Speculative Staging for Interpreter Optimization

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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 programming languages. The key idea is to combine speculative staging of optimized interpreter instructions with a novel technique of incrementally and iteratively concerting them at run-time.

This paper introduces the concepts behind deriving optimized instructions from existing interpreter instructions—incrementally peeling off layers of complexity. When compiling the interpreter, these optimized derivatives will be compiled along with the original interpreter instructions. Therefore, our technique is portable by construction since it leverages the existing compiler’s backend. At run-time we use instruction substitution from the interpreter’s original and expensive instructions to optimized instruction derivatives to speed up execution.

Our technique unites high performance with the simplicity and portability of interpreters—we report that our optimization makes the CPython interpreter up to more than four times faster, where our interpreter closes the gap between and sometimes even outperforms PyPy’s just-in-time compiler.

General Terms  Design, Languages, Performance

Keywords  Interpreter, Optimization, Speculative Staging, Partial Evaluation, Quickening, Python

1. Introduction
The problem with interpreters for dynamically typed programming languages is that they are slow. The fundamental lack of performance is due to following reasons. First, their implementation is simple and does not perform known interpreter optimizations, such as threaded code [3, 4, 14] or superinstructions [19, 20, 39]. Second, even if the interpreters apply these known techniques, their performance potential is severely constrained by expensive interpreter instruction implementations [6].

Unfortunately, performance-conscious implementers suffer from having 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, hard to debug, and substantial implementation effort. An alternative route is to explore the area of purely interpretative optimization 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 [7, 8]. As a result, investigating a general and principled strategy for optimizing high abstraction-level 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 in order 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.

In this paper we combine ideas from staged compilation with partial evaluation and interpreter optimization to devise a general framework for interpreter optimization. From staged compilation, we take the idea that optimizations can spread out across several stages. From partial evaluation, we take inspiration from the Futamura projections to optimize programs. From interpreter optimization, we model a general theory of continuous optimization based on rewriting instructions. These ideas form the core of our framework, which is purely interpretative, i.e., it offers ease-of-implementation and portability while avoiding dynamic code generation, and delivers high performance. As a result, close to three decades after Deutsch and Schiffman [16] described the ideas of what would eventually become the major field of just-in-time compilation, our framework presents itself as an alternative to implementing JIT compilers.
Summing up, this paper makes the following contributions.

- We introduce a general theory for optimizing interpreter instructions that relies on speculatively staging of optimized interpreter instructions at interpreter compile-time and subsequent concering at run-time (see Section 3).
- We present a principled procedure to derive optimized interpreter instructions via partial evaluation. Here, speculation allows us to remove previous approaches’ requirement to specialize towards a specific program (see Section 3.2).
- We apply the general theory to the Python interpreter and describe the relevant implementation details (see Section 4).
- We provide results of a careful and detailed evaluation of our Python based implementation (see Section 5), and report substantial speedups of up to more than four times faster than the CPython implementation for the spectral-norm benchmark. For this benchmark our technique outperforms the current state-of-the-art JIT compiler, PyPy 1.9, by 14%.

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 `sum` that “adds” its parameters and returns the result of this operation.

```python
1 def sum(a, b):
2     return a + b
```

In fact, this code does not merely “add” its operands: 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 strings, or perform arithmetic addition on either integers, floating point numbers, or complex numbers; or the interpreter could even invoke custom Python code—which is possible due to Python’s support for ad-hoc polymorphism.

In 1984, Deutsch and Schiffman [16] report that there exists a “dynamic locality of type usage,” which enables speculative optimization of code for any arbitrary but fixed and observed type \( \tau \). Subsequent research into dynamic compilation capitalizes on this observed locality by speculatively optimizing code using type feedback [26][27]. From their very beginning, these dynamic compilers—or just-in-time compilers as they are referred to frequently—had to operate within a superimposed latency time. Put differently, dynamic compilers traditionally sacrifice known complex optimizations for predictable compilation times.

Staged compilation provides a solution to the latency problem of JIT compilers by distributing work needed to assemble optimized code among separate stages. For example, a staged compiler might break up an optimization to perform work at compile time, link-time, load-time, or finally at runtime. The problem with staged optimizations for high-level languages such as JavaScript, Python, and Ruby is that they require at least partial knowledge about the program. But, as the example of the `sum` function illustrates, only at run-time we will actually identify the concrete type \( \tau \) for parameters `a` and `b`.

For our target high-level languages and their interpreters, staged compilation is not possible, primarily due to two reasons. First, none of these interpreters have a JIT compiler, i.e., preventing staged partial optimizations. Second, the stages of staged compilation and interpreters are separate. The traditional stages listed above need to be partitioned into stages that we need to assemble the interpreter (viz. compile-time, link-time, and load-time), and separate stages of running the program: at interpreter run-time, it compiles, potentially links, loads and runs hosted programs.

3. Speculative Staged Interpreter Optimization

The previous section sketches the problem of performing traditional staged optimizations for interpreters. In this section we are first going to dissect interpreter performance to identify bottlenecks. Next, we are going to describe which steps are necessary to formalize the problem, and subsequently use speculative staged interpreter optimizations to conquer them and achieve high performance.

3.1 Dissecting Example Performance Obstacles

Python’s compiler will emit the following sequence of interpreter instructions, often called bytecodes, when compiling the `sum` function (ignoring argument bytes for the LOAD_-INSTR instructions):

```
| LOAD | LOAD | BINARY | RETURN |
|------|------|--------|--------|
| FAST | FAST | ADD    | VALUE  |
```

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

Let us consider the application `sum(3, 4)`, i.e., `sum` is used with the specific type `Int \times Int \rightarrow Int`. In this case, the `BINARY_ADD` instruction will check operand types and select the proper operation for the types. More precisely, assuming absence of ad-hoc polymorphism, the Python interpreter will identify that both `Int` operands are represented by a `struct` called `PyLong_Type`. Next, the interpreter will determine that the operation to invoke is `PyLong_Type->tp_as_number->nb_add`, which points to the `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 these operations, 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 state-of-the-art JIT compiler would generate something like this

```
1 movq %rax, -8(%rsp)
2 movq %rbx, -16(%rsp)
3 addq %rax, %rbx
4 ret
```

The first two lines assume a certain stack layout to where to find 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 for improving 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 represent the sum function’s computation for our assumed type in the following way:

```
| LOAD | LOAD | INT  | ADD  | RETURN |
```

In this lower-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; disregarding the different architectures, i.e., register vs. stack.

### 3.2 Systematic Derivation

The previous section informally discusses the goal of our speculatively staged interpreter optimization: optimizing from high to low abstraction-level instructions. This section systematically derives required components for enabling interpreters to use this optimization technique. In contrast with staged compilation, staged interpreter optimization is purely interpretative, i.e., it avoids dynamic code generation altogether. The key idea is that we:

- stage and compile new interpreter instructions at interpreter compile-time,
- concert optimized instruction sequences at run-time by the interpreter.

The staging process involves the ahead-of-time compiler that is used to compile the interpreter. Therefore, this process exercises the compiler’s backend to have 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.

To assemble optimized instruction sequences at run-time, we rely on a technique known as quickening [34]. Quickening means that we replace instructions with optimized derivatives of the exact same instruction at run-time. Prior work focuses on using only one level of quickening, i.e., replacing one instruction with another instruction derivative. In this work, we introduce multi-level quickening, i.e., the process of iteratively and incrementally rewriting interpreter instructions to ever more specialized derivatives of the generic instruction.

#### 3.2.1 Prerequisites

In this section we present a simplified substrate of a dynamically typed programming language interpreter, where we illustrate each of the required optimization steps.

```
1 data Value = VBool Bool
2                  | VInt Int
3                  | VFloat Float
4                  | VString String
5
6 type Stack = [Value]
7 type Instr = Stack → Stack
```

We use `Value` to model a small set of types for our interpreter. The operand stack `Stack` holds intermediate values, and an instruction `Instr` is a function modifying the operand stack `Stack`. Consequently, the following implementation of the interpreter keeps evaluating instructions until the list of instructions is empty, whereupon it returns the top of the operand stack element as its result:

```
1 interp :: Stack → [Instr] → Value
2 interp (x:xs) [] = x
3 interp s (i:is) =
4    let
5        s' = i s
6        in
7        eval s' is
```

Using `interp` as the interpreter, we can turn our attention to the actual interpreter instructions. The following example illustrates a generic implementation of a binary interpreter instruction, which we can instantiate, for example for an arithmetic add operation:

```
1 binaryOp :: (Value → Value → Value) → Stack → Stack
2 binaryOp f s =
3    let
4        (x, s') = pop s
5        (y, s'') = pop s'
6        in
```
The general implementation binaryOp shows the operand stack modifications all binary operations need to follow. The addOp function implements the actual resolving logic of the dynamic types of Values via pattern matching starting on line 13 in function dtAdd.

### 3.2.2 First-level Quickening: Type Feedback

**Definition 1 (Instruction Derivative).** An instruction \( I' \) is an *instruction derivative* of an instruction \( I \), if and only if it implements the identical semantics for an arbitrary but fixed subset of \( I \)’s functionality.

**Example 1.** In our example interpreter \( \text{interp} \), the addOp instruction has type \( \text{Value} \times \text{Value} \to \text{Value} \). An instruction derivative \( \text{intAdd} \) would implement the subset case of integer arithmetic addition only, i.e., where operands have type \( \text{VInt} \). Analogous cases are for all combinations of possible types, e.g., for string concatenation \( \text{VString} \).

To obtain all possible instruction derivatives \( I' \) for any given interpreter instruction \( I \), we rely on insights obtained by partial evaluation \([30]\). The first Futamura projection \([23]\) states that we can derive a compiled version of an interpreted program \( \Pi \) by partially evaluating its corresponding interpreter \( \text{interp} \) written in language \( L \):

\[
\text{compiled}\Pi := \left[ \text{mix} \right]_L[\text{interp}, \Pi] \quad (1)
\]

In our scenario, this is not particularly helpful, because we do not know program \( \Pi \) a priori. The second Futamura projection tells us how to derive a compiler by applying \( \text{mix} \) to itself with the interpreter as its input:

\[
\text{compiler} := \left[ \text{mix} \right]_L[\text{mix}, \text{interp}] \quad (2)
\]

By using the interpreter \( \text{interp} \) as its input program, the second Futamura projection eliminates the dependency on the input program \( \Pi \). However, for a dynamically typed programming language, a compiler derived by applying the second Futamura projection without further optimizations is unlikely to emit efficient code—because it lacks information on the types \([43]\).

Our idea is to combine these two Futamura projections in a novel way:

\[
\bigwedge_{I \in \text{interp}} I'_r := \left[ \text{mix} \right]_L[I, \tau] \quad (3)
\]

That means that for all instructions \( I \) of an interpreter \( \text{interp} \), we derive an optimized instruction derivative \( I' \) specialized to a type \( \tau \) by partially evaluating an instruction \( I \) with the type \( \tau \). Hence, we speculate on the likelihood of the interpreter operating on data of type \( \tau \) but do eliminate the need to have a priori knowledge about the program \( \Pi \).

To preserve semantics, we need to add a guard statement to \( I' \) that ensures that the actual operand types match up with the specialized ones. If the operand types do not match, we need to take corrective measures and redirect control back to \( I \). For example, we get the optimized derivative \( \text{intAdd} \) from \( \text{dtAdd} \) by fixing the operand type to \( \text{VInt} \):

\[
\text{intAdd} := \left[ \text{mix} \right]_L[\text{dtAdd}, \text{VInt}] \quad (4)
\]

The last line in our code example acts as a guard statement, since it enables the interpreter to execute the type-generic \( \text{dtAdd} \) instruction whenever the speculation of \( \text{intAdd} \) fails. The interpreter can now capitalize on the “dynamic locality of type usage” \([16]\) and speculatively eliminate the overhead of dynamic typing by rewriting an instruction \( I \) at position \( p \) of a program \( \Pi \) to its optimized derivative \( I' \):

\[
(\Pi)[I'/I_p] \quad (5)
\]

It is worth noting that this rewriting, or quickening as it is commonly known, is purely interpretative, i.e., it does not require any dynamic code generation—simply updating the interpreted program suffices:

\[
\text{quicken} := [\text{Instr}] \to \text{Int} \to \text{Instr} \to [\text{Instr}] \quad (6)
\]

\[
\text{let} \quad (x, y;ys) := \text{splitAt} \ p \ \Pi \\
\quad r := x ++ \text{derivative} : \ ys
\]

Using this derivation step, we effectively create a typed interpreter instruction set for an instruction set originally only consisting of untyped interpreter instructions.

### 3.2.3 Second-level Quickening: Type Propagation

Taking a second look at the optimized derivative instruction \( \text{intAdd} \) shows that it still contains residual overhead: unboxing the \( \text{VInt} \) operands and boxing the \( \text{VInt} \) result (cf. line three). It turns out that we can do substantially better by identifying complete expressions that operate on the same type and subsequently optimizing the whole sequence.

For identifying a sequence of instructions that operate on the same type, we leverage the type information collected at run-time via the first-level quickening step described in the previous section. During interpretation, the interpreter will optimize programs it executes on the fly and single instruction occurrences will carry type information. To expand this
information to bigger sequences, we use an abstract interpreter that propagates the collected type information. Once we have identified a complete sequence of instructions operating on the same type, we then quicken the complete sequence to another set of optimized derivatives that directly modify unboxed data. Since these instructions operate directly on unboxed data, we need to take care of several pending issues.

First, operating on unboxed data requires modifying the operand stack data passing convention. The original instruction set, as well as the optimized typed instruction set, operates on boxed objects, i.e., all elements on the operand stack are just pointers to the heap, having the type of one machine word (uint64 on modern 64-bit architectures). If we use unboxed data elements, such as native machine integers and floats, we need to ensure that all instructions follow the same operand passing convention.

**Definition 2** (Operand Stack Passing Convention). All instructions operating on unboxed data need to follow the same operand stack data passing convention. Therefore, we define a conversion function c to map data to and from at least one native machine word:

\[
c_\tau : \tau \rightarrow \text{uint64}^+
\]

\[
c_\tau^{-1} : \text{uint64}^+ \rightarrow \tau
\]

Second, we need to provide and specify dedicated (un)boxing operations to unbox data upon entering a sequence of optimized interpreter instructions, and box results when leaving an optimized sequence.

**Definition 3** (Boxing and Unboxing of Objects). We define a function m to map objects to at least one machine word and conversely from at least one machine word back to proper language objects of type π.

\[
m_\pi : \pi \rightarrow \tau^+
\]

\[
m_\pi^{-1} : \tau^+ \rightarrow \pi
\]

Third, this optimization is speculative, i.e., we need to take precautions to preserve semantics and recover from mispeculation. Preserving semantics of operating on unboxed data usually requires to use a tagged data format representation, where we reserve a set of bits to hold type information. But, we restrict ourselves to sequences where we know the types a priori, which allows us to remove the restrictions imposed by using a tagged data format, i.e., additional checking code and decreasing range of representable data. In general, whenever our speculation fails we need to generalize specialized instruction occurrences back to their more generic instructions and resume regular interpretation.

In all definitions, we use the superscript notation to indicate that a concrete instantiation of either c or m is able to project data onto multiple native machine words. For example, the following implementation section will detail one such case where we represent Python’s complex numbers by two native machine words.

**Abstract Interpretation** Taking inspiration from Leroy’s description of Java bytecode verification [33], we also use an abstract interpreter that operates over types instead of values. Using the type information captured in the previous step, for example from quickening from the type generic addOp to the optimized instruction derivative intAdd, we can propagate type information from operation instructions to the instructions generating its operands.

For example, we know that the intAdd instruction expects its operands to have type Int and produces an operand of type Int:

\[
\text{intAdd} : (\text{VInt}.\text{VInt}.S) \rightarrow (\text{VInt}.S)
\]

Similarly to our actual interpreter, the abstract interpreter uses a transition relation \(i : S \rightarrow S'\) to represent an instruction \(i\)'s effect on the operand stack. All interpreter instructions of the original instruction set are denoted by type-generic rules that correspond to the top element of the type lattice, i.e., in our case Value. The following rules exemplify the representation, where we only separate instructions by their arity:

\[
\text{unaryOp} : (\text{Value}.S) \rightarrow (\text{Value}.S)
\]

\[
\text{binaryOp} : (\text{Value}.\text{Value}.S) \rightarrow (\text{Value}.S)
\]

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., (Int, Bool, Float, String). For simplicity, our abstract interpreter ignores branches in the code, which limits our scope to propagate types along straight-line code, but on the other hand avoids data-flow analysis and requires only one linear pass to complete. This is important insofar as we perform this abstract interpretation at run-time and therefore are interested to keep latency introduced by this step at a minimum.

Type propagation proceeds as follows. The following example shows an original example program representation as emitted by some other program, e.g., another compiler:

\[
[\cdots, \text{push}^0, \text{push}^1, \text{addOp}^2, \text{push}^3, \text{addOp}^4, \text{pop}^5, \cdots]
\]

After executing this example program, the first-level quickening captures types encountered during execution:

\[
[\cdots, \text{push}^0, \text{push}^1, \text{intAdd}^2, \text{push}^3, \text{intAdd}^4, \text{pop}^5, \cdots]
\]

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

\[ \cdots, \text{push}^0_{\text{Int}}, \text{push}^1_{\text{Int}}, \text{intAdd}^2_{\text{Int}}, \text{push}^3_{\text{Int}}, \text{intAdd}^4_{\text{Int}}, \text{pop}^5_{\text{Int}}, \cdots \]

We denote the start and end instructions of a candidate sequence by `S` and `E`, respectively. In our example, the six element sequence starts with the first push instruction, and terminates with the pop instruction terminates:

\[ S := \text{push}^0_{\text{Int}} \]
\[ E := \text{pop}^5_{\text{Int}} \]

### Unboxed Instruction Derivatives

Analogous to the previous partial evaluation step we use to obtain the typed instructions operating exclusively on boxed objects, we can use the same strategy to derive the even more optimized derivatives. For regular operations, such as our `intAdd` example, this is simple and straightforward, as we just replace the boxed object representation `Value` by its native machine equivalent `Int`:

\[ \text{intAdd}' :: \text{Int} \rightarrow \text{Int} \rightarrow \text{Int} \]
\[ \text{intAdd}' x y = x + y \]

As a result, the compiler will generate an efficient native machine addition instruction and completely sidestep the resolving of dynamic types, as well as (un-)boxing and reference counting operations.

The problem with this `intAdd'` instruction derivative is, however, that we cannot perform a type check on the operands anymore, as the implementation only allows operands of type `Int`. In consequence, for preserving semantics of the original interpreter instructions, we need a new strategy for type checking. Our solution to this problem is to bundle type checks and unboxing operations together via function composition and move them to the load instructions which push unboxed operands onto the stack. Assuming that we modify the declaration of `Stack` to contain heterogeneous data elements (i.e., not only a list of `Value`, but also unboxed native machine words, denoted by `Ś`), pushing an unboxed integer value onto the operand stack looks like this:

\[ \text{pushInt} :: \text{Value} \rightarrow Ś \rightarrowŚ \]
\[ \text{pushInt} v s = \]
\[ \lambda \text{let} \]
\[ \text{unboxConvert} = \text{m}_{\text{Int}} \cdot \text{ci}_{\text{Int}} \cdot \text{pop} \]
\[ \text{boxPopInt} = \text{m}_{\text{Int}} \cdot \text{ci}_{\text{Int}} \cdot \text{pop} \]
\[ (\lambda x \text{ update } e \text{ ident } obj) \rightarrow s' \]

### Generalizing When Speculation Fails

In our example of the `pushInt` interpreter instruction, we see on the last line that there is a case when speculation fails. A specific occurrence of `pushInt` verifies that the operand matches an expected type such that subsequent instructions can modify its unboxed representation. Therefore, once the interpreter detects the misspeculation, we know that we have to invalidate all subsequent instructions that speculate on that specific type.

The interpreter can back out of the misspeculation and resume sound interpretation by i) finding the start of the speculatively optimized sequence, and ii) generalizing all specialized instructions up by at least one level. Both of these steps are trivial to implement, particularly since the instruction derivation steps result in having three separate instruction sets. Hence, the first step requires to identify the first instruction `i` that does not belong to the current instruction set, which corresponds to the predecessor of the start instruction `S` identified by our abstract interpreter. The second step requires that we map each instruction starting at offset `i + 1` back to its more general parent instruction—a mapping we can create and save when we create the initial mapping from an instruction `I` to its derivative `I'`.

To be sound, this procedure requires that we further restrict our abstract interpreter to identify only sequences that have no side-effects. As a result, we eliminate candidate sequences that have call instructions in between. This is however only an implementation limitation and not an approach limitation, since all non-local side-effects possible through function calls do not interfere with the current execution. Therefore, we would need to ensure that we do not re-execute already executed functions and instead push the boxed representation of a function call’s result onto the operand stack.
We use an abstract interpreter to identify candidate sequences of instructions. All instructions circled by the dotted line of Figure 1 are in-boxing or out-boxing of objects of type \( \pi \). This third instruction set operates on unboxed native machine data types, and therefore requires generic ways to handle (un)-boxing of objects of type \( \pi \) (cf. \( m_\pi \) and \( m_\pi^{-1} \)), as well as converting data to and from the operand stack (cf. \( c_\pi \) and \( c_\pi^{-1} \)).

### 4. Implementation

This section presents implementation details of how we use speculative staging of optimized interpreter instructions to substantially optimize execution of a Python 3 series interpreter. This interpreter is an implementation vehicle that we use to demonstrate concrete instantiations of our general optimization framework. We use an example sequence of instructions to illustrate both the abstract interpretation as well as deriving the optimized interpreter instructions. Python itself is implemented in C and we use casts to force the compiler to use specific semantics.

**Figure 1** shows, in a general form, how speculative staging of interpreter optimizations works. The first part of our technique requires speculatively staging optimized interpreter instructions at interpreter compile-time. In **Figure 1** the enclosing shaded shape highlights these staged instructions. We systematically derive these optimized interpreter instructions from the original interpreter instructions. The second part of our technique requires run-time information and converts the speculatively staged interpreter instructions such that optimized interpreter preserves semantics.

The interpreter starts out executing instructions belonging to its original instruction set (see (0) in **Figure 1**). During execution, the interpreter can capture type feedback by rewriting itself to optimized instruction derivatives. **Figure 1** shows this in step (1), where instruction \( I_j' \) replaces the more generic instruction \( I_j \), thereby capturing the type information \( \pi \) at offset \( j \). The next step, (2), propagates the captured type information \( \pi \) to a complete sequence of instructions, starting with instruction \( S \) and terminating in instruction \( E \).

We use an abstract interpreter to identify candidate sequences operating on the same type. Once identified, (3) of **Figure 1** illustrates how we rewrite a complete instruction sequence \( S, \ldots, E \) to optimized instruction derivatives \( S', \ldots, E' \). This third instruction set operates on unboxed native machine data types, and therefore requires generic ways to handle (un-)boxing of objects of type \( \pi \) (cf. \( m_\pi \) and \( m_\pi^{-1} \)), as well as converting data to and from the operand stack (cf. \( c_\pi \) and \( c_\pi^{-1} \)). All instructions circled by the dotted line of **Figure 1** are instruction derivatives that we speculatively stage at interpreter compile-time.

### 3.3 Putting It All Together

**Figure 1** shows our example Python instruction sequence and how we incrementally and iteratively rewrite this sequence using our speculatively staged optimized interpreter instruction derivatives. We use the prefix `INCA` to indicate optimized interpreter instruction derivatives used for inline caching, i.e., the first-level quickening. The third instruction set uses the `NAMA` prefix, which abbreviates native machine execution since all instructions directly operate on machine data and hence use efficient machine instructions to implement their operation semantics. This corresponds to the second-level quickening. Note that the `NAMA` instruction set is portable by construction, as it leverages the back-end of the ahead-of-time compiler at interpreter compile-time.

The `LOAD_FAST` instruction pushes a local variable onto the operand stack, and conversely `STORE_FAST` pops an object off the operand stack and stores it in the local stack frame. Table 1 lists the set of eligible start and end instructions for our abstract interpreter, and **Figure 2** illustrates the data flow of the instruction sequence as assembled by the abstract interpreter. In our example, the whole instruction sequence operates on a single data type, but in general the abstract interpreter needs to be aware of the type lattice implemented by the Python interpreter. For example, dividing two long numbers results in a float number and comparing two complex numbers results in a long number. We model these type conversions as special rules in our abstract interpreter.

Having identified a complete sequence of instructions that all operate on operands of type `PyFloat_Type`, we can replace all instructions of this sequence with optimized derivatives directly operating on native machine `float` numbers.

### 4.1 Deriving Optimized Python Interpreter Instructions

In this section we present details to implement speculative staging of optimized interpreter instructions in a methodological fashion. First, we are going describe the functions we use to (un-)box Python objects and the conventions we use to pass operand data on the mixed-value operand stack. We treat arithmetic operations for Python’s integers, floating point and complex numbers, though our technique is not limited...
to these. Second, we illustrate the derivation steps in concrete Python code examples—while in theory we could use a partial evaluator to generate the derivatives, the manual implementation effort is so low that it does not justify using a partial evaluator.

### 4.1.1 (Un-)boxing Python Objects

The Python interpreter supports uniform procedures to box and unbox Python objects to native machine numbers, and we just briefly mention which functions to use and give their type.

#### Integers

Python represents its unbounded range integers by the C struct `PyLong_Type`.

- `m_{PyLong_Type} := PyLong_AS_LONG : PyLongObject* → int64`
- `m_{PyLong_Type} := PyLong_FROM_LONG : int64 → PyLongObject*`

#### Floating Point Numbers

Floating point numbers are represented by the C struct `PyFloat_Type`.

- `m_{PyFloat_Type} := PyFloat_AS_DOUBLE : PyFloatObject* → double`
- `m_{PyFloat_Type} := PyFloat_FromDouble : double → PyFloatObject*`

#### Complex Numbers

Complex numbers are represented by the C struct `PyComplex_Type`, but we cannot directly access a native machine representation of its data. This is due to a complex number consisting of two parts, a real and an imaginary part:

```c
typedef struct {
  double real;
  double imag;
} complex_t;
```

Furthermore, we need to know something about the internals of the `PyComplex_Type` implementation to access the native machine data. Internally, Python uses a similar struct to `complex_t (Py_complex)` to hold the separate parts and we can access the data via `((PyComplexObject*)x)->cval`.

- `m_{PyComplex_Type} := PyComplexObject* → (double, double)`
- `m_{PyComplex_Type} := (double, double) → PyComplexObject*`

### 4.1.2 Operand Stack Data Passing Convention

Across all three instruction sets, instructions pass operands using the operand stack. The original Python instruction set operates exclusively on Python objects which reside on the heap, i.e., the operand stack passes pointers to the heap, of type `uint64` on a 64-bit machine. The lowest level instruction set operates on native machine data, i.e., we need to map native machine data types to the existing operand stack. We rely on C constructs of explicit casts and unions to ensure that we attach the proper semantics to the bits passed around.
Passing Integers  Naturally, it is trivial in C to support passing integers on the mixed operand stack: we simply cast from the signed integer representation to the unsigned representation used for pointers, too.

\[
\begin{align*}
&c_{\text{int64}}(o : \text{int64}) := (\text{uint64})o \\
&c_{\text{int64}}^{-1}(o : \text{uint64}) := (\text{int64})o
\end{align*}
\]

Passing Floats  To pass floating point numbers, we need to avoid implicit casting a C compiler would insert when using a cast from double to uint64. A solution is to use the following union:

```c
typedef union { uint64 word; double dbl; } map_t;
```

Map_t allows us to change the semantics by using the corresponding field identifier and thus suffices to map doubles to uint64 representation in a transparent and portable fashion.

\[
\begin{align*}
&c_{\text{double}}(o : \text{double}) := (\text{map_t m}; \text{m.dbl} = o; (\text{uint64})m.\text{word}) \\
&c_{\text{double}}^{-1}(o : \text{uint64}) := (\text{map_t m}; \text{m.word} = o; \text{m.dbl})
\end{align*}
\]

Passing Complex Numbers  As previously described, we represent a complex number using two double numbers. Therefore, we can reuse the functions that map floating point numbers:

\[
\begin{align*}
&c_{\text{complex}}(o : \text{complex_t}) := (c_{\text{double}}(o.\text{real}), c_{\text{double}}(o.\text{imag})) \\
&c_{\text{complex}}^{-1}(i : \text{uint64}, r : \text{uint64}) := (\text{complex_t} c; \\
&\quad c.\text{real} = c_{\text{double}}^{-1}(r); c.\text{imag} = c_{\text{double}}^{-1}(i)
\end{align*}
\]

But, the operand stack passing convention alone does not suffice since passing native machine complex numbers requires two stack slots instead of one. Consequently, we double the operand stack size such that all instruction operands on the stack could be two-part complex numbers. Since the abstract interpreter identifies whole sequences of instructions, there is always a termination instruction that boxes the two-part double numbers into a PyComplexObject instance. As a result, this temporary use of two operand stack slots is completely transparent to all predecessor instructions of the sequence as well as all successor instructions of the sequence.

4.1.3 Example Instructions

The previous section contains all details necessary to inductively construct all optimized interpreter instructions that modify native machine data types. In this section, we give concrete Python interpreter instruction implementation examples for completeness.

Original Python Instruction  The following program excerpt shows Python’s original implementation of the arithmetic subtraction operation:

```c
v = TOP();
BINARY_SUBTRACT_MISS:
\begin{align*}
x &= \text{PyNumber}\_\text{Subtract}(v, w); \\
\text{Py}\_\text{DECREP}(v); \\
\text{Py}\_\text{DECREP}(w); \\
\text{SET}\_\text{TOP}(x);
\end{align*} 
if (x != NULL) DISPATCH();
\begin{align*}
goto \text{on}\_\text{error};
\end{align*}
```

The resolving procedure of dynamic types is not visible and resides in the PyNumber\_Subtract function. The resolving is much more complicated than our simplified interpreter substrate suggests, in particular due to the presence of ad-hoc polymorphism and inheritance. In our simplified interpreter substrate all dynamic types were known at compile-time and we could use pattern matching to express semantics properly and exhaustively. For languages such as Python, this is in general not possible. For example, one could use operator overloading for integers to perform subtraction, or perform the traditional integer addition by inheriting from the system’s integers.

First-level Quickening  By fixing operands v and w to the type PyFloat\_Type, we can derive the following optimized instruction derivative, expressed as INCA_FLOAT\_SUBTRACT.

```c
\begin{align*}
\text{case INCA_FLOAT\_SUBTRACT:}
\end{align*}
```

On lines four to seven, we see what happens on misspeculation. After the type check (stylized by symbol \(\exists\)) fails, we resume execution of the general instruction that INCA_FLOAT\_SUBTRACT derives from, BINARY\_SUBTRACT in this case. We change the implementation of BINARY\_SUBTRACT to add another label that we can use for resuming correct execution.

Directly calling \text{nb}\_\text{sub} on PyFloat\_Type optimizes the complex resolving of dynamic typing hinted at before.

Furthermore, this type-specialized instruction derivative illustrates that we can in fact infer that both operands as well as the result (x) are of type PyFloat\_Type.

Second-level Quickening  The second-level quickening step optimizes sequences of interpreter instructions to directly modify native machine data. Hence, we move the required type check to the corresponding load instruction:

```c
\begin{align*}
\text{case INCA_FLOAT_LOAD_FAST:}
\end{align*}
```

The resolving procedure of dynamic types is not visible and resides in the PyNumber\_Subtract function. The resolving is much more complicated than our simplified interpreter substrate suggests, in particular due to the presence of ad-hoc polymorphism and inheritance. In our simplified interpreter substrate all dynamic types were known at compile-time and we could use pattern matching to express semantics properly and exhaustively. For languages such as Python, this is in general not possible. For example, one could use operator overloading for integers to perform subtraction, or perform the traditional integer addition by inheriting from the system’s integers.

```c
\begin{align*}
\text{case INCA_FLOAT_LOAD_FAST:}
\end{align*}
```
The corresponding floating point subtract operation need not perform any type checks, reference counting, or (un-)boxing operations anymore:

```c
case NAMA_FLOAT_SUBTRACT:
    w = POP();
    v = TOP();
{
    map_t s, t;
    s.word = (uint64)v;
    t.word = (uint64)w;
    s.dbl -= t.dbl;
    SET_TOP(s.word);
    DISPATCH();
}
```

Both of the native floating point interpreter instructions make use of the `map_t` union as previously explained to avoid implicit conversions as emitted by the compiler.

In general, the type-specific load instructions have to validate all assumptions needed to manipulate unboxed native machine data. For example, integers in Python 3 are by default unbounded, i.e., they can exceed native machine bounds. As a result, we modify the corresponding integer load instruction to check whether it is still safe to unbox the integer. However, it is worth noting that these are only implementation limitations, as for example we could expand this technique to use two machine words and perform a 128-bit addition because we already doubled the stack size to accommodate complex numbers.

**Implementation Remarks** The first-level quickening step has already been explored in 2010 by Brunthaler [7, 8], and we used his publicly available implementation [9] as a basis for ours. In the remainder of this paper, we refer to the original interpreter as INCA (an abbreviation for inline caching), and the modified interpreter that supports the new optimizations as MLQ, which is short for multi-level quickening.

We use a simple code generator written in Python that generates the C code for all instructions of the Python interpreter. We run our code generator as a pre-compile step when compiling the interpreter, and rely on the existing build infrastructure to build the interpreter. In consequence, all of the instruction derivatives speculatively added to the interpreter and available for concerting at run-time; sidestepping dynamic code generation altogether.

We provide templates of the C instructions using the language of the Mako template engine [2]. The semantics of all instruction derivatives is essentially identical, e.g., adding numbers, which is why derivative instructions are merely optimized copies operating on specialized structures or types. Hence, these templates capture all essential details and help keeping redundancy at bay. If we were to create a domain-specific language for generating interpreters, similar to the VMgen/Tiger [10] project, we could express the derivative relationship for instructions, thereby reducing the costs for creating these templates. The next section provides lines-of-code data regarding our interpreter implementation generator (see Section 5.2).

## 5. Evaluation

**Systems and Procedure** We ran the benchmarks on an Intel Nehalem i7-920 based system running at a frequency of 2.67 GHz, on Linux kernel version 3.0.0-26 and gcc version 4.6.1. To minimize perturbations by third party systems, we take the following precautions. First, we disable Intel’s Turbo Boost [28] feature to avoid frequency scaling based on unpublished, proprietary 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, thereby minimizing bias towards outliers.

**Benchmarks** We use several benchmarks from the computer language benchmarks game [22]. This is due to the following reasons. First, since we are using a Python 3 series interpreter, we cannot use programs written for Python 2 to measure performance. Unfortunately, many popular third party libraries and frameworks, such as Django, twisted, etc., have not released versions of their software officially supporting Python 3. Compatibility concerns aside, the Python community has no commonly agreed upon comprehensive set of benchmarks identified to assess Python performance. Second, some popular libraries have custom C code modules that perform computations. Effectively, benchmarking these programs corresponds to measuring time not spent in the interpreter, and therefore would skew the results in the wrong direction. Instead, we use the following benchmarks that stress raw interpreter performance: binarytrees, fannkuch, fasta, mandelbrot, nbody, and spectralnorm.

Finally, we rely on those benchmarks because they allow comparison with other implementations, such as PyPy. PyPy officially only supports Python 2, but since none of those benchmarks use Python 3 specifics—with the notable exception of fannkuch, which required minor changes—we run the identical programs under PyPy. This may sound like a contradiction, but is in fact only possible with the chosen set of programs and cannot in general be expected to hold for other programs.

### 5.1 Benchmark Results

Figure 4 shows the performance results obtained on our test system. We report a maximum speedup by up to a factor of 4.222 over the CPython 3.2.3 interpreter using switch dispatch. INCA itself improves performance by up to a factor of 1.7362. As a result, the MLQ system improves upon the previous maximum speedups by 143%.

**PyPy Comparison** Even though our speculatively staged MLQ interpreter is no match in comparison to the multi-year, multi-person effort that went into the PyPy implementation (see implementation measurements in the discussion in Section 5.3), we want to give a realistic perspective of the potential of MLQ interpretation. Therefore, we evaluated the
Table 2: Speedups of PyPy 1.9 and our MLQ system normalized by the CPython 3.2.3 interpreter using switch-dispatch.

| Benchmark       | PyPy 1.9 | MLQ    | $\text{PyPy}_{\text{MLQ}}$ |
|-----------------|----------|--------|-----------------------------|
| binarytrees     | 3.2031   | 1.8334 | 1.7471                      |
| fannkuch        | 8.2245   | 1.5240 | 5.2884                      |
| fasta           | 13.4537  | 1.6906 | 7.9579                      |
| mandelbrot      | 6.3224   | 1.9699 | 3.2095                      |
| nbody           | 12.3592  | 2.0639 | 5.9883                      |
| spectralnorm    | 3.5563   | 4.0412 | 0.8800                      |

Table 2 lists the geometric mean of speedups per benchmark that we measured on our Intel Nehalem system. During our experiment we also measured overall memory consumption and report that our system uses considerably less memory at run-time: PyPy uses about 20 MB, whereas our MLQ interpreter uses less than 7 MB. This is primarily due to the systems using different memory management techniques: MLQ uses CPython’s standard reference counting, whereas PyPy offers several state-of-the-art garbage collectors, such as a semi-space copying collector and a generational garbage collector. Surprisingly, we find that using a more powerful memory management technique does not automatically translate to higher performance. Since MLQ is particularly effective at eliminating the overhead of reference counting—reducing required reference count operations, as well as using native-machine data instead of boxed objects—we can take full advantage of its benefits: determinism and space-efficiency [15].

5.2 Interpreter Data

We rely on David Wheeler’s sloccount utility [44] to measure lines of code. For calculating the number of interpreter instructions, we use a regular expression to select the beginning of the instructions and wc -l to count their occurrences.

**Instruction-Set Extension** The CPython 3.2.3 interpreter has 100 interpreter instructions spanning 1283 lines of code. The INCA instruction set of the INCA interpreter adds another 53 instructions to the interpreter, totaling 3050 lines of code (i.e., a plus of 138% or 1767 lines of code). NAMA itself requires additional 134 interpreter instructions adding another 1240 lines of code (increase by 41% over INCA). We adapted the existing Python code generator of the INCA system to generate the NAMA instruction derivatives’ C implementation. The original code generator has 2225 lines of Python code, where 1700 lines of code just reflect the type structure code extracted from the C structs of Python objects via gdb. The required changes were about 600 lines of Python code, resulting in the updated code generator having 2646 lines of Python code. The INCA code generator uses 2225 lines of C code templates. To support the NAMA instruction set, we added another 1255 lines of templated C code—giving 3480 lines of template code in total. In addition to this, our abstract interpreter identifying eligible sequences requires around 400 lines of C code.

**Portability** As we have briefly mentioned before, our speculative staging leverages the existing backend of the ahead-of-time compiler that is used to compile the interpreter. There-
fore, our technique is portable by construction, i.e., since we implemented our optimized derivatives in C, the interpreter is as portable as any other C program. We confirm this by compiling the optimized interpreter on a PowerPC system. This did not require changing a single line of code.

**Space Requirements** Table 3 presents the effect of implementing our speculatively staged MLQ Python interpreter on the binary size of the executable. We see that going from a switch-based interpreter to a threaded code interpreter requires additional 12 kB of space. Finally, we see that adding two additional instruction sets to our Python interpreter requires less than 110 kB of additional space (when discounting the space requirement from threaded code).

### 5.3 Discussion

The most obvious take-away from Figure 4 is that there is clearly a varying optimization potential when using our optimization. Upon close investigation, we found that this is due to our minimal set of eligible start and end instructions (see Table 1). For example, there are other candidates for start instructions that we do not currently support, such as LOAD_ATTR, LOAD_NAME, LOAD_GLOBAL, LOAD_DEREF. In consequence, expanding the abstract interpreter to cover more cases, i.e., more instructions and more types, will improve performance even further. Spectralnorm performs best, because our abstract interpreter finds that all of the instructions of its most frequently executed function (eval_lambda) can be optimized.

Finally, we were surprised about the performance comparison with PyPy. First, it is striking that we outperform PyPy 1.9 on the spectralnorm benchmark. Since we include start-up and warm-up times, we decided to investigate whether this affects our result. We timed successive runs with higher argument numbers (1000, 1500, 2000, and 4000) and verified that our interpreter maintains its performance advantage. Besides this surprising result, we think that the performance improvement of our interpreter lays a strong foundation for further optimizations. For example, we believe that implementing additional instruction-dispatch based optimizations, such as superinstructions [19, 39] or selective inlining [37], should have a substantial performance impact.

Second, we report that the interpreter data from Section 5.2 compares favorably with PyPy, too. Using sloccount on the pypy directory on branch version-1.9 gives the following results. For the interpreter directory, sloccount computes 25,991, and for the jit directory 83,435 lines of Python code. The reduction between the 100kLOC of PyPy and the 6.5kLOC of MLQ is by a factor of almost 17×. This is a testament to the ease-of-implementation property of interpreters, and also of purely interpretative optimizations in general.

### 6. Related Work

**Partial Evaluation** In 1996, Leone and Lee [31] present their implementation of an optimizing ML compiler that relies on run-time feedback. Interestingly, they mention the basic idea for our system:

> 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.

In similar vein to Leone and Lee, other researchers addressed the prohibitive latency requirements of dynamic compilation [12, 13, 18, 25, 36] by leveraging ideas from partial evaluation. While we take inspiration from these prior results, we address the latency problem superimposed by dynamic code generation by avoiding it altogether. Instead, we speculate on the likelihood of the interpreter using certain kinds of types and derive optimized instructions for them. At run-time, we rely on our novel procedure of concerting these optimized derivatives via abstract interpretation driven multi-level quickening. That being said, since these approaches are orthogonal, we believe that there are further advancements to be had by combining these approaches. For example, C, or the recently introduced Terra/Lua [17], could be used to either stage the optimized derivatives inside of the interpreter source code, or generate the necessary derivatives at run-time, thereby eliminating the speculation part.

The initial optimization potential of partial evaluation applied to interpreters goes back to Futamura in 1971 [23]. But, prior work has repeatedly revisited this specific problem. In particular, Thibault et al. [43] analyze the performance potential of partially evaluated interpreters and report a speedup of up to four times for bytecode interpreters. This result is intimately related to our work, in particular since they note that partial evaluation primarily targets instruction dispatch when optimizing interpreters—similar to the first Futamura projection. In 2009, Brunthaler established that instruction dispatch is not a major performance bottleneck for our class of interpreters [6]. Instead, our approach targets
known bottlenecks in instruction implementation: dynamic typing, reference counting operations, and modifying boxed value representations.

Glick and Jørgensen also connect interpreters with partial evaluation [24], but as a means to optimize results obtained by applying partial evaluation. Our technique should achieve similar results, but since it is speculative in nature, it does not need information of the actual program P that is interpreted, which is also a difference between our work and Thibault et al. [43].

**Interpreter Optimization** The most closely related work in optimizing high-level interpreters is due to Brunthaler [7, 8]. In fact, the first-level quickening step to capture type feedback goes back to the discovery by Brunthaler, and we have compared his publicly available system against our new technique. In addition to the second-level quickening that targets the overheads incurred by using boxed object representations, we also describe a principled approach to using partial evaluation for deriving instructions.

**Just-in-time compilers** Type feedback has a long and successful history in just-in-time compilation. In 1994, Hölzle and Ungar [26, 27] discuss how the compiler uses type feedback to inline frequently dispatched calls in a subsequent compilation run. This reduces function call overhead and leads to a speedup by up to a factor of 1.7. In general, subsequent research gave rise to adaptive optimization in just-in-time compilers [11]. Our approach is similar, except that we use type feedback for optimizing the interpreter.

In 2012, there has been work on “repurposed JIT compilers,” or RJITs, which take an existing just-in-time compiler for a statically typed programming language and add support for a dynamically typed programming language on top [11, 29]. This approach is interesting, because it tries to leverage an existing just-in-time compilation infrastructure to enable efficient execution of higher abstraction-level programming languages—similar to what has been described earlier in 2009 by Bolz et al. [3] and Yermolovich et al. [45], but more invasive. Unfortunately, the RJIT work is unaware of recent advances in optimizing interpreters, and therefore misses some important optimization opportunities available to a repurposed just-in-time compiler. Würthinger et al. [45] found that obtaining information from the interpreter has substantial potential to optimize JIT compilation, and we anticipate that this is going to have major impact on the future of dynamic language implementation.

Regarding traditional just-in-time compilers, Python nowadays only has one mature project: PyPy [41]. PyPy follows a trace-based JIT compilation strategy and achieves substantial speedups over standard CPython. However, PyPy has downsides, too: because its internals differ from CPython, it is not compatible with many third party modules written in C. Our comparison to PyPy finds that it is a much more sophisticated system offering class-leading performance on some of our benchmarks. Surprisingly, we find that our technique outperforms PyPy by up to 14% on the spectralnorm benchmark, and requires substantially less implementation effort.

**Miscellaneous** Prior research addressed the importance of directly operating on unboxed data [32, 35]. There are certain similarities, e.g., Leroy’s use of the $\text{wrap}$ and $\text{unwrap}$ operators are related to our (un-)boxing functions, and there exist similar concerns in how to represent bits in a uniform fashion. The primary difference to the present work is that we apply this to a different language, Python, which has a different sets of constraints and is dynamically typed.

In 1998, Shields et al. [42] address overhead in dynamic typing via staged type inference. This is an interesting approach, but it is unclear if or how efficient this technique scales to Python-like languages. Our technique is much simpler, but we believe it could very well benefit of a staged inference step.

7. **Conclusions**

We present a general theory and framework to optimize interpreters for high-level languages such as JavaScript, Python, and Ruby. Traditional optimization techniques such as ahead-of-time compilation and partial evaluation only have limited success in optimizing the performance of these languages. This is why implementers usually resort to the expensive implementation of dynamic compilers—evidenced by the substantial industry efforts on optimizing JavaScript. Our technique preserves interpreter characteristics, such as portability and ease of implementation, while at the same time enabling substantial performance speedups.

This important speedup is enabled by peeling off layers of redundant complexity that interpreters conservatively re-execute instead of capitalizing on the “dynamic locality of type usage”—almost three decades after Deutsch and Schiffman described how to leverage this locality for great benefit. We capitalize on the observed locality by speculatively staging optimized interpreter instruction derivatives and concerting them at run-time.

First, we describe how speculation allows us to decouple the partial evaluation from any concrete program. This enables a principled approach to deriving the implementation of optimized interpreter instruction derivatives by speculating on types the interpreter will encounter with a high likelihood.

Second, we present a new technique of concerting optimized interpreter instructions at run-time. At the core, we use a multi-level quickening technique that enables us to optimize untyped instructions operating on boxed objects down to typed instructions operating on native machine data.

From a practical perspective, our implementation and evaluation of the Python interpreter confirms that there is a huge untapped performance potential waiting to be set free. Regarding the implementation, we were surprised how easy it was to provide optimized instruction derivatives even without automated support by partial evaluation. The evaluation indicates that our technique is competitive with
a dynamic compiler w.r.t. performance and implementation effort: besides the speedups by a factor of up to 4.222, we report a reduction in implementation effort by about 17×.

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