an identified sequence with yet more specialized instructions all of which operate on the same type. This last step allows us to safely and directly operate on unboxed, native machine data types instead of Python objects or tagged values. The optimization is speculative, and capitalizes on type locality. Whenever our speculation fails, we take the opposite path and subsequently replace specialized instructions with their more general counterparts.

We generate the optimized instructions before compiling the interpreter using a simple code generator, i.e., we speculate on the interpreter being able to make use of our staged, optimized instructions. As a result of using a standard ahead-of-time compiler, we leverage this compiler’s back-end for portability and avoid dynamic code generation altogether.

Our technique unites high performance—our system is up to more than five times faster than the standard Python interpreter—with the simplicity and portability interpreters are commonly known and appreciated for.

KEYWORDS

Interpreter, Optimization, Inline Caching, Type Feedback, Type Specialization, Quickening, Python

1 MOTIVATION

The problem with interpreters for dynamically-typed programming languages is that they are slow. The fundamental lack of performance is due to the following reasons. First, their implementation usually is simple and does not perform known interpreter optimizations, such as threaded code [5, 6, 16] or superinstructions [19, 20, 38]. Second, even if the interpreters apply these known techniques, their performance potential is severely constrained by expensive interpreter instruction implementations [9].

Unfortunately, performance-conscious implementers have only a limited set of options at their disposal to solve this problem. For peak performance, the current best-practice is to leverage results from dynamic compilation. But, implementing a just-in-time, or JIT, compiler is riddled with many problems, e.g., a lot of tricky details, difficult to debug, and substantial implementation effort. Furthermore, dynamic compilation has other costs, too. For example, just-in-time compilers require writable and executable pages, which makes them attractive targets for mounting attacks [7]. Another downside of just-in-time compilers is that inline caching [17, 28] requires instruction cache flushes that can be expensive on some architectures, such as ARM. Finally, some environments, such as Apple’s iOS, simply do not allow dynamic code generation.

An alternative route is to explore the area of purely interpretative optimizations instead. These are optimizations that preserve innate interpreter characteristics, such as ease-of-implementation and portability, while offering important speedups. Prior work in this area already reports the potential of doubling the execution performance [10, 11]. As a result, investigating a general and principled strategy for optimizing such interpreters is particularly warranted.

Interpreting a dynamically-typed programming language, such as JavaScript, Python, or Ruby, has its own challenges. Frequently, these interpreters use one or a combination of the following features:

- dynamic typing to select type-specific operations,
- reference counting for memory management, and
- modifying boxed data object representations.

To cope with these features, interpreter instructions naturally become expensive in terms of assembly instructions required to implement their semantics. Looking at successful research in just-in-time compilation, we know that to achieve substantial performance improvements, we need to reduce the complexity of the interpreter instructions’ implementation. Put differently, we need to remove the overhead introduced by dynamic typing, reference counting, and operating on boxed data objects.

Our method successfully addresses all of those challenges and as a result—three decades after Deutsch and Schiffman [17] described the ideas of what would eventually become the major field of just-in-time compilation—presents itself as an attractive alternative to the expensive implementation of a JIT compiler. Summing up, this article makes the following contributions:

- We introduce multi-level quickening interpretation (MLQ, for short), which delivers advanced run-time type specialization previously reserved for just-in-time compilers, but is purely interpretative, i.e., is easy to implement, portable, is compatible with existing libraries, and requires no dynamic code generation (see Section 3).
- We illustrate the implementation of MLQ interpretation using Python 3 as an example, but without loss of generality (see Section 4). In particular, our interpreter supports:
  - tagless native-machine data-type manipulation for integer, double and complex numbers, as well as reads and writes to lists and dictionaries, and indexed reads from Unicode strings (see Section 4.3),
  - caching of unboxed, tagless integer and floating point constants (see Section 4.5), and
  - use of static superinstructions for instruction sequence operating on the same native-machine data type (see Section 4.6).
2 EXAMPLE

In this section we walk through a simple example that illustrates how interpreters address—or rather fail to address—the challenge of efficiently executing a high-level language. The following listing shows a Python function \texttt{sum} that “adds” its parameters and returns the result of this operation:

\begin{verbatim}
def sum(a, b):
    return a + b
\end{verbatim}

In fact, this code does not merely “add” its parameters: depending on the actual types of the parameters \(a\) and \(b\), the interpreter will select a matching operation. In Python, this means that it will either concatenate lists, strings, or tuples, or perform arithmetic addition on either integers, floating point numbers, or complex numbers; or the interpreter could even invoke some custom Python code—which is possible due to Python’s support for ad-hoc polymorphism.

In 1984, Deutsch and Schiffman report that there exists a “dynamic locality of type usage,” which enables speculative optimization of code for any arbitrary but fixed and observed type \(\tau\) [17]. Subsequent research into dynamic compilation capitalizes on this observed locality by speculatively optimizing code using type feedback [27, 29]. From their very beginning, these dynamic compilers—or just-in-time compilers as they are commonly referred to—had to operate within a superimposed latency time constraint. Put differently, dynamic compilers traditionally sacrifice known, complex optimizations for predictable compilation times.

**Interpreter Performance Obstacles.** Python’s compiler emits the following sequence of interpreter instructions, often called bytecodes, when compiling the \texttt{sum} function (ignoring operand bytes for the \texttt{LOAD\_FAST} instructions):

\[
\begin{array}{cccc}
\text{LOAD\_FAST} & \text{LOAD\_FAST} & \text{BINARY\_ADD} & \text{RETURN\_VALUE} \\
\end{array}
\]

We see that the interpreter emits untyped, polymorphic instructions that rely on dynamic typing to actually select the matching operation. Furthermore, we see that Python’s virtual machine interpreter implements a stack architecture.

Let us consider a concrete call, such as \texttt{sum(3, 4)}, i.e., where \texttt{sum} is called with integer arguments and returns an integer result. In this case, the \texttt{BINARY\_ADD} instruction will first check operand types and then select integer addition for execution. More precisely, assuming absence of ad-hoc polymorphism, the Python interpreter will identify that both integer operands are represented by a \texttt{C} \texttt{struct} called \texttt{PyLongObject}. Next, the interpreter will determine that the operation to invoke is \(a\rightarrow o\_b\_type\rightarrow o\_p\_as\_number\rightarrow o\_n\_add\), which points to the \texttt{long\_add} function. This operation implementation function will then unbox operand data, perform the actual integer arithmetic addition, and box the result. In addition, necessary reference counting operations enclose the implementation, i.e., we need to decrease the reference count of the arguments, and increase the reference count of the result. Both, (un-)boxing and adjusting reference count operations add to the execution overhead of the interpreter.

Contrary to the interpreter, a JIT compiler might emit native machine code along the following lines:

\begin{verbatim}
move $rax, -8(%rsp)
movl $16(%rbp), %edx
addl $rax, %rbx
ret
\end{verbatim}

The first two lines assume a certain stack layout that identifies the location for operands \(a\) and \(b\), both of which we assume to be unboxed. Hence, we can use the native machine addition operation (line 3) to perform arithmetic addition and return the operation result in %rax.

Bridging the gap between the high abstraction-level representation of computation in Python bytecodes and the low abstraction-level representation of native machine assembly instructions holds the key to improve interpreter performance. To that end, we classify both separate instruction sets accordingly:

- Python’s instruction set is untyped and operates exclusively on boxed objects.
- Native-machine assembly instructions are typed and directly modify native machine data.

An efficient, low-level interpreter instruction set allows us to capture the \texttt{sum} function’s computation for our concrete call with integer types in the following way:

\[
\begin{array}{cccc}
\text{LOAD\_INT} & \text{LOAD\_INT} & \text{INT\_ADD} & \text{RETURN\_INT} \\
\end{array}
\]

In this low-level instruction set the instructions are typed, which allows using a different operand data passing convention, and directly modifying unboxed data—essentially operating at the same semantic level as the assembly instructions shown above; modulo the differences in machine architectures, i.e., register vs. stack.

3 OVERVIEW OF MULTI-LEVEL QUICKENING

Bridging the gap between the high and low level instructions requires two steps:

i) **Staging step:** stage and compile new interpreter instructions at interpreter compile-time;

ii) **Arranging step:** arrange optimized instruction sequences at run-time by the interpreter.
Multi-level Quickening: The Key to Interpreter Performance

Stefan Brunthaler

Figure 2: Arranging step of multi-level quickening compared to the standard Python interpreter.

Figure 1 illustrates the staging step. The top half—using horizontal arrows—shows the original interpreter compile-time setup of Python, consisting of the C files of the CPython implementation and then using a C compiler to generate the Python interpreter binary. Our system uses its own code generator written in Python that generates C code for optimized interpreters. In consequence, this process exercises the compiler’s backend resulting in portable code generation and furthermore allows the interpreter implementation to remain simple. The whole process is, however, speculative: only by actually interpreting a program, we know for sure which optimized interpreter instructions are required. As a result, we restrict ourselves to generate optimized code only for instructions that have a high likelihood of being used.

Figure 2 illustrates the second step: the arranging of optimized instructions. The left half of Figure 2 shows the standard Python executable that uses a small compiler to emit a sequence of bytecodes for a Python source code program. This sequence of bytecodes will then be processed by an interpreter \( I \), identified by the self-loop on the right hand side of the interpreter box \( I \).

The right half of Figure 2 explains the arranging that leads to optimized execution in MLQ. Replacing interpreter instructions at run-time is known as quickening in the literature [35]. Quickening means that we replace instructions with optimized derivatives of the exact same instruction at run-time. Prior work exclusively uses only one level of quickening, i.e., replacing one instruction with another one. Figure 2 presents this as the quickening step \( q_1: I \rightarrow I' \). In this article, however, we introduce multi-level quickening, i.e., the process of continuously replacing interpreter instructions with ever more specialized derivatives of the generic instruction. Figure 2 describes this as the subsequent quickening step \( q_2: I' \rightarrow I'' \). It is worth noting that the MLQ system does not change the implementation of the original Python compiler and interpreter components. Furthermore, the type speculation requires that we take corrective action when our assumptions about a given, expected type fail. Figure 2 shows these generalization steps as successive quickening functions \( q_i \), which replace optimized instructions with their “parent” instructions.

4 MLQ IMPLEMENTED

This section presents implementation details on the multiple levels of quickening and the interaction between them. Furthermore, we will give an account of how we specialize instructions of each level, such that the quickening eventually improves performance.

First, we collect type feedback by replacing dynamically-typed Python instructions with type-specialized instructions. This is identical to inline caching, which is why those instructions share the common prefix INCA. Then, we use an abstract interpreter to propagate the captured type information across sequences of instructions. Next, we replace all instructions belonging to an identified sequence with yet more specialized instructions all of which operate on the same type. This last step allows us to safely and directly operate on unboxed, native machine data types instead of Python objects or tagged values. Instructions operating on native machine data share the common prefix NAMA We refer to the set of all INCA instructions as INCA, and to the set of all NAMA instructions as NAMA.

4.1 First-level Quickening: Type Feedback

This section describes how our implementation collects type feedback. We follow our own previous approach to collect type feedback via inline caching with quickening [10, 11]. Contrary to the known type feedback optimization in just-in-time compilers (cf. [2, 29]), this technique sidesteps dynamic code generation and uses quickening based on types observed at run-time. This has two important implications. First, our interpreter needs type-specialized instruction derivatives for each type-generic instruction of the original Python interpreter. Second, capturing the type information in a purely interpretative way avoids instruction cache flushes of traditional inline caching, which can be expensive on some architectures, such as ARM. Furthermore, just-in-time compilers need pages that are both writable and executable; this is a security liability, as it prevents existing page protections, such as W@X or NX bits.

This first-level quickening proceeds as follows. Recall our example sum function and the sequence of instructions emitted by Python’s compiler:

\[
\begin{align*}
\text{LOAD} & \quad \text{LOAD} & \quad \text{BINARY ADD} & \quad \text{RETURN} \\
\text{FAST} & \quad \text{FAST} & \quad \text{ADD} & \quad \text{VALUE}
\end{align*}
\]

After observing that both operands in our example call `sum(3, 4)` are integers, inline caching with quickening will have replaced the BINARY_ADD instruction with an INCA_LONG_ADD instruction:

\[
\begin{align*}
\text{LOAD} & \quad \text{LOAD} & \quad \text{INCA} & \quad \text{RETURN} \\
\text{FAST} & \quad \text{FAST} & \quad \text{LONG ADD} & \quad \text{VALUE}
\end{align*}
\]

Summing up the first-level quickening step replaces instructions from the original Python instruction set with type-specialized
instructions from the INCA instruction set. Therefore, the quickening function is defined as $q_1 : \text{PyObject} \times T \rightarrow \text{INCA}$, where $T$ is the set of types eligible for optimization. For example, in the previous example, evaluating the first-level quickening function identifies the optimized instruction we want to replace with: $q_1(\text{INCA\_ADD}, \text{PyLong\_Type}) = \text{INCA\_LONG\_ADD}$. Figure 3 shows multiple $q_1$ quickening examples for a concrete sequence of interpreter instructions.

### 4.2 Second-level Quickening: Type Propagation

The previous section describes how to collect type information in an interpreter using quickening based inline caching. The existing type information, however, only applies to specific operations. For example, while the INCA\_LONG\_ADD instruction expects its operands to be of type PyLong\_Type, it does not identify which instructions push the corresponding operands on the stack. Frequently, preceding load instructions will push operands onto the operand stack. However, operands often are results of preceding operations, too. Consequently, we need to analyze the data-flow of the interpreter to identify in general which instructions put objects onto and pop objects off the operand stack, respectively.

**Abstract Interpretation.** Taking inspiration from Leroy’s description of Java bytecode verification [34], we use an abstract interpreter that operates over types instead of values. Using the type information captured in the first-level quickening step, we can propagate type information from operation instructions to both: (i) preceding instructions that computed its operands, and (ii) as well as to succeeding instructions that use their computed result (see dotted and solid lines in the second step in Figure 3).

Our abstract interpreter uses a transition relation $i : S \rightarrow S'$ to model the operand stack effect of an instruction $i$. We represent all instructions as such equations describing this transition relation. For example, the original Python interpreter instructions are dynamically typed, i.e., all Python objects on the operand stack have the most generic type, represented by PyObject, a C record data structure. Therefore, we encode all dynamically-typed operation instructions using the following two equations:

$$
\begin{align*}
\sigma_1 &: \text{PyObject} \times \text{PyObject} \rightarrow \text{PyObject} \\
\sigma_2 &: \text{PyObject} \rightarrow \text{PyObject}
\end{align*}
$$

We see that the only difference between these equations is their arity: while the first equation—the unary equation—only expects one reference to a PyObject object on the top of the operand stack, the second equation—the binary equation—expects two such references. Both equations only have one result, which is modeled by having one PyObject reference on the stack. We use the .operator to denote concatenation of operand stack elements.

Propagating type information requires that we make use of the type information collected by the previous step, i.e., the first-level quickening step. To that end, we add type-dependent equations to our abstract interpreter. For example, we know that the INCA\_LONG\_ADD instruction expects its operands to be integers and computes an integer result:

$$
+_L : (\mathbb{L} \cdot \mathbb{L} \cdot S) \rightarrow (\mathbb{L} \cdot S)
$$

Where $\mathbb{L}$ corresponds to PyLongObject, i.e., objects of type PyLong\_Type, which have a more specific type than the generic PyObject.

The set of types our abstract interpreter operates on corresponds to the set of types we generated instruction derivatives for in the first-level quickening step, i.e., integers, floating point, and complex numbers, as well as lists and dictionaries. For simplicity, our abstract interpreter ignores branches in the code, effectively restricting our propagation step to basic blocks, but on the other hand requiring only a linear pass to complete. This is important insofar as we perform this abstract interpretation at run-time and therefore favor efficient, low-complexity procedures over potentially long running transformations.

**Illustrated Type Propagation Example.** The following example shows the program bytecode representation as emitted by Python’s compiler for some function $f$:

```
| LOAD_FAST | LOAD_FAST | BINARY_ADD | LOAD_FAST | BINARY_ADD | RETURN_VALUE |
|-----------|-----------|------------|-----------|------------|--------------|
```

After executing this example program, the first-level quickening captures types encountered during execution:
Multi-level Quickening: The Key to Interpreter Performance

Start Instructions $S$ | End Instructions $E$
---|---
LOAD_CONST | POP_JUMP_IF_FALSE, POP_JUMP_IF_TRUE
LOAD_FAST | RETURN_VALUE, YIELD_VALUE

Table 1: Valid start and end instructions used for abstract interpretation.

Now, we propagate the type information by abstract interpretation. Since INCA_LONG_ADD expects integer operands, we can infer that the first two LOAD_FAST instructions must push integer operands onto the operand stack. Analogously, the second occurrence of INCA_LONG_ADD allows us to infer that the first INCA_LONG_ADD computes an integer result, as does the third occurrence of the LOAD_FAST instruction. Finally, by inspecting the type stack when the abstract interpreter reaches the RETURN_VALUE instruction, we know that it must pop an integer operand off the stack. Therefore, after type propagation our abstract interpreter will have identified that the complete sequence of instructions actually operates exclusively on integers:

$$
\begin{array}{c|c}
\text{LOAD_FAST} & \text{LOAD_FAST} \\
\text{LOAD_FAST} & \text{INCA_LONG_ADD} \\
\text{LOAD_FAST} & \text{LOAD_FAST} \\
\text{INCA_LONG_ADD} & \text{INCA_LONG_ADD} \\
\text{INCA_LONG_ADD} & \text{RETURN_VALUE} \\
\end{array}
$$

Where $L$ denotes Python’s integer representation, PyObject, and $S$ and $E$ denote the start and end instructions of a candidate sequence, respectively. The goal of our abstract interpreter is to identify sequences where it is safe to use native-machine data-types instead of Python objects. We define such a sequence conservatively to start with any of the load instructions in the left column of Table 1, and end with any of the store instructions in the right column of Table 1. It is worth noting that our abstract interpreter allows optimization of attributes, or properties as they are frequently called, via LOAD_ATOM and STORE_ATOM, as well as optimized reading and writing into data structures for lists and dictionaries plus optimized indexed reading of Unicode strings.

Between a start and an end instruction, any sequence of instructions that has no side-effects, i.e., all computations in such a sequence that only exchange temporary data on the operand stack, can be optimized. In particular, this also allows calling other functions in an eligible sequence, as a function call cannot have a side effect on the temporary values stored on the operand stack.

In Figure 3, we see how the abstract interpreter identifies the complete sequence of instructions operating on floating point numbers, denoted by $F$ as a shorthand for PyFloat_Type. We see that our second-level quickening function $q_2$ replaces instructions from both, the original Python instruction set and the optimized INCA instruction set. Therefore, we define $q_2$ as follows: $(\text{Python}\cup \text{INCA}) \times F \rightarrow \text{NAMA}$. Examples from Figure 3 include:

$$
\begin{align*}
q_2(\text{LOAD_FAST}, \text{PyFloat_Type}) &= \text{NAMA_FLOAT_LOAD_FAST} \\
q_2(\text{INCA_FLOAT_MULT}, \text{PyFloat_Type}) &= \text{NAMA_FLOAT_MULT}
\end{align*}
$$

4.3 Optimized Instruction Derivatives

Optimized instruction derivatives operate on unboxed native-machine data. To that end, we need to define two things: (i) the boxing and unboxing functions, as well as (ii) a uniform operand stack access convention. The former relies on functions provided by the Python implementation when available, and on accessing data structure internals when not. The latter task defines how to represent all data—such as integers and floating point numbers—such that all instructions operating on the same type follow the same convention.

Figure 4 illustrates these steps. Instructions A and B push native-machine data onto the operand stack, therefore, these instructions must unbox data from a Python object. Furthermore, we see that instruction C needs to know about the native-machine data-type representation to “make sense” of the bits it pops off the operand stack. Put differently, the instruction must know what the shaded square represents to operate on the data.

4.3.1 Mapping Integer Numbers. Let’s discuss the trivial case of mapping integers from PyLong_Type to a native-machine integer. The following listing shows how to unbox a Python unbounded range integer object:

```python
if \text{PyLong}_{\text{AS_LONG}}(r):
    \text{PUSH}(\text{uint64}_t) \text{PyLong}_{\text{AS_LONG}}(r);
else:
    \text{deopt Section 4.7} /\\;
\text{NEXT_INSTR();}
```

In this case, the mapping function consists of the if statement on line 3 and 4. After guarding the expected type (denoted by the stylized $\exists$), we use a type-dependent unboxing function (cf. $\text{PyLong}_{\text{AS_LONG}}$ on line 4) to get a native-machine data-type representation, which we just push onto the operand stack. It is worth noting that we do not require tagging of the data.

Every interpreter instruction operating on native-machine integers, must know that it needs to cast these data from an unsigned integer (uint64_t) to its signed representation (int64_t).

4.3.2 Mapping Floating Point Numbers. The previous section details how we can use just a cast to operate on native-machine integers. In general, however, this is not always possible, as is the case for using floating point numbers. If we cast a floating point number to an unsigned integer, the compiler will generate conversion code and we would therefore lose information about the floating point value:

```python
double d = 3.1;
x = (uint64_t) d; // conversion to integer
```
To circumvent this, we use C’s `union` construct, which allows us to attach different semantics to the same bits. For mapping floating point data to and from native-machine data-types, we define the following union:

```c
typedef union {
    uint64_t word;
    double dbl;
} map_t;
```

A complete example for loading a native-machine floating point number onto the Python operand stack looks like this:

```c
case NAMA_FLOAT_LOAD_FAST_FLOAT:
    PyObject *x = fastlocals[oparg];
    map_t r, i;
    r.dbl = ((PyComplexObject *)x)->cval.real;
    i.dbl = ((PyComplexObject *)x)->cval.imag;
    /* deopt Section 4.7 */
    PUSH(r.word);
    PUSH(i.word);
    NEXT_INSTR();
```

We implement an arithmetic operation working on native-machine floating point numbers instead of Python objects like this:

```c
case NAMA_FLOAT_ADD:
    PyObject *x, *y;
    map_t a, b;
    x = POP();
    y = POP();
    a.word = x;
    b.word = y;
    a.dbl1 = b.dbl1;
    PUSH(a.word);
    NEXT_INSTR();
```

Note that on line 7 the compiler emits a fast native-machine assembly operation to add the two floating point numbers, instead of the high-level dynamically-typed `BINARY_ADD` operation, or even the typed `INCA_FLOAT_ADD` operation, which still needs to unbox the data, box the result, and perform reference count operations. Since the operands are already in tagless native-machine data representation, our implementation avoids the necessary bit-fiddling and shifting of data plus the branching on types identified by the corresponding tags.

### 4.3.3 Mapping Complex Numbers

In contrast to many other programming languages, Python offers more standard data types. Besides integer and floating point numbers, Python also supports complex numbers. Unfortunately, our operand stack only allows using one word per data. Since complex numbers have a real and an imaginary part, we cannot put them into one word.

A straightforward way to deal with complex numbers is to just double the operand stack size and push the real and imaginary parts of a complex number onto the stack, and always pop both parts off the operand stack again. The higher abstraction-level instructions never notice this and therefore cannot interfere. The optimized NAMA instructions, however, need to follow the exact same convention for pushing onto, and popping off the stack.

An alternative, much more general technique is to reserve some scratch space in the global memory to operate on native-machine data. In such a scratch space, we can arbitrarily unbox Python data (such as tuples, lists, etc.) and operate on them using native-machine instructions.

Our implementation follows the first approach and doubles the operand stack size during compilation from Python source to bytecode. Note that this has no performance implications as Python stack frames are heap allocated and the operand stack is only a small part of the stack frame object. For example, unboxing a complex number that uses this operand stack access convention looks like this:

```c
case NAMA_COMPLEX_LOAD_FAST:
    PyObject *x = fastlocals[oparg];
    if (!Py(X, PyComplex_Type))
        /* deopt Section 4.7 */
    else
        map_t r, i;
        r.dbl = ((PyComplexObject *)x)->cval.real;
        i.dbl = ((PyComplexObject *)x)->cval.imag;
    PUSH(r.word);
    PUSH(i.word);
    NEXT_INSTR();
```

On lines 8 and 9, we see that this NAMA instruction needs to know about internals of the Python complex object implementation, so that we can access the real and imag fields of the `cval` record data structure. Subsequently, we see on lines 11 and 12 that we first push the real part onto the stack and then the imaginary part. The corresponding consuming instruction must adhere to this convention.

### 4.4 Optimizing Non-Scalar Data-Types

The previous examples provide details on how to map scalar data-types to native-machine data-types. This suffices for optimizing operations operating on scalar variables, but is in general insufficient for optimizing many programs that rely on non-scalar data types. In Python, these are the following data types: lists, dictionaries, sets, and tuples. To read from any of these data structures, Python emits a `BINARY_SUBSCR` instruction. For writing into any of these data-structures, Python emits a `STORE_SUBSCR` instruction. Both of these instructions are dynamically typed and provide a generic interface to reading/writing that closely resembles the corresponding syntax.

For example, the statement `x[2]` where `x` is a local variable bound to any of the non-scalar data structures mentioned above, translates to the following sequence of bytecodes:

```c
LOAD_FAST LOAD_CONST BINARY_SUBSCR
```

Similarly, the statement `x[0] = a` where `x` is a local variable bound to any of the mentioned non-scalar data structures and `a` is a bound local variable translates to:

```c
LOAD_FAST LOAD_CONST STORE_SUBSCR
```

#### 4.4.1 Optimizing Reads and Writes to Lists

Mapping a Python list to a C array does not require any copying since a Python list internally uses an ordinary C array, too. The first `LOAD_FAST` instruction in the `BINARY_SUBSCR` example pushes a reference to the list object onto the stack, whereas the `LOAD_CONST` instruction pushes the index (in our example the constant integer 2) onto the operand stack.
We already know how to unbox integer objects (see Section 4.3.1) and reuse the load instructions to deal with the indexes.

In consequence, we can focus on unboxing Python’s list objects, which works as follows:

```
case NAMA_LIST_LOAD_FAST:
  PyObject *xx = fastlocals[oparg];
  if (!\fep, PyList_Type))
    /* deopt Section 4.7 */
  PyObject *xx = ((PyListObject *)xx)->ob_item;
  cur_list_size = PyList_GET_SIZE(xx);
  NEXT_INSTR();
```

We see that the member ob_item of a PyListObject points to an array of Python objects. In addition to bounds checking, Python’s list access semantics allows programmers to specify negative indexes, causing Python to return the list’s element at the index calculated backwards from the end. For this reason, we need to temporarily store the list size, see line 9. We store the list size in a local variable (cur_list_size) because this allows us to optimize many situations of reading from a list. For example, Python sometimes emits a rotation or duplication instruction that modifies the operand stack. In those cases, keeping the list size in a local variable instead of on the operand stack simplifies the implementation considerably.

With these load instructions preparing the operand stack accordingly, we can implement the optimized read instruction like this:

```
case NAMA_FLOAT_LIST_SUBSCR_FLOAT:
  PyObject *xx = POP();
  PyObject *xx = POP();
  void **r = (void **)w; /* := C array */
  int64_t t = (int64_t)v; /* := index */
  if (t < -cur_list_size || cur_list_size < t)
    /* deopt Section 4.7 */
  if (t < 0) t+= cur_list_size;
  map_t f;
  if ((x, PyFloat_Type))
    f.dbi = PyFloat_AS_DOUBLE(x);
  else /* deopt Section 4.7 */
    PUSH(f.word);
    NEXT_INSTR();
```

Lines 5 and 6 show the assignments of the corresponding stack slots to local variables. Line 8 performs the bounds check, line 10 implements the backwards indexing, and finally, line 12 shows how we can now use an efficient C array access to read from the array. Lines 14-16 show the type check and unboxing instructions, followed by line 18 that pushes the uint64_t representation of the floating point number onto the operand stack.

Writing into the array requires modification of the reference count of the object stored in the array before actually updating the element:

```
case NAMA_FLOAT_LIST_STORE:
  PyObject *xx = POP();
  PyObject *xx = POP();
  PyObject *xx = POP();
  if (!\fep, PyDict_Type))
    /* deopt Section 4.7 */
  if (s < 0) s+= cur_list_size;
  map_t t = ( .word = (uint64_t) u );
  x= PyFloat_FromDouble(t.dbi);
  Py_DECREF((PyObject *)r[s]);
  if ((x, PyObject *))r[s]= (PyObject *)x;
  NEXT_INSTR();
```

4.4.2 Optimizing Reads and Writes to Dictionaries. In Python hash tables are called dictionaries and are used frequently. Unfortunately, we cannot directly store addresses of hash table entries for optimization purposes, as it is highly volatile—hash tables could be reclaimed or re-sized during operation or have different addresses between different invocations of code accessing them. But, looking up entries inside a hash table has a different type of locality: with a high likelihood, the first look-up hits. Therefore, we can speculate on that by inlining the fast-path to accessing this element and falling back to the slow path when our speculation fails. As is always the case for operating on unboxed data-types, we need a custom load instruction to push the first slot of the hash table onto the operand stack:

```
case NAMA_DICT_LOAD_FAST_DICT:
  x = GETLOCAL(oparg);
  if (!\fep, PyDict_Type))
    /* deopt Section 4.7 */
  PyDictObject *xx = (PyDictObject *)x;
  dict_ref = d;
  Py_INCREF(d);
  PyDictKeyEntry *ep0 = DICT_GET_FIRST_SLOT(d);
  PUSH(ep0);
  NEXT_INSTR();
```

Whenever our speculation on the first table entry fails, we need to be able to access the hash table object again, which is why we keep a reference to the object in dict_ref. The reason for using a local variable in this case are identical to the ones for the cur_list_size above.

Now, we can implement an optimized instruction that predicates on the high hit ratio of the hash table:

```
case NAMA_FLOAT_DICT_SUBSCR_FLOAT:
  w= POP();
  v= POP();
  PyDictKeyEntry *ep0= (PyDictKeyEntry *)v;
  size_t mask= DICT_GET_MASK(dict_ref);
  Py_hash_t hash= DICT_GET_HASH(w);
  size_t i= (size_t) hash & mask;
  PyDictKeyEntry *ep= &ep0[i];
  if (ep && ep->me_key == w) /* hit */
    x= ep->me_value;
  else /* miss */
    x= PyDict_GetItem(dict_ref, w);
  NEXT_INSTR();
```
4.5 Reducing Unboxing Overhead

Python's interpreter implements a stack-based architecture, where all operands need to be pushed onto the operand stack before an operation can be executed. Therefore, load instructions belong to the topmost frequently executed instructions in stack-based interpreters [40], and as a result need to be as efficient as possible. Unfortunately, the pairing with the unboxing makes load instructions less efficient, as they now contain at least a branch implementing a type check as well as the unboxing step.

Often, however, both of these steps, i.e., the type checking and the unboxing, are redundant. This is due to the nature of load instructions: they refer to the same object until a store instruction updates them. As a result, we introduce a separate cache to store unboxed local variables and constants, which reduce load instructions to a minimum amount of assembly instructions that do not even require conditional branches anymore:

```c
    case NAMA_FLOAT_LOAD_CONST_FLOAT_SLOT_0:
        PUSH( unboxed_consts[ 0 ] );
        NEXT_INSTR();

    case NAMA_FLOAT_LOAD_FAST_FLOAT_SLOT_0:
        PUSH( unboxed_locals[ 0 ] );
        NEXT_INSTR();
```

To maintain soundness, we need to ensure the following:

- the corresponding STORE_FAST instructions verify type assumptions and update the unboxed cache elements;
- the interpreter initializes the unboxed cache before execution starts;
- the interpreter updates the actual local variables before execution of a function terminates.

We instrumented our Python-based code generator and conducted all experiments of Section 5 with the following unbox cache sizes: 0, 2, 4, 6, 8, 10. While the choice of optimal cache size depends on the number of local variables and constants used in frequently executed code, we found that a cache size of four slots for local variables and four slots for constants gives the best performance for almost all benchmarks. When interpreting a function that has more than four local variables or constants, it makes sense to optimize the most frequently used variables, for example, by computing a score for each variable/constant identifier [10]. Currently, our MLQ implementation does not perform such a computation, but we could add this to our abstract interpreter and simply swap slots such that more frequently used variables benefit from the unbox cache. It is likely that computing the optimal assignment of variables to unboxed slots allows us to use fewer slots to achieve the same performance.

4.6 Superinstructions

There is a well-known optimization called superinstructions [20, 37, 38] that concatenates frequently occurring sequences of interpreter instructions to minimize instruction dispatch overhead. For standard Python, however, instruction dispatch overhead is not a performance bottleneck [9].

But, our NAMA instructions successfully reduce instruction implementation complexity such that optimizations targeting instruction dispatch become more effective again. In addition, all NAMA instructions are effectively partitioned into separate groups that expect identical native machine data. Consequently, the sequences of instructions identified by our type propagation step are ideal candidates for superinstructions. Furthermore, multiple sequences of NAMA instructions occur with a high frequency; e.g., the sequence to compare Python objects based on their address occurs 85 times in all of our benchmarks.

Since we are already using a code generator that produces the C implementation for all interpreter instructions, we added a small module (134 lines of Python code) that generates static superinstructions (see Figure 1). To record the instruction sequences that our abstract interpreter identifies, we first need to run the interpreter with a set of chosen programs. This is similar to a profiling run used in traditional feedback-directed optimizations.

4.7 Generalizing When Speculation Fails

Examples in the preceding sections already mention deoptimization (cf. /* deopt */ in the listings). In the context of multi-level quickening interpreters, this means that we have to constantly verify our assumptions about type stability. Based on the observation of the “dynamic locality of type usage” [17], we speculate that types for a certain piece of code remain constant with a high likelihood. Therefore, once the interpreter detects the misspeculation, we know that we have to generalize all instructions of the current sequence that speculate on that specific type.

The interpreter can back out of the misspeculation and resume interpretation by (i) finding the start of the speculatively optimized sequence, (ii) generalizing all specialized instructions up by at least one level, and finally (iii) box all unboxed objects on the stack. From the beginning of a sequence instruction, we use a simple abstract interpreter that computes the current stack height and the types of the in-flight instructions kept on the operand stack. Next, we box those data. During the linear pass, we also quicken the specialized instructions by at least up one level. As a result, the interpreter can resume interpretation with correctly boxed objects.

4.8 Further Considerations and Implications

Our second-level quickening step allows direct access of unboxed native-machine data instead of operating on boxed Python objects. In CPython, all values are represented by Python objects, whereas implementations for other dynamically typed programming languages often use tagged values. A tagged value superimposes specific native-machine word layout to use the same word for multiple types. For example, on 64-bit architectures if pointers are aligned to eight byte boundaries, the lowest 3 bits of the pointer value will always be zero. Now, implementers can designate the lowest bit to
signal another type, e.g., an integer. Doing this has the advantage that integers can be represented directly, avoiding heap allocation.

But, in general, operating on tagged values means that we need to check the tags to select the operation to perform. This dynamic selection of operations requires branch instructions. Another downside of tagged values is that they restrict the values that can be represented in the bits not reserved for tags. For example, a native-machine integer on a 64-bit machine can represent and manipulate $2^{63}$ integers. In the tagged value representation, however, integers can only represent integers of a magnitude of $2^{60}$. We refer the interested reader to a technical report by David Gudeman that details multiple techniques regarding tagged value representation [24].

Operating on unboxed values, as is possible through multi-level quickening, addresses both of these problems and thus results in improved performance. MLQ allows us to (i) optimize away the tagging checks, and (ii) represent more information in the native-machine words directly.

In addition, operating on native-machine data allows implementers to follow new directions in interpreter implementation. For example, by means of multi-level quickening to unboxed native-machine words and using the ahead-of-time compiler to compile interpreter instructions allows interpreters to access SIMD registers and use special assembly instructions accessible only via library intrinsics.

Our concrete MLQ implementation maintains the original stack architecture of the CPython interpreter. This is an implementation limitation chosen for simplicity reasons. However, a more sophisticated implementation could also target a register-based ISA. Similarly, our current MLQ implementation only implements two quickening levels. However, the approach itself generalizes to multiple levels.

5 EVALUATION

5.1 Experimental Design

Our experimental goals are to validate the effects of multi-level quickening on the following system characteristics:

### Performance

We evaluate performance by comparing several interpreters with a baseline interpreter: the standard CPython interpreter using switch-dispatch as the instruction dispatch mechanism. We compare against a threaded code dispatch interpreter [5, 16, 32] to illustrate the effect of instruction dispatch based optimizations. In addition, we compare with an interpreter that performs purely interpretative inline caching [10, 11] to calibrate our new results against the previously best known results. Finally, we evaluate the performance of the MLQ interpreter presented in this paper. Table 2 lists the exact configuration of all implemented optimizations and supported data types. We evaluate the effect of the three different optimizations in this paper to demonstrate their relative impact, i.e., we evaluate performance using a multi-level quickening interpreter, an MLQ interpreter using the presented unbox caching, and finally an interpreter applying static superinstructions on top of the other optimizations. We complement this evaluation by comparing MLQ performance with the performance of a JIT compiler, PyPy 3, the only just-in-time compiler supporting Python 3.

### Portability

We evaluate portability of multi-level quickening by using two different hardware platforms, a little-endian CISC x86 Intel Nehalem system, and a big-endian RISC PowerPC system. We use the exact same interpreter configuration to evaluate performance on both systems. This experiment validates our claim that multi-level quickening preserves an existing interpreter’s portability property.

### Compatibility

We evaluate an interpreter’s compatibility with existing C code extensions by selecting benchmarks that rely on those third party C extensions. Often, incompatibility with popular third party extensions prevents widespread adoption of just-in-time compilers in industry. Since MLQ is purely interpretative it can directly interact with all existing C extensions.

---

### Table 2: Detailed list of supported optimizations.

| Operators | Long (L) | Float (F) | Complex (C) | Dict | List | Unicode (U) |
|-----------|---------|-----------|-------------|------|------|-------------|
| Arithmetic | +, −, ∗, /, %, ≦, ≧ | +, −, ∗, /, % | +, −, ∗, ∧, ∨, ¬ | +, −, ∗ | +, −, ∗ | +, −, ∗ |
| Logical | ∧, ∨, ⊖ | ∧ | ∧ | ∧ | ∧ | ∧ |
| Relational | ≦, ≠, ≧, ≧ | ≦, ≠, ≧, ≧ | ≦, ≠, ≧, ≧ | ≦, ≠, ≧ | ≦, ≠, ≧ | ≦, ≠, ≧ |

---

We refer the interested reader to a technical report by David Gudeman that details multiple techniques regarding tagged value representation [24].
Table 3: Maximum possible speedups computed via Amdahl’s law for each benchmark. The asterisk indicates that we chose this benchmark to evaluate performance.

| Benchmark       | Max. Speedup | Benchmark       | Max. Speedup |
|-----------------|--------------|-----------------|--------------|
| binarytrees     | 2.6356       | E27            | 4.4460       |
| mandelbrot      | 2.6833       | E31            | 4.3584       |
| nbody           | 4.1428       | E39            | 5.5117       |
| spectralnorm    | 5.4247       | E50            | 4.4485       |
| nqueens         | 1.6834       | Django         | 1.3491       |
| richards        | 1.8553       | Mako           | 1.3060       |
| bm_django       | 1.3270       | html5lib       | 1.3943       |
| Atlas           | 1.4190       | Karate club    | 1.1709       |
| Atlas2          | 1.1714       | Knuth miles    | 1.2127       |
| Davis club      | 1.1642       | Krackhardt centrality | 1.1533 |
| Erdos Renyi     | 1.1491       | Rcm            | 1.1430       |
| Expected degree sequence | 1.2571 | Roget         | 1.2342       |
| Iterated dynamical systems | 1.6962 | Words         | 1.3066       |

*Expected degree sequence* is considered to be a representative of real-world JavaScript [39]. The situation is similar for Python, except that there is no large-scale analysis of how real-world Python code looks like.

A separate, but even more important concern is how to evaluate interpreter performance objectively. Prior work already points out that a program will only benefit from an interpreter optimization if it actually spends most of its compute time in the interpreter, and not in native code libraries [19]. Instead of using unrealistic programs or an ad-hoc selection of benchmark programs, we rely on a fundamental law governing quantitative analysis and design of computer systems: Amdahl’s law.

More precisely, we use Amdahl’s law to compute the maximum speedup obtainable by an interpreter optimization for each benchmark. We assume infinite speedup of the Python interpreter, which allows us to use the corollary to Amdahl’s law as pointed out by Hennesy and Patterson [26]:

\[
\text{Max. Speedup} = \frac{1}{1 - \text{Time}_{\text{Interpreter}}}
\]  

(1)

To compute this speedup, we have to collect data on the actual time spent in the interpreter for each benchmark. We use the trace() function symbol and therefore cycle counts we include in the Time_{Interpreter} percentage. Our list of function symbols includes functions matching the following patterns: PyEval_EvalFrameEx, binary_op1, (l|L)ong_*, (f|F)loat_*, (c|C)omplex_*, PyNumber_*, PyObject_(Malloc|Free|RichCompare). Out of this list, we only attribute a third of all PyObject_Malloc cycles to the interpreter.

5.2 System Setup

Hardware Systems and Procedure. We ran the benchmarks on the following system configurations:

- Intel Nehalem i7-920 running at a frequency of 2.67 GHz, on Linux kernel version 3.11.0-15 and gcc version 4.6.4.
- PowerPC 970 running at a frequency of 1.8 GHz, on Linux kernel version 3.2.0-31 and gcc version 4.6.3.

To minimize perturbations by third party systems, we take the following precautions. First, we disable Intel’s TurboBoost [31] feature to avoid frequency scaling based on unknown heuristics. Second, we use nice -n -20 to minimize operating system scheduler effects. Third, we use 30 repetitions for each pairing of a benchmark with an interpreter to get stable results; we report the geometric mean of these repetitions, to account for outliers.

Benchmark Selection. We evaluated our full-fledged implementation using a wide variety of benchmarks. First, we use the following micro-benchmarks from the computer language benchmarks game [21]: binarytrees, mandelbrot, nbody, and spectralnorm. Second, we used a set of publicly available solutions to the first 50 Project Euler problems [1], where we selected programs that show a longer than average run-time (solutions to problems no. 27, 31, 39, and 50). Third, we used some benchmarks that are traditionally considered to be real-world benchmarks. Among those, we filtered out those benchmarks that are not yet compatible with Python 3. The remaining benchmarks are: the well-known richards benchmark simulating an object-oriented operating system kernel, the html5lib which uses a pure Python HTML5 parser to parse the...
Figure 5: Detailed speedups per benchmark normalized by the CPython 3.3.2 interpreter using switch-dispatch. Bars in the upper figure correspond to maximum possible speedups from Table 3.

HTML5 standard, and the bm_django benchmark that uses the popular Django web application framework to render a HTML table having 100×100 cells.

Finally, we supplemented the selection of real-world benchmarks by using two other benchmarks. We found a separate HTML template rendering benchmark that compares several template engines rendering a real-world HTML page, using separate header and footer pages [3]. Among candidate HTML rendering frameworks, we found that only Mako [4] and Django [18] fully support Python 3. Next, we used several example programs shipping with the popular networkx [25] graph library. The motivation for using networkx is two-fold: first, many graph algorithms are quite compute-intensive, and second, networkx relies on popular third party C libraries, such as matplotlib [30], and numpy [36], which allows us to evaluate the compatibility of MLQ.

Table 3 lists the maximum possible speedups for each of the selected programs. We see that not all programs benefit equally from interpreter optimizations. For example, most programs in the second and third parts of Table 3 show less than 50% speedup potential. Put differently, no interpreter optimization will speed up those programs beyond 50%. Looking at the data collected by perf, we find, e.g., that html5lib spends substantial amounts of time in the regular expression library and will therefore benefit more from using an optimized library instead.

We also looked into the programs in the lower third, the graph-based benchmarks taken from the networkx library. We find that all of the benchmarks that show a speedup potential of about 1.15× spend almost no time in the interpreter actually interpreting the program. The 15% measured speedup potential is spent entirely in setting up the run-time environment.

As a result of these observations, we focus only on a subset of programs where interpreter performance is the actual bottleneck. We selected all benchmarks identified by an asterisk in Table 3. This choice was motivated by the following reasons. The top third of benchmarks are primarily bound by interpreter performance, we use all of the programs to evaluate performance. The second third represents our selection of real-world programs; we find that only Richards suffers primarily from an interpreter bottleneck. The third part of Table 3 represents our selection of benchmarks to evaluate compatibility with existing Python libraries; we find that only Iterated Dynamical Systems is constrained by the interpreter. Finally, please note that our MLQ interpreter executes all of the benchmarks, and that our selection reflects a best effort to find a representative sample to objectively evaluate performance.

Third-party system parameters and versions. We report speedup factors relative to a baseline interpreter: CPython 3.3.2 using switch-dispatch for instruction dispatch. Our threaded code interpreter corresponds to the “computed gotos” option in CPython 3.3.2 source code and implements a token threaded-code instruction-dispatch technique.

Our PyPy3 measurements use the most recent version (2.1 beta 1). More often than not, PyPy3 is incompatible with the many popular CPython extensions written in C. Therefore, we have to limit our comparison of MLQ with PyPy3 to an even smaller subset of benchmarks. For example, the benchmarks in the third part
of Table 3 cannot be evaluated. Furthermore, PyPy3 uses custom implementations of several CPython libraries, for example heavily optimizing regular expressions. Consequently, our system cannot compete on equal footing with PyPy3 on any of the benchmarks of the second part in Table 3.

5.3 Performance Results

Figure 5 details the performance results we obtained on both architectures. We report the maximum speedup by up to a factor of 5.5023 over our baseline interpreter on the Intel Nehalem system. For our second system, we report a maximum speedup by a factor of 5.3290 over the baseline interpreter. INCA itself achieves speedups by a factor of up to 1.9099 on our Intel Nehalem system, and by a factor of up to 1.4450 on the PowerPC system. As a result, we improve upon the previous maximum speedups by 188% and 269%, respectively.

The geometric mean of performance improvement measured for our MLQ system on the Intel Nehalem and the PowerPC system were 2.4937× and 2.0022×, representing improvements over INCA by 72% and 74%, respectively.

Table 4 contains our performance comparison of MLQ to PyPy3. Comparing the geometric means of all the speedups we report that our MLQ interpreter is, on average, almost 50% faster than PyPy3. Considering the complete spectrum of performance, we find that PyPy3 is at most about 66% faster than MLQ (E27), and that MLQ is at most more than seven times faster than PyPy3 (E31).

Table 4: Speedups of PyPy3 and MLQ on our Intel Nehalem system over the CPython 3.3.2 interpreter using switch-dispatch.

| Benchmark    | PyPy3 | MLQ       | MLQ over PyPy3 |
|--------------|-------|-----------|----------------|
| binarytrees  | 1.8225× | 1.7081×  | 0.9372×        |
| mandelbrot   | 0.9403× | 2.0986×  | 2.2318×        |
| rbbody       | 1.5112× | 3.7010×  | 2.4490×        |
| spectralnorm | 2.7900× | 4.4012×  | 1.5775×        |
| Geometric Mean | 1.6984× | 2.5367×  | 1.4936×        |

Hardware Performance Counters. We use Linux’ perft tool to measure performance in terms of hardware performance counters. Our analysis of the data gathered indicates that the reduction of branches, cycles, and instructions executed varies proportional to the speedup, e.g., a four-fold increase in speedup results in a four-fold decrease in branches, cycles, and instructions executed. Two hardware performance metrics break this rule: branch misses and stalled backend cycles. The reduction in branch misses relative to our baseline interpreter indicates a 29 fold decrease in branch misses, and a 12 fold decrease in stalled backend cycles (both values represent the geometric mean).

5.4 Discussion

Using Amdahl’s law allows us to objectively quantify how well multi-level quickening is performing. We find that on almost all of our selected benchmarks MLQ outperforms other known interpreter optimizations—sometimes to such a large extent that interpretive overhead becomes negligible. Two notable exceptions are E31 and Iterated Dynamical Systems. We analyzed both benchmarks and identified the following two implementation limitations of our system: (i) E31 uses tuples, which we do not support at the moment (cf. Table 2), and (ii) Iterated Dynamical Systems uses a function call instruction that prevents our abstract interpreter from optimizing the sequence. Note that these are not approach limitations, i.e., an extended implementation can address both of these shortcomings.

Our comparison with PyPy3 leads to the following conclusions. First, our results for E31 indicate that PyPy3 does not JIT compile this benchmark, as it is much slower than even our baseline interpreter. This is either due to their profiling strategy, or due to problems with the trace recorder. At this point, it is worth noting that our MLQ system optimizes whole methods instead and consequently cannot suffer from the known trace compilation problems.

Second, the measured performance of PyPy3 does not compare favorably with the performance reported from regular PyPy. The reasons for the decline in performance are unknown and we believe that future releases of PyPy3 will address this for sure. As a result, PyPy3 will eventually outperform MLQ; which we would have expected. What is unexpected, however, is that the baseline performance delivered by MLQ is in fact competitive with a just-in-time compiler. Therefore, we believe that multi-level quickening offers a lot of “bang for the buck,” particularly when considering that it preserves the portability and implementation simplicity of an interpreter.

6 RELATED WORK

In 2014, Wang et al. present a system called ORBIT that optimizes the GNU R bytecode interpreter [41]. The ORBIT system is an independent discovery of the idea presented in this article, which explains the many similarities on a conceptual level. Besides the obvious difference of implementation vehicle—i.e., ORBIT optimizes R, our MLQ system speeds up Python—there are multiple differences between both our system and ORBIT. First, instead of the type-feedback collected via INCA, the ORBIT interpreter uses a dedicated profiling phase, which adds computational overhead of about ten percent. Instead, our INCA technique not only does not add any overhead, but eliminates dynamic typing costs right away [10, 11]. Second, our MLQ system does not implement a full-blown dataflow analysis in the second-level quickening step, which is what ORBIT does. Consequently, the ORBIT system will find longer bytecode sequences to optimize. Third, ORBIT seems to require a JIT
Multi-level Quickening: The Key to Interpreter Performance

Stefan Brunnhauser

In 2013, Würthinger et al. describe a system called Truffle that is geared towards programming language implementers targeting the Java virtual machine [43, 44]. An integral part of Truffle rests on a generalization of our own earlier work on optimizing bytecode interpreters [10, 11] to AST interpreters [44]. This generalization allows interpreters written in Java to efficiently capture type information. In the next step, Truffle uses a partial evaluation on the AST interpreter that is similar to a template just-in-time compiler, except that it collects the Java AST node implementations into one big Java method that corresponds to a function/method of the interpreted language. Then this partially evaluated Java code is compiled by the Graal just-in-time compiler to emit highly optimized native machine code.

There are several differences between multi-level quickening and Truffle. First, Truffle demonstrates the potential of using an optimizing interpreter over using a template JIT compiler as the first execution layer in an adaptive compilation environment. In contrast, MLQ targets existing interpreters that do not use a JIT compiler and does not need a partial evaluator—which would require dynamic code generation as well. Second, most candidate programming languages for multi-level quickening have a vibrant library ecosystem that often use C code to improve performance. For these systems, MLQ not only offers performance, but preserves compatibility with the standard library, too. Third, Truffle does not perform unboxing of interpreted language objects, which is the primary purpose of our second-level quickening step.

It is worth noting, however, that Truffle and MLQ are not mutually exclusive: since quickening for bytecode interpreters and node replacing in AST interpreters are identical, we believe that the more optimizations the AST interpreter performs, the better the resulting native machine code generated by Truffle will be. For example, incorporating our unboxing technique into the Truffle framework will be beneficial in terms of performance.

Compared to both, ORBIT and Truffle, MLQ does not require dynamic code generation. While there are downsides to this speculative approach, such as not being able to optimize some programs that do not use the types we can specialize, the advantage is that it also works on systems that prohibit dynamic code generation, such as Apple’s iOS, and preserves existing security mechanisms, such as W@X page protections.

For historical reference, note that the multi-level quickening shown in this article predates both, ORBIT and Truffle: in February 2011, we presented the key idea of MLQ [12, pg. 88]. In addition, we presented the final system at several Austrian universities in October 2012 and at a Mozilla Research talk on April 3rd 2013 [13].

To the best of our knowledge, all prior work in interpreter optimizations that deals with quickening only performs single-level quickening. For example, Lindholm and Yellin [35] use quickening to replace expensive look-up procedures for fields in the Java bytecode. This replacement is not speculative and happens only once per instruction. There is related work on how to deal with quickening in the presence of superinstructions [20, 38], Gagnon and Hendren describe preparation sequences [22] to quicken within superinstructions, and Casey at al. [14] use a simpler technique that delays optimizing with superinstructions until all member instructions have been quickened first. In 2010, we used quickening to do inline caching [11] and to remove reference count operations [10]. The quickening-based inline caching is the first step in MLQ, and is speculative, i.e., if the speculation fails, the inline cached instructions need to rewrite themselves to the parent instructions again and wait to be re-quickened to type specialized instructions. The staging is also speculative: we add instructions to the interpreter estimating that they have a high utility for optimizing. In 2010, Williams et al. [42] present a similar approach that compiles new instruction derivatives at run-time using a separate ahead-of-time compiler invoked at run-time. This is somewhat similar to using a JIT compiler as in the ORBIT system mentioned above [41]. But, as mentioned above, none of the prior work follows the concept of MLQ.

From a just-in-time compiler perspective, type-specialization has been known to be effective for optimizing dynamically-typed programming languages [8, 15, 23]. Note that we are not claiming novelty on the type specialization. To the best of our knowledge, however, MLQ is the first, general technique that shows how to perform purely interpretative advanced type specialization.

In 1996, Leone and Lee present the implementation of an optimizing ML compiler that relies on runtime feedback [33]. Interestingly, they mention the core idea behind multi-level quickening interpretation:

It is possible to pre-compile several alternative templates for the same code sequence and choose between them at run time, but to our knowledge this has never been attempted in practice.

Substituting ”interpreter instructions”—or derivatives, as we frequently refer to them—for the term ”templates” in the quote, reveals the striking similarity. In addition, both approaches leverage the compiler back-end of the ahead-of-time compiler assembling the run-time system—in our case the interpreter. This approach therefore automatically supports all target architectures of the base compiler and hence there is no need for building a custom back-end.

7 CONCLUSIONS

In this article we introduce multi-level quickening, or MLQ for short. This technique substantially improves interpreter performance, while maintaining the core properties we like interpreters for: easy to implement and portability. Furthermore, MLQ remains compatible with exiting C third party libraries and is not constrained by any particular automatic memory management mechanism.

MLQ achieves type run-time specialization that was previously reserved for just-in-time compilers, using a combination of speculatively staged optimized interpreter instructions and principled arranging of those instructions at run-time. Our evaluation shows that multi-level quickening is effective: besides reporting a maximum speedup by a factor of 5.5023, we find that on average MLQ achieves 77% of the maximum possible speedup. As a result, other optimizations to common bottlenecks become more important. For example, optimizing heap allocated activation records holds the potential to further increase performance of existing virtual machine interpreters.
Recent trends in computer security favor interpreter-only techniques, specifically page protections interfere with the read-write-executable permissions required by just-in-time compilers. Also, on architectures where instruction cache flushes are expensive, such as ARM systems, our technique presents itself as an ideal alternative. In a JIT compiler environment, applying the mixed-mode compilation strategy in combination with an optimizing interpreter like the one described in this article allows generating better code in less time when compared to existing approaches.

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Stefan Brunthaler

Multi-Level Quickening: Ten Years Later

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3 REVIEW

3.1 PLDI’13

3.1.1 Overview. Before using the abbreviation MLQ, short for multi-level quickening, the project’s working title has been “NAMASTE”, which was the abbreviation for native-machine typed interpreter instructions. For this reason, these interpreter instructions also carry the NAMA_ prefix.

Reviewers remark on two issues, the compiler error on PowerPC, and the small set of benchmarks. The compiler error turned out to be a “fun” platform quirk of gcc: My analysis of types used the C type char, since this sufficed to for abstract interpretation of the operand stack. Unfortunately, however, gcc on Intel machines made chars to be unsigned, but on PowerPC machines, they were signed by default. After finding this issue, which literally required just to put the unsigned at the right place, everything worked out just fine. (And taught me the value of using uint8_t the hard way.)

The second comment regarding the benchmarks was apt, but not really much I could do, as these were pretty much the standard benchmarks for Python performance evaluation at the time. I remember coming across a larger set of Python benchmarks sometime later on, but could not implement some other benchmarks by myself. From a reviewer perspective, I did not, and still do not, understand a rejection on such grounds, as it is fairly easy to ask an author to provide more benchmarks.

3.1.2 First reviewer’s review.

Classification. B: I can accept this paper, but I will not champion it (accept, but could reject).

Summary of the submission. This paper presents a dynamic compilation technique in which a script interpreter dynamically replaces instructions between multiple level of abstraction. Feedback is gathered by replacing Python-Level instructions with medium level instructions with type information encoded. Type propagation helps lower these instructions to low level instructions operating on native-machine data types instead of python objects. The approach is speculative, so de-quickening is done when necessary. The prototype demonstrates real speedup.

Evaluation. Points in Favor:
- While not exceeding the JIT on average, the performance results look promising.
- Complexity is likely to be less than a JIT.
- The idea is interesting. The proposed technique quickens a sequence of instructions into a new sequence (many-to-many optimization) through type propagation. This allows changes of the in-memory representation for some of the values on the stack. Since the techniques are speculative, de-quickening is done when necessary.

Points Against:
- The paper does not make clear how much less complexity (if any) this approach has over a JIT.
- The paper argues that language implementers need a viable alternative JITs, and that quickening interpreters fit that niche because they require less development and maintenance effort, even though they are likely to achieve less performance. While JITs are expensive to develop and maintain, pervasive and free JITs exist. Several projects have identified this opportunity, creating Python implementations to leverage these JITs: PyPy, JPython, IronPython, Unladen Swallow. And although PyPy is a "multi-year, multi-person effort," it’s incorrect to say that all of that programmer effort went toward targeting the Java and .NET VMs. Thus, the claim that JITs require prohibitive development costs may be unfair.
The paper proposes non-trivial changes to the interpreter. Specifically, it nearly triples the number of instruction opcodes, uses two different in-memory representations of common data types, and calls for a dynamic recompilation system. The total increase in code size is not fully quantified (how big is the CPython event loop?), but requires at least 2500 new lines of code (out of how many?) and changes to another 2100 lines. I estimate that this complexity adds to the development and maintenance costs of the MLQ interpreter. Does it contradict the stated goal of "a viable alternative to the costly implementation of a JIT compiler."

Comments for Improvement:

- Only a small set of small benchmarks are evaluated. Evaluation more.
- http://speed.pypy.org shows performance results for PyPy (trunk) on fannkuch.
- The discussion section would benefit from an analysis of the remaining performance differences with PyPy. Why does PyPy outperform MLQ most of the time? What is the remaining inefficiency—is it dispatch cost, or would MLQ need to optimize longer sequences? Support those answers with empirical data.
- The paper would benefit from a clear explanation of ‘quickening’ in Section 2.
- Avoid color. Not all printers are color. The proceedings are not in color.

Evaluation:

- Interesting paper and a novel technique. At this early stage, more convincing needs to be done.

3.1.3 Second reviewer’s review.

Classification. C: This paper should be rejected, though I will not fight strongly against it (reject, but could accept).

Summary of the submission. This paper introduces the next step in a applying quickening to give more efficient interpreters. Previous work in DLS 10 and ECOOP 10 introduced quickening, a new instruction format, and the use inline caching to enable further type-specialized quickening. This paper introduces the next step, which builds upon the types observed in the inline cache version to allow for even more specialization of the instructions and hence more efficient interpretation.

Evaluation. I like the general area of investigating how to make interpreters more efficient. The idea presented in this paper does seem like a nice next step along the road of quickening. However, I think that it is important to look at this paper in terms of the delta from the previous papers on quickening. There definitely is something new here ... the dynamic profiling and switching to the even more specialized NAMASTE IR is new. However, it is a bit hard to extract from the paper that this is the case.

The experimental results in Figure 9 use the switch-dispatch interpreter as the baseline and then show the threaded version, the INCA version and the MLQ versions as speedups relative to the baseline. Only the MLQ is new, the previous best was INCA, and the performance of the others is already reported (on the same benchmarks) in the DLS 10 paper. Thus, it would seem to me that the results in this paper should concentrate on the improvements over the previous best.

I also think, that given that this is the next step in an established line of research, that the number of benchmarks needs to be increased. I believe that this is a relatively small benchmark set (it looks a bit larger because of using several different input sizes), and each benchmark is also quite small.

Some smaller points,

- table 9 should really be normalized on INCA
• in section 3.5 you say you do not need an elaborate undo mechanism because you only use NAMSASTE on side-effect free sequences. What is the impact of the decision to limit to side-effect free sequences?
• you say you cannot run the INCA interpreter on PowerPC because of compilation errors - doesn’t that somewhat negate your claim that interpreters are great because they are very portable. Why isn’t INCA portable?
• in your comparison on space (end of section 4.2) you first give some numbers, 7MB vs 20MB, but then say it is not a fair comparison. If it is not something that can be compared, then it shouldn’t be compared.
• in related work, the work by Gagnon on SableVM (CC 2003) used instruction specialization (what you call quickening) in inline threaded code, so it might be worth mentioning. Recent work on specializing on types for JITS was by Chevalier-Boisvert (CC 2010).

3.1.4 Third reviewer’s review.

Classification. C: This paper should be rejected, though I will not fight strongly against it (reject, but could accept).

Summary of the submission. The paper proposes a new interpreter design that uses three levels (high, intermediate, low level) of instruction sets in executing Python for high performance. It describes the details of the design of the new interpreter and made experiments by running six programs of computer languages benchmark game on both PowerPC and Nehalem and compare performance over cPython Interpreter and PyPy interpreter. The performance improvements are up to 4X over cPython. The new interpreter outperforms PyPy for one benchmark program.

Evaluation.
• + a new innovative design of the interpreter for dynamically typed languages and decent performance improvements while maintaining portability.
• - limited set of benchmark programs - more real-world applications with dynamic type changes should be tested.
• - little information on how to generate low-level instructions except for a statement of “We adapted the existing Python code generator of the INCA system to generate the C NAMASTE instruction derivatives”
• - missing information on how often deoptimizations (undo) occurred for each benchmark program

3.1.5 Fourth reviewer’s review.

Classification. C: This paper should be rejected, though I will not fight strongly against it (reject, but could accept).

Summary of the submission. The paper describes a bytecode interpreter that performs just-in-time trace compilation, not to native assembly code like many tracing JITs, but to an intermediate language named NAMASTE that is roughly at the same abstraction level as C. During the JIT translation to NAMASTE, the system performs type specialization, but only for a statically determined set of type combinations, which includes arrays of floating point numbers.

Evaluation. Pros:
• The idea of JITing to a portable intermediate language is a good idea.

Cons:
• There are major holes in the description; the paper reads like a mystery novel.
• The idea of only doing type specialization for a fixed set of type combinations is not such a good idea, as it misses out on many opportunities for optimization.

Comments for improvement:
• page 1
  - “Next, we use type propagation to further specialize down to a low abstraction-level instruction set...” This sounds a lot like a JIT, what’s the essential difference?
  - “for powering much of Internet, and increasingly smartphones,” -> missing “the” “for powering much of the Internet, and increasingly smartphones.”
  - “that is easy to implement, portable, and requires no dynamic code generation” But isn’t quickening a form of code generation?
  - “We automatically generate the instruction sets before compiling the interpreter using a standard ahead-of-time compiler;” This process is never described in the paper.

• page 2
  - “by rewriting—or quickening” Why do you use the term “quickening” when there’s already a term for this: type specialization?
  - “Figure 1 shows the idea: we quicken complete sequences of the original instructions to their optimized derivatives...” Sounds like a tracing JIT.

• page 3
  - “This is contrary to a JIT compiler, which needs a dedicated back-end for each target architecture...” Does Namaste have these portability problems too? At this point in the paper it’s unclear whether and how Namaste differs from assembly code.
  - “only inline caching taking place at first” The connection between inline caching and type profiling needs to be explained!
  - “arbitrarily large interpreter instruction set” Why does MLQ have an arbitrarily large instruction set?

• page 4
  - “holds the instruction number of target instruction” grammar problem
  - “The previous section describes how to collect type information...” Not really.
  - “TARGET(PROF_JUMP_ABSOLUTE): ...” Is this C code? It would be nice to know what these macros do.

• page 5
  - section 3.3.1 What about handling the overflow into big integers during an addition?
  - “ else PUSH(result.word); NEXT_INSTR(); “ Bad indentation.
  - “A straightforward way to deal...” This description is too hand wavy.
  - “Our implementation follows the first approach and doubles...” This approach is wasteful of space and not scalable for languages with user-defined unboxed structure types.

• page 6
  - “TARGET(NAMASTE_FLOAT_LIST_SUBSCR)” When does this specialized code get created? Is this manual and you only optimize certain combinations?

• page 7
  - “Unfortunately, we could not run the INCA interpreter on our PowerPC system, because of compilation errors.” This discredits your portability claim.

• page 8
  - “We adapted the existing Python code generator of the INCA system to generate the C NAMASTE instruction derivatives” This needs to be explained... should have been explained earlier in the paper.
  - “written in C” Say this earlier!
- "other candidates for start instructions that we do not currently support, such as LOAD_ATTR, LOAD_NAME, LOAD_GLOBAL, LOAD_DEREF" These seem pretty important, especially LOAD_ATTR.
- "This is in contrast to the Python work mentioned above, which generates instruction derivatives statically and thus leverages the ahead-of-time compiler when compiling the interpreter" What does MLQ do? Does it use the same approach as Brunthaler? How does MLQ determine which specializations to generate?
- "the core idea behind multi-level quickening interpretation: ... pre-compile several alternative templates for the same code sequence and choose between them at run time" Say this earlier!

3.1.6 Fifth reviewer’s review.

Classification. B: I can accept this paper, but I will not champion it (accept, but could reject).

Summary of the submission. This paper describes Multi-Level Quickening (MLQ), a technique to improve the performance of an interpreter for dynamically typed languages. MLQ reduces the overhead of dynamic typing and boxing/unboxing by rewriting (or quickening) bytecodes dynamically at runtime based on profile information. The results showed MLQ gave 1.5x to 4x performance improvement over the default CPython 3.2.3 on Intel Nehalem in small benchmarks.

Evaluation. Overall, this paper is well written and the motivation of MLQ is very clear. I enjoyed reading the paper. MLQ is simple but effective to eliminate runtime overhead in interpreters for dynamic languages.

I feel that the biggest weakness of this paper is its evaluation. The author(s) uses only small benchmarks for the evaluation. Though I understand that this is because there is no major large benchmark for Python 3, I really want to see the results for realistic workload to confirm that the MLQ really improves the performance of real-world programs.

I feel that the related work section could be more complete by discussing the following paper, which presents a technique to reduce boxing/unboxing overhead in pypy’s tracing JIT. They aim the same goal of reducing the boxing overhead by specializing the execution path though they used the dynamic compiler instead of interpreter for execution.

- Carl Friedrich Bolz, Antonio Cuni, Maciej FijaBkowski, Michael Leuschel, Samuele Pedroni, and Armin Rigo. 2011. Allocation removal by partial evaluation in a tracing JIT. In Proceedings of the 20th ACM SIGPLAN workshop on Partial evaluation and program manipulation (PEPM ’11). The object allocation removal techniques based on escape analysis in (method-based) JIT compilers are also interesting to discuss as related work.

An example of the papers on escape analysis is - Ajeet Shankar, Matthew Arnold, and Rastislav Bodik. 2008. Jolt: lightweight dynamic analysis and removal of object churn. In Proceedings of the 23rd ACM SIGPLAN conference on Object-oriented programming systems languages and applications (OOPSLA ’08).

Question: The paper claims that this technique can be applicable to other languages. However, it might be much difficult to rewrite bytecodes at runtime safely if the language supports multi threading (e.g. Ruby). Do you have a good idea on how to implement the quickening efficiently in multi-threaded environments?
3.2 PLDI’14

3.2.1 First reviewer’s review.

Classification. C

Summary of the submission. The authors present an optimized interpreter for Python. It essentially compiles high-level bytecode into lower-level typed bytecode speculatively and falling back on the original when needed. The paper demonstrates improvements over the baseline CPython interpreter ranging from very small to 4x in a couple cases.

Strengths. The paper tackles one of the most heavily used interpreters - the standard Python interpreter. It demonstrates nice speedups there (up-to 4x) on certain codes. The technique should not interfere with the usage of popular Python libraries (which often use native code underneath).

Weaknesses. CPython is a fairly poor baseline for performance. There is no comparison with other Python systems that are arguably similar - Jython, IronPython - that they are implemented over a lower-level typed (but other substantially different) bytecode.

Evaluation. This paper investigates improving the performance of the standard Python interpreter through a technique called quickening. The authors created an optimized interpreter that provides type-specialized variants to standard Python bytecodes. Python bytecode is analyzed to propagate type information and replace generic bytecodes with type specific ones. Common sequences of type-specialized bytecodes are lowered further to remove redundant checks. The lowering can be speculative - the system will fall back on the original generic bytecodes if speculation fails.

The lower-level instructions are created in a “staging” step. The paper doesn’t really go into enough detail on how this is done. It appears this is ahead of time, and a new optimized interpreter is created. I’m not sure how it is trained / bootstrapped or what the impact is on interpreter size.

The second step appears to be a bytecode precompilation step - though perhaps some of this could be done just-in-time on execution. This step lowers the general bytecode to specialized bytecode. It uses speculative type propagation (via abstract interpretation) to drive this. It is able to specialize for types including integers, floats, strings, and lists.

The evaluation demonstrates speedups on Python benchmarks - mostly modest, but in some cases a factor of 2-4x over the baseline interpreter.

I found the paper somewhat confusing to read. I’m not clear on when/where the staging and quickening steps happen. A more detailed architecture section would be very helpful in this regard.

It would also be helpful to see comparisons with Jython and IronPython - I expect they run all the benchmarks listed here.

Is there any impact on startup time or memory footprint with this system? Both are often important considerations for interpreters.

Finally, the system has a fair bit of complexity - it’s not really clear this is a worthwhile step instead of moving to a simple JIT.

3.2.2 Second reviewer’s review.

Classification. B
Summary of the submission. The paper presents a strategy to improve performance of interpreters based on profiling, type inference, and the use of type-specialized byte code instructions. The strategy was implemented as an extension to the Python 3.3.2 interpreter and evaluated using a few codes with good results.

Strengths. The proposed strategy of improving the interpreter for performance makes sense since extending the interpreter is not only easier than adding a JIT compiler, but it also enables portability to new instruction sets.

Weaknesses. The main drawback of the paper is that the strategy of using unboxing, guards, and type-specialization is not that original. Also, the evaluation section needs improvement in the presentation.

Evaluation. The proposed strategy of type specialization is not tremendously novel. This does not mean that the paper is not interesting since it has experimental value. It shows how well this strategy applies to the Python interpreter. The overall presentation of the paper is good, but it seems that some clarifications are needed. Here are a few suggestions:

1. The reference to inline caching in the introduction to section 4. is not clear. It needs at least a reference and better a short description of what it means.
2. On page 3, the INCA_LONG_ADD function has parameter type (PyLongObject.PyLongObject.S). A short description of what this type means would be useful.
3. The whole reason behind Section 4.3.2 is not clear. Why do casting? I believe that casting does not arise naturally in Python. Is this assumption wrong?
4. Figure 3 needs an explanation. Right now the figure is only mentioned in the text.
5. The reference to Andahl’s law in Section 5.2 is not clear. In the end I don’t know how maximum speedup is computed. Is the computation of numerical values assumed to take zero time?
6. Are superinstructions used? What is the effect of the superinstructions?
7. What does it mean to have only INCA? Is it just avoiding the type check at the beginning of the generic arithmetic instruction?
8. Would it be possible to correlate maximum speedup to frequency of arithmetic operations in the program of Table 3?

3.2.3 Third reviewer’s review.

Classification. B

Summary of the submission. This paper presents a multi-level quickening optimization for interpreters. General interpreter instructions are replaced by type specific ones, and they can be reverted when the speculation fails.

Strengths. The approach improves performance while maintaining the interpreter’s core properties. The speedup is up to 450

Weaknesses. The evaluation is insufficient. Many of the benchmarks cannot gain enough performance improvement, which limits the applicability?

Evaluation. There should be more detailed evaluation on the individual techniques and parameters of the approach. For example:

1. Doubling the operand stack size enables the optimization for complex numbers, but does it incur more cache misses? (possibly not, but prove it)
Table 3 lists 29 benchmarks, but only 10 of them are evaluated (Figure 4), including ones with minor improvements. The other 19 benchmarks are not evaluated because they have little potential, but do they have any slowdown?

In section 5.2, you collected the interpreter’s execution time by perf tools. Did you assume an ideal speedup for the interpreter, so that you could calculate the maximum possible speedup (potential) with Amdahl’s law? If so, is the ideal speedup a pre-defined fixed value or infinity?

In section 5.4, you mentioned the overall “efficiency”. From the context, I guess it is the actual speedup divided by the potential one, but this should be clarified in the paper.

In Figure 1, should the last solid line be a dotted one, from STORE_FAST to NAMA_FLOAT_MULT?

3.2.4 Fourth reviewer’s review.

Classification. B

Summary of the submission. Interpreters typically do not use typed based optimizations. The paper presents a multi-level optimization scheme for interpreters. In the first level, instructions that express typed operations are presented. Optimization to the second level allows unboxed operands (hardware primitive types) to be consumed and produced by operations within a basic block, further reducing the overhead.

Strengths. The paper describes an interesting and important problem and provides a complete system that solves the problem. Significant speedups are achieved on the targeted Python programs.

Weaknesses. The paper lays out the trade-offs between interpreters and dynamic compilers: interpreters are more secure, portable and easier to develop. Compilers are faster. Part of the goal of the interpreter was to allow faster performance to to reduce the advantage of dynamic compilers in this trade-off. Having a quantitative comparison vs. a dynamic compiler would be useful.

The paper is largely (but not entirely) a well-engineered collection of techniques that existed in (often) less powerful forms in other systems.

Evaluation. The paper is overall well written and very clear. Concepts are explained well and the necessary background is provided.

The paper begins with a description of why interpreters are good and why dynamic compilers (hereafter called compilers) are not good. The main drawback of interpreters is that they offer slower performance than compilers for most programs. The paper then describes a two level optimization strategy that gives good speedups (close to 4 in programs that have high interpretation overheads) and that mitigates this advantage of compilers. It would be good to know how close the MLQ systems performance is to, e.g., Numba or PyPy’s performance. Clearly, the closer MLQ is the greater the reason to use interpreters. In fairness, almost all dynamic compilation systems start with an interpreter phase so speeding that up (and gathering the information that MLQ will gather) improves even compiler based systems, as the paper notes.

I have a second question related to performance. The IBM Nnija project (Moreira, et al.) designed special Complex classes that could be easily unboxed by a compiler in strings of operations without global side effects. The intention
of this was to allow arithmetic to be performed on objects without creating objects to hold temporaries. This made a significant performance improvement. I would think the same is true of your system. Do you have a feel for how much of your performance improvement comes from knowing types, how much from not unboxing, how much from not having spurious object created on the heap, how much from not having to have the operation check for the specific type each time, etc.

Are there issues with multithreading? It appears not since when you unbox you make a local shared copy and since this is necessarily in straight-line code you necessarily keep something that might be shared across threads in, e.g., CPython, private for a relatively short period of time.

In the Amdahl’s law discussion, you talk about the "top-quadrant" of Table 3, but Table 3 is divided into either 3 or 6 parts, not 4.
3.3 TACO’14

As mentioned before, I renamed the paper from NAMASTE to MLQ to focus on the essence of the technique. Besides fixing the PowerPC issue (also mentioned above), I did manage to put a lot more thought and work into carefully designing a proper evaluation methodology. In addition, I put in some more effort in optimizing native-machine mapping of compound, non-scalar data types, such as lists and dictionaries.

3.3.1 Editor’s comments. As the referees describe, a more complete submission (particularly in terms of experiments) is needed to better evaluate the ideas in the submission. It is possible that a new submission that reports the results of these experiments and addresses the referees’ concerns will be accepted by TACO.

3.3.2 Referee 1. Recommendation: Needs Major Revision

Comments:

(1) 1. Related work. It seems that ORBIT has no native code generation, either. The paper of ORBIT mentioned the native code generation as a future work.
(2) 2. Related work. It’s not required to use a paragraph to show MLQ predates ORBIT and Truffle. The citation of your previous work is clear. The section is used to introduce the related work in this domain, and address the differences.

Additional Questions: Review’s recommendation for paper type: Full length technical paper
Should this paper be considered for a best paper award?: No
Does this paper present innovative ideas or material?: Yes
In what ways does this paper advance the field?: Explored the new space that the optimization of dynamic scripting language focuses on pure interpreter level optimization.
Is the information in the paper sound, factual, and accurate?: Yes
If not, please explain why:
Rate the paper on its contribution to the body of knowledge in architecture and code optimization (none=1, very important=5): 3
What are the major contributions of the paper?:
(1) 1. Introduced an on-the-fly byte-code rewriting approach (called MLQ, Multi-Level Quickening by the author) to do specialization in the interpreter of a dynamic language.
(2) 2. Gave the reference MLQ implementation for the interpreter of Python 3

Rate how well the ideas are presented (very difficult to understand=1 very easy to understand =5): 3
Rate the overall quality of the writing (very poor=1, excellent=5): 3
Does this paper cite and use appropriate references?: No
If not, what important references are missing?: Other Python optimization work, for example "On the benefits and pitfalls of extending a statically typed language JIT compiler for dynamic scripting languages", OOPSLA 2012.

Should anything be deleted from or condensed in the paper?: Yes
If so, please explain.: Sec 4.4, may use more generic pseudo code.
Is the treatment of the subject complete?: No
If not, What important details / ideas/ analyses are missing?:

28
Multi-Level Quickening: Ten Years Later

(1) 1. For completeness, more background about the optimization of dynamic scripting languages should be included. There are a lot of research work in optimizing SELF, JavaScript, Python, Lua, etc. A high level summary may be required to distinguish this work’s progress.

(2) 2. Many details in Sections 4 are dependent on the CPython’s implementation. It’s better to include some related CPython design, such as object format. For example, in order to understand sec 4.4, the reader should know the CPython’s local variable look-up mechanism.

What type of paper is this?: This is an extended version of a previously published conference/symposium paper with significantly (generally > 30%) new material

Recommendations to the authors. Please list some concrete actionable items to improve the paper. When the paper is resubmitted, the authors will at least have to explain how they dealt with these recommendations:

(1) 1. You may define the term JIT in the context, since JIT is not only limited to generate machine native code. JIT only means on-the-fly compilation. It also could refer to translation to another format, for example byte-code to byte-code.

(2) 2. It’s hard to understand “gather type feedback by replacing dynamically typed Python instructions with type-specialized instructions” without reading the author’s previous work on Inline Caching with quickening. The replacing action itself cannot provide the type information. It’s better to explain the detail in this paper.

(3) 3. It is not clear when/under which condition the optimization of the first/second level quickening is triggered.

(4) 4. The first level transformation is coupled with inline cache. The paper may explain an alternative way to do the rewriting if the language has no inline cache, or it may mention the limitation of MLQ.

(5) 5. MLQ is only inside a basic block. So after the basic block boundary, will all the unboxed objects be boxed? It’s better to explain it, and also show the pros and cons.

(6) 6. Section 4.7, Specialization fails. Suppose there are two basic blocks A –>B. If the specialization fails in A, the interpreter triggers the de-optimization of A. Will the de-optimization of B also be triggered?

(7) 7. Experiment. Does MLQ encounter specialization failures in the performance evaluation? If yes, please include the analysis of the specialization failure rate. If no, please explain why.

Please help ACM create a more efficient time-to-publication process: Using your best judgment, what amount of copy editing do you think this paper needs?: Moderate

Most ACM journal papers are researcher-oriented. Is this paper of potential interest to developers and engineers?: Maybe

3.3.3 Referee 2. Recommendation: Needs Major Revision

Comments: Although the paper has many positive points, there are some additional shortcomings. These are:

(1) (1) The work claims or implies that it is applicable to a wider range of interpreters than the data supports.

(2) (2) The work claims a high level of novelty that is neither necessary for publication, nor supported by the prior work in the area.

(3) (3) It is not clear why the instruction specialization starts with arithmetic instructions and then propagates the type backwards to earlier executed loads. In other similar systems, such as that of Williams (CGO 2010), specialized versions of the load instructions are inserted when the loads are first executed.

With respect to scope, the title of the paper claims that multi-level quickening (MLQ) is the key to interpreter performance. Even if we leave aside the question of whether the reported speedups are truly the effect of MLQ rather than simply lucky code placement, there is no evidence to suggest that MLQ is the key to interpreter performance. In
truth, interpreters are strongly subject to the Anna Karenina principle: you can make an interpreter slow by getting any one of several things wrong; to make a fast interpreter you need to get all these things right. There is no one key to interpreter performance.

A second, more specific problem with this claim is that MLQ is primarily applicable to dynamically typed languages. If you are building an interpreter for a statically-typed language, MLQ will not help at all. This simple truth stands in stark contrast to the claim in the abstract that “the technique is general in nature and applies to all interpreters”. The abstract and introduction have several examples of such hyperbole that a knowledgable reader will recognize as exaggeration, but will mislead those who have less background in the area.

A similar problem arises when we consider the type of VM bytecode that might benefit from the technique. The examples in the paper all involve propagating types from loads to the stack to computational operations to stores to the stack. In fact, as shown in Table 1, a type propagation sequence ends at a store to the stack. In other words, the approach appears to primarily optimize sequences consisting of LOAD(S), OPERATION, STORE. In a VM that uses virtual registers rather than a virtual stack, this sequence would be a single VM instruction, and there would be no need to propagate types between instructions because within a single instruction it would not be necessary to check the type of any operand more than once. So it appears that single-level quickening is enough for register VMs, and MLQ is useful only where simple operations are broken into a number of VM instructions, as in stack VMs.

Another similar question arises around boxed implementations of dynamic types as compared with tagged implementations. A number of the techniques in the paper are aimed specifically at caching unboxed values. Are the techniques in the paper likely to be just as effective for VM interpreters that use tagged types instead? It’s difficult to say, and the paper doesn’t provide any evidence either way.

So in fact the statement that MLQ is applicable to all interpreter types is deeply misleading because it is only likely to be beneficial for very specific types of interpreter. It is also highly misleading to claim that MLQ is the key to interpreter performance. The purpose of these points is not that the work in the paper is bad. It’s actually very interesting. But the claims made for the work are exaggerated and misleading.

Another problem with the paper is that it claims a degree of novelty that is misleading and arguably untrue. Part of the problem is that the claims are made vague by qualifying words that have no clear meaning. For example “MLQ is the first GENERAL technique that shows how to perform purely interpretive ADVANCED type specialization”. The words “general” and “advanced” are too vague for anyone to judge whether or not this statement is true. The paper should contain statements that are clearly true as supported by evidence, rather than statements that are simply difficult for the reader to prove false.

Let us instead consider whether it is true that MLQ is the first technique to perform purely interpretive type specialization. My first response is that it’s not terribly important whether previous interpretive type specialization are purely interpretive or part of mixed interpreter/JIT system. To my mind the important question is whether the techniques can be used in a purely interpretive environment. Secondly, it is simply false that no earlier purely interpretive system did type specialization. For example, Williams et al. (CGO 2010) described a fully interpretive system that build a linked representation of the code, where each node represents a specialized version of the original instruction. The interpreter traverses this structure and interprets the opcode in each node. (The current paper incorrectly describes this work as using a separate compiler at run time, however that was a different paper by Williams which appeared in LCPC 2009). Furthermore modifying a VM instruction multiple times during execution is by no means novel. For example Williams (CF 2009) uses a scheme that modifies branch VM instructions for taken/not taken directions. No doubt there are many similar schemes used by others, probably including the author of the current paper. The idea of specializing
VM instructions using run-time information is probably almost as old as VM interpreters themselves. The important thing about the current paper is not that it’s the first paper to do purely interpretive instruction specialization (it is not the first such paper); the important thing is the particular way in which the current paper does a well-known transformation.

The third additional shortcoming of the paper is that it is entirely unclear why it should be necessary to propagate types from arithmetic instructions back to their corresponding loads in a stack machine. In other type specialization systems, the loads would be specialized when they are executed. Once the load has been specialized it may make sense to propagate the types forwards to the arithmetic instructions. But failing to specialize the loads when they are executed and then building an elaborate system that propagates the types back to those same loads seems illogical. This must be explained.

**Detailed comments:**

- **Abstract and introduction:** It would be helpful to turn down the marketing, tighten the claims, and avoid making claims that are only true in a legalistic sense.
- **Section 2:** If you show the operand bytes in the example, it will be easier for the reader to recognize this as stack code.
  At the end of section 2 you state clearly that the Python VM operates exclusively on boxed types, even for simple types such as integers. It would be helpful to have this clear statement before the discussion of reference counting. Otherwise readers familiar with type-tagged representations will not understand why there might be a reference count for a simple integer.
- **Section 3:** Presuming that the Python opcode is a single byte, is the limit of 256 opcodes a problem? How many instructions are there in the Python VM, and how many specialized opcodes do you create?
- **Section 4:** Fig. 3 is too small to read. The dotted font is particularly hard to read.
- **Section 4.2:** Tell us what the .-operator does before showing the example.
  The description of "any sequence of instructions that has no side-effects" is unclear. Surely the purpose of any instruction is to change the state of the VM. So how can any instruction have no side-effects?
- **Sections 4.3.1 and 4.3.2** These could be shortened significantly. Anyone familiar with the implementation of stack VMs will be familiar with the using unions to allow a variety of types on the stack.
- **Section 4.3.3** It is worth reminding the reader here that using the regular Python representation of a complex number will require only one stack slot, because the stack slot will contain a pointer to the structure containing the complex number. The problem arises when we unbox the complex number, and have to put two items on the stack.
  Change "more standard types" to "additional standard types".
  At this point it might also be worth mentioning stack caching. Stack caching boxed items is probably much simpler than stack caching unboxed items.
- **Section 4.4** Keeping the list size in a local variable. You should make clear that this is a variable that is local to the C interpreter function, not local to the Python function. A variable that is local to the interpreter is, effectively, global to the Python program. How is it possible to make sure this variable has the correct value at all times? For example, if the code consists of two NAMA_LOAD_LIST instructions back-to-back. We pop the topmost stack item, and now the cur_list_size local variable has the wrong value. How does the interpreter know that the value is wrong?
Section 4.5 You should briefly discuss whether these optimizations are useful for a register VM.

Section 5.1 "We [verb missing] the frequency"

Section 5.2 The geometric mean is an unusual choice when dealing with multiple runs of the same benchmark. Outliers are almost always highly asymmetric when timing programs (you get large outliers on the high side of execution times, but hardly any outliers on the low side).

"50% speedup". The term speedup is often misused, and although you use it correctly here I think there is a danger of confusion. On the other hand everyone knows what a 1.5x speedup is.

Section 5.4 PyPy3 seems to give much worse performance than regular PyPy. Why do you not compare with PyPy rather than a beta version of PyPy3 that seems to have huge performance problems?

Section 6 It's not clear to me that the historical reference note adds much. No doubt the researchers who developed ORBIT and Truffle also wrote down their ideas and gave talks along the way.

Additional Questions:

Review’s recommendation for paper type: Full length technical paper

Should this paper be considered for a best paper award?: No

Does this paper present innovative ideas or material?: Yes

In what ways does this paper advance the field?: The paper presents another variation of VM instruction specialization in interpreters for dynamically typed languages. The idea of dynamic instruction specialization in interpreters is not novel. But the particular techniques proposed are interesting, as is the implementation and experimental evaluation.

Is the information in the paper sound, factual, and accurate?: No

If not, please explain why.: To be more precise, much of the information is factual and mostly accurate but some of the claims are exaggerated or misleading, and some fundamental data is missing.

Rate the paper on its contribution to the body of knowledge in architecture and code optimization (none=1, very important=5): 3

What are the major contributions of the paper?:

- A new variation on instruction specialization for interpreters for dynamically-typed languages
- A good implementation of the proposed technique in an interpreter for Python
- An experimental evaluation that is interesting, even if it neglects to present what is perhaps the key to understanding the effectiveness of the technique

Rate how well the ideas are presented (very difficult to understand=1 very easy to understand =5): 4

Rate the overall quality of the writing (very poor=1, excellent=5): 4

Does this paper cite and use appropriate references?: Yes

If not, what important references are missing?: The paper cites appropriate references but the description of at least one piece of existing work papers is difficult to reconcile with the contents of the referenced paper.

Should anything be deleted from or condensed in the paper?: Yes

If so, please explain.: Sections 4.3.1 and 4.3.2 occupy more than a page but deal with very standard techniques found in almost any interpreter. These subsections could be shortened. It would also be helpful to the reader to know earlier in the paper about the boxed representation of all variables in the Python interpreter, as compared to type-tagged variables in many other implementations of dynamic languages.

Is the treatment of the subject complete?: No

If not, What important details / ideas/ analyses are missing?: It is well known that indirect branch prediction plays a major role in the performance of many interpreters. The results presented in section 5.3 strongly suggest that what the
author is measuring is a second-order effect on indirect branch prediction rather than the primary effect of instruction specialization. But the author does not appear to have investigated this possibility, although it is the explanation that is best supported by previous studies on interpreters.

**What type of paper is this?:** This paper is an original, previously unpublished, paper (to the best of my knowledge)

**Recommendations to the authors. Please list some concrete actionable items to improve the paper. When the paper is resubmitted, the authors will at least have to explain how they dealt with these recommendations.** This is an interesting paper that I enjoyed reading and learned something from. Much of the paper is good and I hope to eventually see it in print. However, there are some shortcomings that need to be fixed before this can happen.

It is well known that there are three main costs in bytecode interpretation:

- (1) Dispatch (fetch opcode and jump to handler code)
- (2) Operand access
- (3) Performing the actual computation

Pretty much all prior research shows that for statically-typed languages with fine-grained VM instruction sets, that interpreter instruction dispatch is the largest of these costs. The main reason is the poor performance of real-processor indirect branch predictors on the interpreter’s dispatch branch.

For dynamically typed languages there are other important interpreter overheads, but there is no clear evidence that indirect branch prediction is unimportant for these types of interpreters. (For a contrary view see Rohou et al. 2013)

There has been prior work on interpreters that attempted to reduce i-cache misses (Brunthaler 2011) in interpreters for dynamically typed languages by changing the layout of the code that implements the VM instructions. However, McCandless (2011) showed conclusively that the technique had no effect on i-cache misses, and the performance effect was entirely due to arbitrary effects on indirect branch prediction. Given that indirect branch prediction appears to be the most common reason for the effectiveness of interpreter optimizations, we should always consider the possibility that the apparent effectiveness of any new technique is simply the result of a lucky interaction with the indirect branch predictor.

It is well known that interpreter VM instruction specialization can have an arbitrary impact on indirect branch prediction (Casey et al. 2005). There are at least three effects: (1) more versions of the code that implements a VM instruction leads to more separate dispatch branches in (token) threaded interpreters; (2) multiple versions of the code that implements a VM instruction located at different points in memory can give more information to a two-level indirect branch predictor (McCandless 2011); (3) Multiple version of the code that implements an instruction can result in more possible targets for the dispatch branch, which can result in worse branch prediction.

Given this well-known result, one would expect that a paper on instruction specialization for interpreters should consider whether the positive results are actually from the proposed techniques, rather than simply from a lucky interaction with the indirect branch predictor.

Section 5.3 deals briefly with hardware performance counters. It reports that the reduction in (executed? retired?) branches is proportional to the speedup. However, there is a 29-fold reduction in branch mispredictions, and a 12-fold reduction in stalled back-end cycles.

These results suggest that the speedup from the author’s techniques is partly the result of a reduction in executed instructions and branches. However, it also appears that a large part of the speed improvement comes from the remaining branches becoming much more predictable.
An obvious question is whether the reduction in branch mispredictions is the result of type checking branches being removed or the result of the dispatch branch being better predicted.

Clearly part of the reduction in branch mispredictions might be explained by type checking branches being removed. However, there is no reason to think that removing one type checking branch might render the others more predictable. On the contrary I would expect that type checking branches would be strongly correlated, allowing a two-level predictor to improve its prediction of the next type checking branch. I would therefore expect that removing type checking branches would leave the remaining branches less predictable rather than more. So this explanation does not seem consistent with the data.

The other likely explanation is that the reduction in branch mispredictions is due to the interpreter dispatch branch(es) becoming more predictable, because of the existing well-known effects of interpreter specialization on indirect branch prediction. If this is the reason for the reductions in branch mispredictions, it is likely to be an effect that greatly depends on the luck of how the C compiler lays out the interpreter code. This explanation seems consistent with the measured data.

The above two explanations are not the only possible ones. But given that the most likely explanation for the branch prediction improvement appears to rely on an arbitrary artifact of the layout of the interpreter code by the C compiler, it is something that must be investigated and explained thoroughly before the paper can be considered ready for publication. An obvious first step would be to look at the indirect branch native performance counters.

References:

- Erven Rohou et al. Branch Prediction and the Performance of Interpreters – Don’t Trust Folklore. INRIA Research Report 8405, 2013.
- Stefan Brunthaler: Interpreter Instruction Scheduling, CC 2011: 164-178
- Jason McCandless, David Gregg: Optimizing interpreters by tuning opcode orderings on virtual machines for modern architectures: or: how I learned to stop worrying and love hill climbing. PPPJ 2011: 161-170

Most ACM journal papers are researcher-oriented. Is this paper of potential interest to developers and engineers?: Maybe

3.3.4 Referee 3 – David Ungar.

Recommendation: Reject

Comments: see attached file [Stefan Brunthaler: reprinted here with David’s permission!]

Additional Questions: Review’s recommendation for paper type: Full length technical paper
Should this paper be considered for a best paper award?: No
Does this paper present innovative ideas or material?: Yes
In what ways does this paper advance the field?: It presents a new methodology for optimizing an interpreter, as far as I can tell.

Is the information in the paper sound, factual, and accurate?: No
If not, please explain why: Unsound evaluation methodology, failure to consider both key sources of overhead and alternative architectures such as meta-circular JITTers. See full comments below.

Rate the paper on its contribution to the body of knowledge in architecture and code optimization (none=1, very important=5): 4
What are the major contributions of the paper?: A method for rewriting bytecodes

Rate how well the ideas are presented (very difficult to understand = 1 very easy to understand = 5): 3

Rate the overall quality of the writing (very poor = 1, excellent = 5): 2

Does this paper cite and use appropriate references?: No

If not, what important references are missing?: Jikes/RVM work See attached file.

Should anything be deleted from or condensed in the paper?: Yes

If so, please explain.: Excessive claims for performance vs complexity: see full review below See attached file.

Is the treatment of the subject complete?: No

If not, What important details / ideas/ analyses are missing?: Omits indirect sources of overhead encountered by interpreters. See attached file.

What type of paper is this?: This paper is an original, previously unpublished, paper (to the best of my knowledge)

Recommendations to the authors. Please list some concrete actionable items to improve the paper. When the paper is resubmitted, the authors will at least have to explain how they dealt with these recommendations.

I hope that the author will run the experiment comparing the performance of his interpreter to the equivalent program written in C++ and compiled with optimization. I also hope that he performs a similar experiment comparing his work to state-of-the-art Java virtual machines, for instance, and that he reports the lines of code required for his system against that of a concisely-written JIT, and also compares the lines of code required for a meta-circular JITTing VM such as Jikes/RVM

Also, work to make the writing more precise: no "This" without a noun after the word, and avoid the construct "We do ..." when you mean that your program does ....

Please help ACM create a more efficient time-to-publication process: Using your best judgment, what amount of copy editing do you think this paper needs?: Moderate

Most ACM journal papers are researcher-oriented. Is this paper of potential interest to developers and engineers?: Maybe
Review by David Ungar

Summary: The paper presents a technique for improving the performance of Python interpreters. It claims to achieve 77% of the maximum possible speedup. I do not believe that this claim is supported by the evidence given in the paper. Quoting from the guidelines for referees:

Reject - … a more complete submission is needed to better evaluate the ideas presented. … need more comparisons to prior work to determine if the proposed approach advances the state of the art, or needs a major rewrite to allow certain points of the paper to be understood. The authors can revise, run new experiments, and decide to potentially submit to TACO as a new submission, or to a different conference or journal at a later date.

Because I feel that the central thesis of the paper about implementation effort vs performance is not supported by the paper, and because I feel that critical sources of overhead are not addressed by the paper, I reluctantly must recommend a rejection. I hope that the author will run the experiment comparing the performance of his interpreter to the equivalent program written in C++ and compiled with optimization. I also hope that he performs a similar experiment comparing his work to state-of-the-art Java virtual machines, for instance, and that he reports the lines of code required for his system against that of a concisely-written JIT, and also compares the lines of code required for a meta-circular JITting VM such as Jikes/RVM.

Details:

Page 1: The paper asserts that poor interpreter performance is caused by: simple implementation, lack of optimizations such as threaded code or superinstructions, or expensive instruction implementations. This statement is unsound because simplicity does not directly slow down an interpreter, because it implies that implementing some of the optimizations is sufficient to speed up interpreters. Were that the case, there would be no need for this paper. Furthermore, and this is a key point: in my experience there are many other reasons for poor interpreter performance, including memory system interactions such as paging and caching behavior, the impossibility of inlining expensive (often virtual) function calls, the lack of inter-procedural optimization, the bytecode dispatch overhead which only be completely eliminated by a compiler, the added expense of foreign function invocation, etc.

On page 2, the claim is made on line 19 that optimized interpreters are easier to implement than JITted systems. But no evidence is given, and I would not be surprised if a simple JIT with a table-driven code generator could not offer better performance with no worse implementation difficulty than sort of optimized interpreters described in this paper. This is an instance of a claim being made in the paper without any evidence. My impression is that it is not the only such instance.
Earlier on page 2, lines 13-14, the claim is made that inline caching requires cache flushes. But I am aware of schemes developed to obtain almost all the benefits without using self-modifying code; for instance by loading the target address from a data region and indirectly branching to it. Confusingly to me, after claiming that inline caching requires cache flushes obviated by the techniques in this paper, this paper claims to perform inline caching on lines 42-43 of page 6. And this argument brings up another point that is not sufficiently addressed in this paper: if its techniques offer the advantage of higher performance obtained by avoid cache flushes, what of the cache flushes (the data cache flushes) required by its technique of quickening bytecodes? I do not believe the paper addresses the severity of that cost.

On page 2, line 30, the paper asserts that the combination of dynamic typing, reference counting, and modifying box data object representations cause interpreter instructions to become expensive, concluding that “we need to reduce the overhead introduced” by these features. But I find the prose to be deceptive, implying that these are the only overheads requiring reduction. My experience with Berkeley Smalltalk, SOAR, and Self suggest otherwise: there are many other sources of interpreter overhead that combine to incur a great performance penalty over, say optimized C++.

On page 3, the paper cites our 1994 work with Hölzle to support the claim that: “Put differently, dynamic compilers traditionally sacrifice known, complex optimizations for predictable compilation times.” in order to support the case for the techniques described herein. I find this logic to be fallacious and misleading: I find it fallacious because the stated goal is performance, not the application of known, complex optimizations. I find it misleading because computers have gotten so much faster since 1994 that there are many more cycles available within a perceptible pause in which to perform compilation.

On page 4, there is an example of code that a JIT compiler might emit consisting of two moves, and add, and a return. But most JITs that I have known would not usually need the move instructions or the return, because they could optimize data movement and inline many small functions.

Page 4 line 34 states that: “An efficient, low-level interpreter instruction set” but it does not define efficient. All that I think can be justified would be to say “A more efficient...” because such an instruction set is not what I believe many would call “efficient”, especially many C programmers.

Page 6 lines 27-30: “Contrary to the known type feedback optimization in just-in-time compilers (cf. [Hö]lzle and Ungar 1994; Aycock 2003]), this technique sidesteps dynamic code generation and uses quickening based on types observed at runtime. This has two important implications...” But type feedback in our 1994 work does use types observed at run-time. Or, if the sentence (which I find to be a bit unclear) is intended to suggest that the salient difference between previous work and this paper is the use of quickening, the point would seem to be
either vacuous or false. If “quickening” is by definition limited to interpreters, the point is merely a tautology, if by “quickening” is meant the replacement of slower instructions with faster ones, than our 1994 work does indeed perform it.

On page 8, the penultimate paragraph “Between a start and an end instruction, any sequence of instructions that has no side-effects, i.e., all computations in such a sequence that only exchange temporary data on the operand stack, can be optimized. In particular, this also allows calling other functions in an eligible sequence, as a function call cannot have a side effect on the temporary values stored on the operand stack.” suggests some questions: How significant is this characteristic in optimizing performance? Without alias analysis, one wonders if the situation might not occur too often? Also, this statement would seem to weaken the paper’s thesis, that the optimized interpreter described herein can perform as well as an interprocedurally-optimizing compiler. (More in this claim later, when I discuss the “Amdahl’s Law” argument in the performance section of the paper.)

Page 10, lines 37-40: “Since the operands are already in tagless native-machine data representation, our implementation avoids the necessary bit-fiddling and shifting of data plus the branching on types identified by the corresponding tags.” What about all of the overhead resulting from the decision to use boxed integers and floats instead of either tagged ones? Furthermore, it seems to me that the system described in this paper requires far more branching on type information than an adaptively-optimizing dynamic compiling system. And branching on tag bits is likely cheaper than branching on a header for a boxed object because fewer memory references are required.

Page 11, section 4.4 discusses the techniques for optimizing lists, dictionaries, sets, and tuples; which I gather are built-in data types in Python. But this section reveals what I believe is a fundamental weakness of these techniques, compared to adaptive optimization with a JIT: these techniques rely on substituting predefined operations for predefined types (the “staging step”), such as those built into the language. As such, the application programmer is prevented from getting optimized performance with his own data structures. This tradeoff seems to me that would result in lower-quality software, as the programmer is encouraged to use what may not be the best data structure for a particular situation. An adaptively-optimizing, inlining, dynamic compiler can generate good code for whatever sequence of bytecodes it encounters.

Page 15, line 9: “For standard Python, however, instruction dispatch overhead is not a performance bottle- neck [Brunthaler 2009].” I believe that, compared to the performance of good JITTing VMs such as HotSpot, dispatch overhead would be a performance bottleneck, so this statement needs clarification if it is not to mislead the unwary. I suspect that standard Python would be much slower than the equivalent Java program.

Page 16, line 22: “Another downside of tagged values is that they restrict the values that can be represented in the bits not reserved for tags. For example, a native-machine integer on a 64-bit machine can represent and manipulate 2^63 integers. In the tagged value representation,
however, integers can only represent integers of a magnitude of \([2^{60}]\)." Even in Blue Book Smalltalk-80, which used a tagged representation with 16-bit words, integers could represent arbitrary large values, such as 100 factorial. (There is a video by Dan Ingalls, I think, showing this demo.) The statement in the paper is incorrect, and misleading regarding the drawbacks of tagging.

Page 16: "In addition, we compare with an interpreter that performs purely interpretative inline caching [Brunthaler 2010b; Brunthaler 2010a] to calibrate our new results against the previously best known results." I doubt that the cited papers are either the most-well-known results, or the most impressive results for optimizing dynamically-typed virtual machines. Along with other similar statements in this paper, I fear that many readers are likely to be misled. It seems to me that if the results cited in the paper represent the state of the art for Python systems, the reader will be served only by being quite explicit about the limitation on the claims, and by pointing out that better levels of performance may well have been achieved by systems for other dynamic languages.

Page 17 line 30: "Prior work already points out that a program will only benefit from an interpreter optimization if it actually spends most of its compute time in the interpreter, and not in native code libraries [Ertl and Gregg 2003]." I believe that the base-level statement is false because of indirect but large penalties I have observed in interpreted systems that were removed by compilers. I downloaded the referenced paper (http://www.jilp.org/vol5/v5paper12.pdf) and could find no such claim in it with a quick skim.

Now I come to what I feel to be a fatal flaw in the paper: the claim to measure the “maximum speedup obtainable” by subtracting out the time measured to be spent in the interpreter. Because of all of the indirect costs of interpretation such as lack of inlining, poor use of the memory hierarchy, poor use of instruction fetch hardware such as branch prediction, high call frequency, and more (for instance poor use of registers on many architectures) I do not believe this methodology to be at all sound. The author would need to code up the equivalent programs in optimized C++ and demonstrate that this methodology yielded consistent results to persuade me otherwise. As it stands claims such as “We find that on almost all of our selected benchmarks MLQ outperforms other known interpreter optimizations—sometimes to such a large extent that interpretive overhead becomes negligible.” on page 21, line 7 render this paper deserving of rejection without extremely major changes.
Comments: This paper proposes and evaluates an optimization ("multi-level quickening") that works by rewriting the byte code of an interpreter, similar to the "quickening" optimization in the JVM. While the original "quickening" rewrites each byte code at most once, multi-level quickening rewrites it in two stages; also, the optimizations are speculative, and may have to be undone (unlike quickening). The first optimization level, inline caching, type-specializes individual byte codes. The second optimization level rewrites whole sequences of instructions; it propagates the type information to the other instructions in the sequence using abstract interpretation; as a result, some of the byte codes can work directly on unboxed data, instead of unboxing and boxing data in every byte code.

The author implemented this optimization in a Python interpreter and presents an empirical evaluation. One interesting feature of the evaluation is that it takes into account and corrects for a common problem when benchmarking interpreters: many benchmarks spend a lot of time in library code written in another language, for which interpreter optimizations don’t help at all. In the paper the actual speedup is compared to the speedup that would be achieved by optimizing the interpreted part away completely; the reported speedups are impressive, and remarkably close to the limit in many cases.

Additional Questions: Review's recommendation for paper type: Full length technical paper
Should this paper be considered for a best paper award?: No
Does this paper present innovative ideas or material?: Yes
In what ways does this paper advance the field?: It presents an optimization for interpreters for dynamically typed interpreters, evaluates it, and it proves effective. That’s surprising, because earlier stuff I saw in that area were not, and I had almost given up hope.
Is the information in the paper sound, factual, and accurate?: Yes
If not, please explain why:.
Rate the paper on its contribution to the body of knowledge in architecture and code optimization (none=1, very important=5): 4
What are the major contributions of the paper?: It presents an optimization for interpreters for dynamically typed interpreters, evaluates it, and it proves effective.
It also provides an innovation in the evaluation of interpreter performance: many benchmarks spend a lot of time in library code written in another language, for which interpreter optimizations don’t help at all. In the paper the actual speedup is compared to the speedup that would be achieved by optimizing the interpreted part away completely
Rate how well the ideas are presented (very difficult to understand=1 very easy to understand =5): 2
Rate the overall quality of the writing (very poor=1, excellent=5): 4
Does this paper cite and use appropriate references?: Yes
If not, what important references are missing?:
Should anything be deleted from or condensed in the paper?: No
If so, please explain:.
Is the treatment of the subject complete?: No
If not, What important details / ideas/ analyses are missing?: See "recommendations to the authors"
What type of paper is this?: This paper is an original, previously unpublished, paper (to the best of my knowledge)
Recommendations to the authors. Please list some concrete actionable items to improve the paper. When the paper is resubmitted, the authors will at least have to explain how they dealt with these recommendations. The main problem I have with this paper is that the presentation leaves a number of questions open:

- During reading sections 4.3-4.5, the connection between the high-level stuff in section 4.2 and the low-level stuff in section 4.3 was too thin for my taste. There were some explanations missing; e.g., I would be unable to implement the unboxing cache from the description.
- What is the benefit of using two optimization levels? Could you not just directly optimize to the NAMA level?
- One problem I have noticed when considering optimizing languages like Python and Ruby is that Integers can turn into Bigints on every arithmetic operation, invalidating any following type specialization. I do not see this problem addressed in the paper (indeed the addition example on page 4 ignores it).
- Section 4.7 is very short. Maybe you should give an example.

Detailed comments.

- In Figure 5, for E50 MLQ+UC+SI provides a speedup that’s higher than the limit. Please explain this result.
- I am wondering whether you should present your speedup data in another way in addition: Speedup of the interpreted part only (of course, this would produce funny results for E39 and E50), or alternatively, the remaining portion of time in the interpreter compared to the original time (which would be the inverse of the speedup).
- The Leone and Lee paper did not use run-time feedback as far as I remember. Instead, it simply compiled code with currying such that passing a parameter would run-time code generate a version specialized for that parameter.
- Proof-read the references carefully; I have not checked everything, but the Wang, Wu, Padua 2014 reference looks incomplete.

Please help ACM create a more efficient time-to-publication process: Using your best judgment, what amount of copy editing do you think this paper needs? Heavy

Most ACM journal papers are researcher-oriented. Is this paper of potential interest to developers and engineers? Yes
4 REVIEWER FEEDBACK

Most of the information presented in the reviews is provided as is and the reader is free to interpret them to their liking. For the archival purposes intended for this version of the paper, I merely want to address three specific issues identified by the reviewers:

(1) Incorrect paper citation.
(2) Requested focus on indirect branch prediction analysis.
(3) Missing data on implementation efficiency.

4.1 Incorrect Paper Citation

Reviewer 2 from the TACO’14 submission (see Section 3.3.4) commented on the paper falsely citing the Williams et al. paper from CGO 2010. I remember that some details were missing in the paper, which led me to look for the corresponding PhD thesis to complement the missing information. My entry in the corresponding Bibtex file confirms my memory:

20111018/sbr: this is unfortunately incomplete, because it does not include the technical details that were presented in Williams’ PhD thesis, where he describes the use of a background thread that starts the system compiler (gcc) to generate the new instructions and link them in

Since this paper is the only one co-authored by Kevin Williams in my Bibtex file, I must not have inferred that what I read in the thesis is part of multiple separate papers. Doing thorough related work is important and I do make this an important point for all of my graduate students. Apologies for this error, even ten years ago this should not have happened.

4.2 Indirect Branch Prediction Analysis

Reviewer 2 from the TACO’14 submission (see Section 3.3.4) has another important remark on the importance of branch prediction. Even in today, in August 2021, I am still stunned by this remark, primarily for two simple reasons.

First, the reviewer states that the model of prior work clearly shows importance of branch prediction for interpreters and that all of the speedups could also "depend on the luck of how the C compiler lays out the interpreter code." Somehow this remark completely misses the fact that several interpreters with focus on optimizing branch prediction, e.g., by way of applying some form of threaded code, did not experience the same amount of speedups. In a mailing list, the Python implementers stated that applying threaded code (called "computed gotos" there) only brought about 14% speedups. Similarly, the paper by Vitale and Abdelrahman from 2004 showed that applying threaded code could also lead to slowdowns for some programs.

As a result of these observations, I fundamentally oppose the reviewer’s view: "Given that indirect branch prediction appears to be the most common reason for the effectiveness of interpreter optimizations, [...]". Optimizing branch prediction is effective only for low abstraction-level interpreters, such as those for Java, Forth, and OCaml. All studies I have read that tried to replicate this success for high abstraction-level interpreters, such as JavaScript, Python, Perl, Tcl, failed to achieve reported speedups.

Second, lucky placement by the C compiler is highly unlikely to make up the reported speedups, as evidenced by almost identical speedup profiles for both PowerPC 970 and Intel Nehalem i7-920 architectures (see Figure 5 in the paper). The Intel CPU uses a two-level branch predictor but it only results in little improvements over the PowerPC’s branch predictor. What Figure 5 does show, and is also explained in Section 4.6 on superinstructions, is that instruction
4.3 Missing Data on Implementation Efficiency

The paper did not contain any data on implementation efficiency. Since David Ungar was kind enough to sign his review, I contacted him afterwards to address some of his comments. I did measure all of the following artifacts and provide them here for reference.

4.3.1 Collected Raw Data. Table 1 lists implementation efforts in terms of lines of code required for three separate systems with comparable aspects. Table 1b lists data in the corresponding directory, with `pypy/pypy/interpreter` corresponding to the interpreter, using another 27,018 lines of Python code. Table 1c lists data for Google’s V8 JavaScript engine. Since there are many parallels between JavaScript and Python, I also downloaded and measured against. Unfortunately, the structure of the C++ code is not ideal for measurement, so the presented data is merely an approximation.

Table 2 lists the raw data for the multi-level quickening system described in the preceding paper. The code generator component generates about 15,000 lines of C code for the interpreter dispatch loop and another 12,000 lines of C code for its superinstructions. The generated code is trivial, highly regular and thus amenable to simple code generation.

4.3.2 Interpretation of Implementation Efficiency Data. Jikes and PyPy/V8 are not really comparable, primarily because of differences in the programming language they optimize. Python and JavaScript are much more like Smalltalk and Self, particularly from an implementation perspective, as they all are more dynamic than Java.

For comparison, I am going to assume that MLQ requires 6,500 lines of code (5,000 lines of C code plus 1,500 lines of Python code). This system is nowhere near production, and many things could be implemented more efficiently.
Table 3 contains the data comparing the control group with the MLQ system. There are several shortcomings and reservations I have with such a comparison, but it is the easiest and quickest thing I can do right now. In my opinion, the MLQ system compares favorably to the other systems in terms of implementation complexity. Note that I expect that a full-blown adaptive JIT compiler will, depending on the evaluation conditions, show better peak performance than the MLQ interpreter.
5 CONCLUSIONS

Ten years appears to be a long time; upon re-reading and remembering the parts of the story, I noticed that it was not that long after all. There are, I believe, two sets of conclusions to be drawn from the archival version of this paper: (i) an objective assessment of the contributions, and (ii) my subjective takeaways from the experience.

5.1 Contributions

The paper makes the following contributions, in no particular order:

*General mechanism.* MLQ provides a general mechanism for incremental, iterative refinement of interpreter instructions based on continuous rewriting. Quickening in the original sense of the JVM (see Lindholm and Yellin, 1996) replaces a single instruction with another single instruction. Continuous replacing on the same semantic level, for example, to collect profiling information or branch frequencies, differs from the presented multi-level quickening in the following ways. First, such information is mostly on the single-instruction level, so no larger set of instructions will be rewritten. Second, the observed information is not used to optimize with increasingly specialized instructions.

A different perspective is that profiling information or branch frequencies collect *meta* information, whereas a native machine-type specialized instruction collects information specifically geared towards a specific instruction occurrence. Note that the MLQ implementation also uses a quickening-based approach to collect loop frequencies to determine whether or not code should be optimized.

The MLQ approach gives way to multiple successive refinements, where implementers can choose which overheads to address to further improve performance. An idea, for example, that I started implementing in 2014, but never gotten around to complete, is to use MLQ to develop a hybrid instruction-set architecture interpreter that combines a stack-based interpreter instruction set with a register-based instruction set. The stack-based instruction set would be the default instruction set, providing space efficiency whilst incurring higher instruction dispatch costs. Once a function qualifies for optimizations through profiling, one could use a register-based interpreter instruction set that trades of increased space requirements for reduced dispatch costs.

*Type-based superinstructions.* Prior work on superinstructions focuses on superinstructions of a pre-determined length, say superinstructions comprising four single instructions. In a high-abstraction level interpreter, length-based superinstructions are mostly useless, as the performance penalty is not due to instruction dispatch, but due to costly interpreter instruction implementations. Once MLQ successfully addressed these overheads—costly interpreter instruction implementations—known instruction dispatch optimization techniques, such as threaded code and superinstructions can unfold their full potential. When MLQ detects frequent patterns, however, their length is based on native-machine data types that are ill suited for deconstruction into frequently occurring pattern “tiles.”

An important advantage of using type-based superinstructions is that the full optimization potential of the ahead-of-time compiler used to compile the interpreter (called the *staging step* in the paper) is applied. Since the complexity of the interpreter-instruction implementation is now at the native-machine level, incorporating information about native-machine data representations, MLQ exposes much more “surface” for compiler optimizations than when used with high-level interpreter instructions. In other words, just sticking together *n* Python interpreter instructions and compiling them with a C compiler will not result in large performance benefits, whereas the compilation of a superinstruction comprising *n* type-specific low-level instructions can produce native-machine code that even an optimizing JIT compiler may not apply due to latency.
**Evaluation methodology.** The paper investigates the sources of interpretative overheads to examine how much optimization potential an interpreter can unfold in theory. Prior work, and for that matter, also most other work I am aware of as of time of this writing (August 2021), just use a set of benchmarks, run and time them, and report the results. With the MLQ paper, I was interested in finding a conclusive answer of the varying optimization potential experienced in well known benchmarks. Only for benchmarks dominated by the interpreter, optimizing the interpreter will yield benefits.

Note that the same observation pretty much holds for most other benchmark suites. In SPEC, for example, I most often find that xalanc is most indicative of real-world behavior of performance optimizations and/or applied security techniques. More investigation into what actually dominates performance is needed and certainly warranted to really understand what is going on. Such an investigation is usually not glamorous, and most scientists would probably not care, or maybe not even see a contribution in it, but it is important nevertheless.

**Purely-interpretative focus.** In MLQ, all compilation is done at interpreter compile-time, meaning no code will ever be dynamically emitted. This purely-interpretative way of optimizing interpreters has the following advantages.

First, one can piggyback onto an existing ahead-of-time compiler’s backend, meaning one can have a reasonably fast baseline performance without requiring the complex and error prone task of creating a new compiler backend. Second, one need not have executable and writable memory privileges, thereby decreasing attack surface and increasing interpreter security. (Note that, recently, Microsoft has experimented with turning off the V8 JIT compiler in the MS Edge browser for the same reason. For some more data, I refer the interested reader to the corresponding blog [https://microsoftedge.github.io/edgevr/posts/Super-Duper-Secure-Mode/#project-super-duper-secure-mode](https://microsoftedge.github.io/edgevr/posts/Super-Duper-Secure-Mode/#project-super-duper-secure-mode) Third, an optimizing interpreter, exemplified by the MLQ system, could also be directly put into hardware. If, for example, one were to “burn” the code onto a ROM, then one could decrease energy consumption whilst increasing security. This scheme could also be using in slightly altered scenarios, namely in FPGAs that could adapt their optimization-level according to shifting needs, for example in a data center. Another exemplary scenario would be to provide computation on memory chips, where one could distribute Python code to memory chips, instead of transferring and manipulating data on the CPU. Fourth, the general MLQ infrastructure allows for cross native-code modules optimizations, i.e., a library, such as numpy could provide its own optimized instructions and/or instruction sequences, and the hook them into the optimizing interpreter. This aspect combines the general mechanism with the purely-interpretative nature of MLQ, and offers an interesting alternative to often problematic use of foreign-function interfaces in JIT compilers, which often limit optimizations to code that has been emitted by JIT compilers themselves. (In fact, I have started working on a prototype implementation of that system in 2012, but due to lack of academic incentives focused my attention on my work in language-based security.) Fifth, the described MLQ system poses new and exciting opportunities for interpreter code generation. The present system uses an unsophisticated template-based code generator producing C code, written in Python. An improved system could leverage the insights from the Tiger system, combined with the rewriting and type-refinement depending on the type system of a programming language and “derive” the proper optimized interpreter instructions. Sixth, bypassing dynamic code-generation enables us to formalize and verify the semantics preserving nature of the optimizations. (Which I did with a grad student and published in early 2021, but have tried and failed to publish at POPL’14, POPL’15, and ECOOP’17.)
5.2 Personal Conclusions

My personal conclusions of both conducting the research and failing at publishing its results are as follows. The former part, conducting the research, was and still is fun. I strongly believe that we have not yet reached the maximum possible performance of what can be achieved in single-threaded program performance, and very much so in interpreter performance. (Though my gut feeling is that there won’t be another 4× improvement to be had, more like a 2×—that’s at least what I expect my next optimization idea will yield.)

My failure of publishing the MLQ-system, including consideration of compounding factors, resulted in my effectively leaving the SIGPLAN community. My aim at publishing this paper was pure vanity: Having a single-authored paper at PLDI would increase my chances for faculty applications, at least that’s what I had hoped for. These hopes were not only dashed by the negative reviews, but much more by the 2013 PLDI PC chair (Cormac Flanagan), who stated in his opening address that the least likely chance for acceptance to PLDI was research in compiler optimization. These facts indicated that interest interpreter optimization had become out of fashion. If I had read the signals right, or if some of the reviewers had pointed this out to me, then I would have submitted this paper to CGO instead, but nobody did and my vanity blinded me. At the same time, our research in language-based security, particularly in software diversity took off. The security reviewers liked our work and I felt that what we did there, was equally important to my work in interpreter optimization.

Scientific research is driven by fashion to a surprising degree. When important topics become out of fashion, some members of the scientific community move on, while others stay and continue research. Looking back over the past ten years, scientists who move on to greener pastures, often picking low-hanging fruit, seem to do better on bibliometric scales, i.e. publishing more and acquiring more citations. Scientists who continue to stay in their original research areas then often find themselves between chairs: conferences change their focus to accommodate new research areas, thus altering the corresponding communities. I did not understand this social component of CS publishing ten years ago and it still seems strange to me. Ten years ago, a change of communities was most welcome, although this required a change of focus, I could still remain true to my interests in programming language design and implementation. Now, in 2021, the signals in the systems security community closely resemble the situation I found myself in ten years ago—maybe now would be a good time to change back to programming languages again?