Bringing Performance and Scalability to Dynamic Languages

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Dynamic Languages

Ruby

JavaScript

python

php

Julia

MATLAB

The Language of Technical Computing

R

J

SMALLTALK

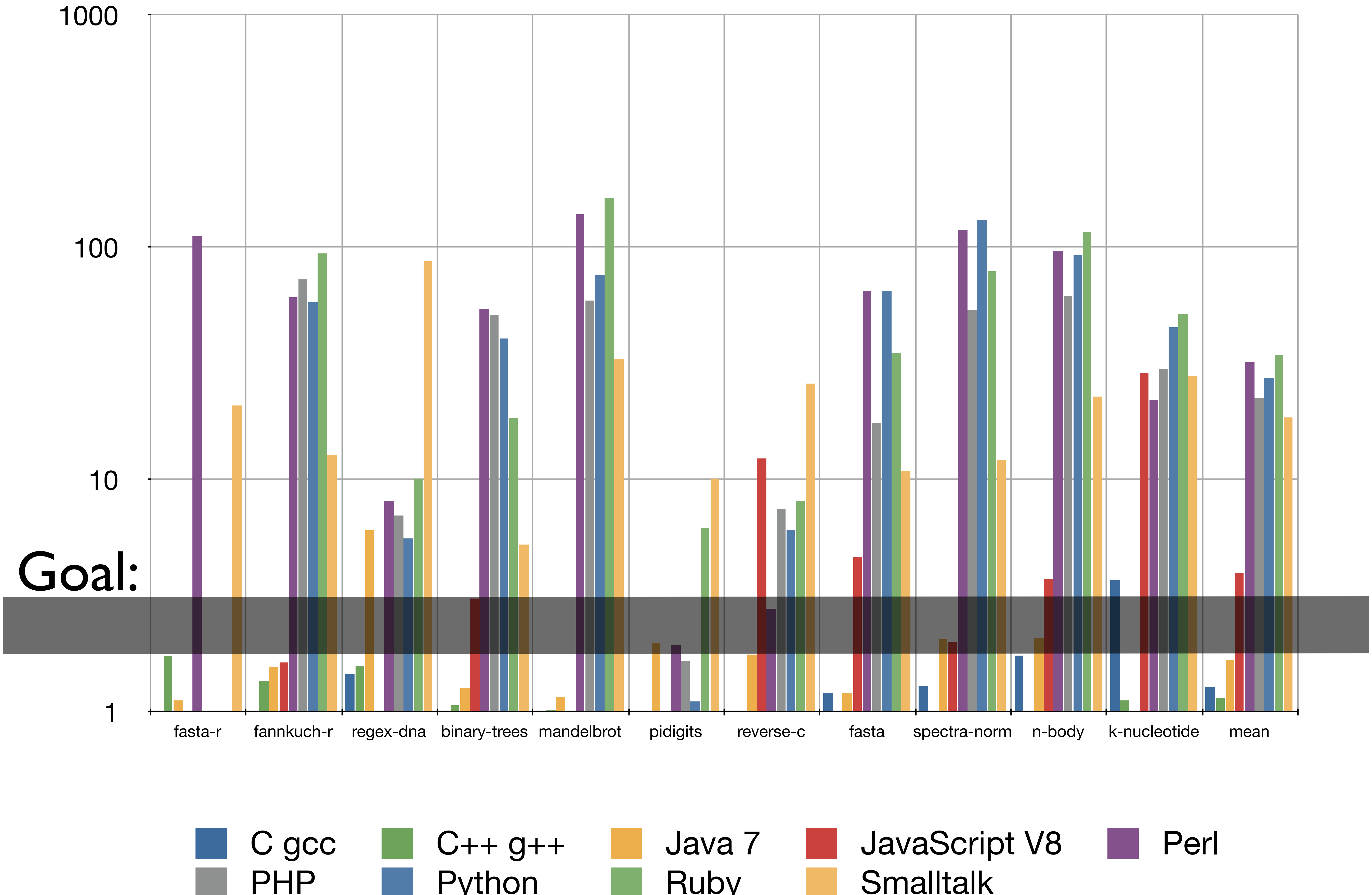
APL

perl

Common Characteristics of Dynamic Languages

- Modest adoption (~10^4–10^6 users/developers)
  - Easy to get started
  - Well adapted to a niche
    - Web: JavaScript, Perl, PHP, Python, Ruby
    - Technical: R, Julia, MATLAB, APL, J
- Features:
  - Absence of type declarations
  - Objects and/or vectors/strings at the core
  - Lexical scoping, closures, reflection, eval
- Fairly slow implementations (10–100x off optimal)

Relative speeds of various languages (Language Shootout benchmarks)



Why are they slow?

- Interpretation is easy to implement, but highly inefficient
- Consider the execution of a simple expression, `a+b:`
  - Find out the type of `a`
  - Find out the type of `b`
  - Find out what + means
  - Check that the operation is applicable to the data types, throw error if not
  - Prepare the data (e.g, strip tags)
  - **Invoke the operation**
  - Convert the result to canonical form (add tags)

VM implementation history, part 1 of 3:
Bytecodes plus simple Just-In-Time compilation: dragging performance out of the mud (1983–89)

- Instead of interpreting a parse tree, create an instruction set for a *virtual* machine (often a stack machine) and interpret those instructions
  - BCPL O-code, 1960s, UCSD Pascal (1978), Smalltalk (1976)
  - Somewhat denser representation, using bytecode

```
push a
push b
add
```

- Faster still: “macro-expand” instructions into machine code, just-in-time (ParcPlace Smalltalk, 1983)
  - Trades interpreter decode and dispatch overhead for compilation cost
  - 10x faster

VM implementation history, part 2:
Feedback-driven, adaptive compilation: Respectable performance (1989–95)

- Q. High performance comes from compiled code with known types–but where is the type information?
- A. The types are in the data, not in the code.
  The data are only available at run time.
- Thankfully, most expressions in real programs are *monomorphic* (i.e., use only one type combination).
- Solution: interpret for a short while, observe the actual types, and then compile code with optimistic assumptions and aggressive inlining (Self, Sun Labs, 1992).
- If assumptions are wrong, take slow path, or discard compiled code, revert to interpretation (*deoptimization*), recompile again later.
- Another 5x performance gain

VM implementation history, part 3:
Reduction to practice, deployment in production (1996–present)

- Java, even though typed, can benefit:
  - No ahead-of-time compilation
  - Types can drive method resolution, inlining
  - Large inlined regions present plenty of opportunity for optimization (another 3x?)
  - Current HotSpot JVM is ~50x faster than JDK1.0 (interpreted bytecodes)
- Similar techniques adopted by other production VMs: IBM J9 JVM, Microsoft CLR, JavaScript V8.

The state of the art: performance, at a price

- High performance, at a high price in complexity:
  - 1–2MLOC? 200–500 engineer years? $100M?
- Responses: research JVMs, written in Java, to reduce the high price (safer language, better tools, better factoring).
  - Jikes (IBM), Maxine (Sun/Oracle): Neither is in production.
- None of the dynamic languages have had this kind of investment (except JavaScript, partially).

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Alphabet Soup: Fusing interpretation and compilation

- What does the compiler need?
  1. The region of code being compiled
  2. The types of the operands
  3. The semantics of the operations, as code
- In a conventional VM, #3 is implemented twice:
  1) in the interpreter (easy) or JIT compiler (moderate)
  2) in the optimizing compiler (hard)

Can we do better?

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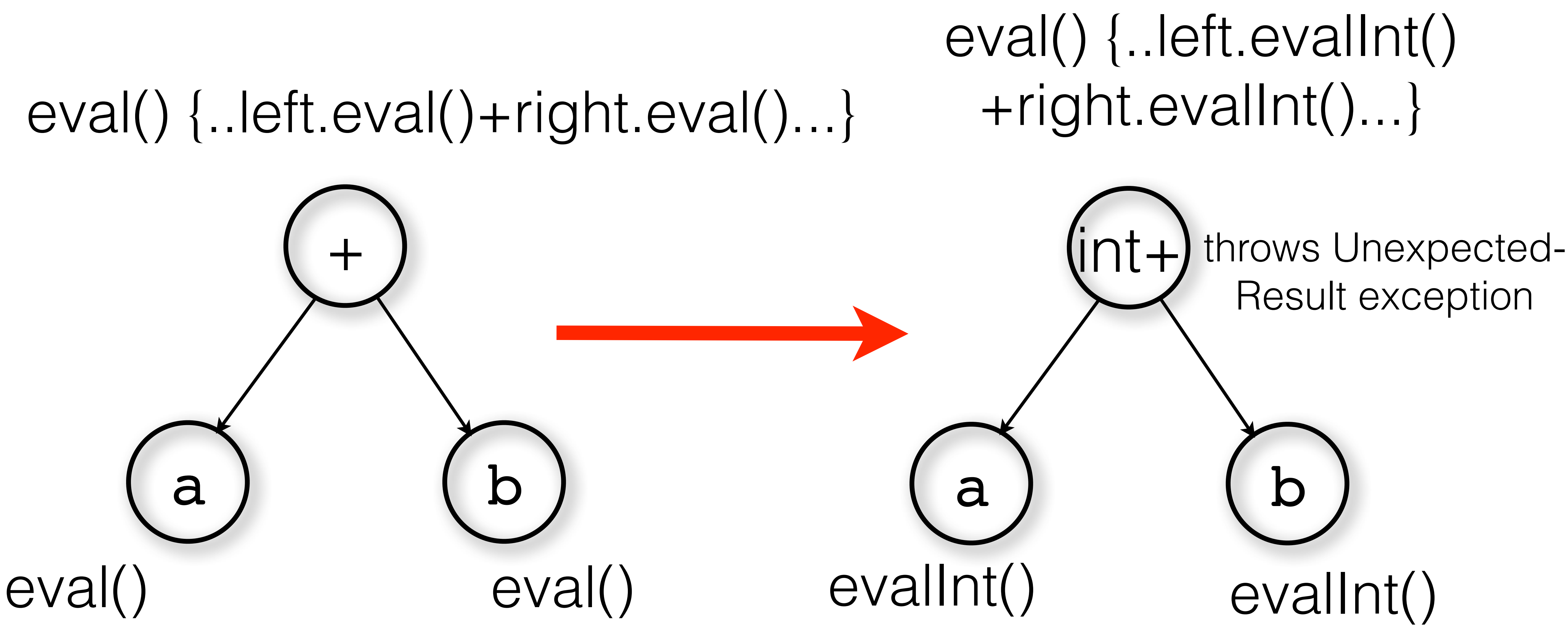
AST rewriting during interpretation to gather types



Rewritten node does less work in subsequent evaluations

Before:

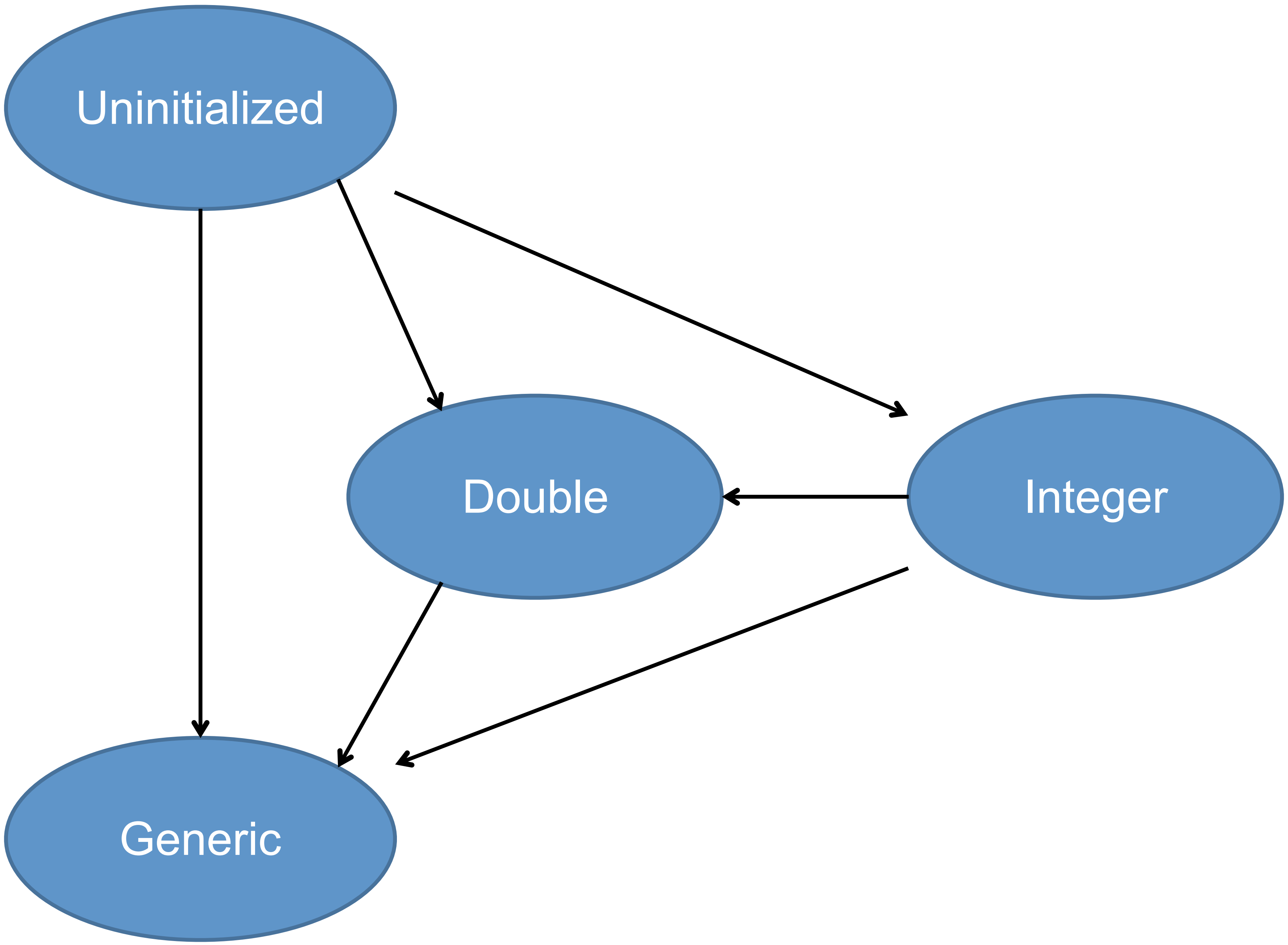
- Find out the type of `a`
- Find out the type of `b`
- Find out what + means
- Check that the operation is applicable to the data types, throw error if not
- Prepare the data (e.g, strip tags)
- **Invoke the operation**
- Convert the result to canonical form (add tags)

Rewritten node does less work in subsequent evaluations

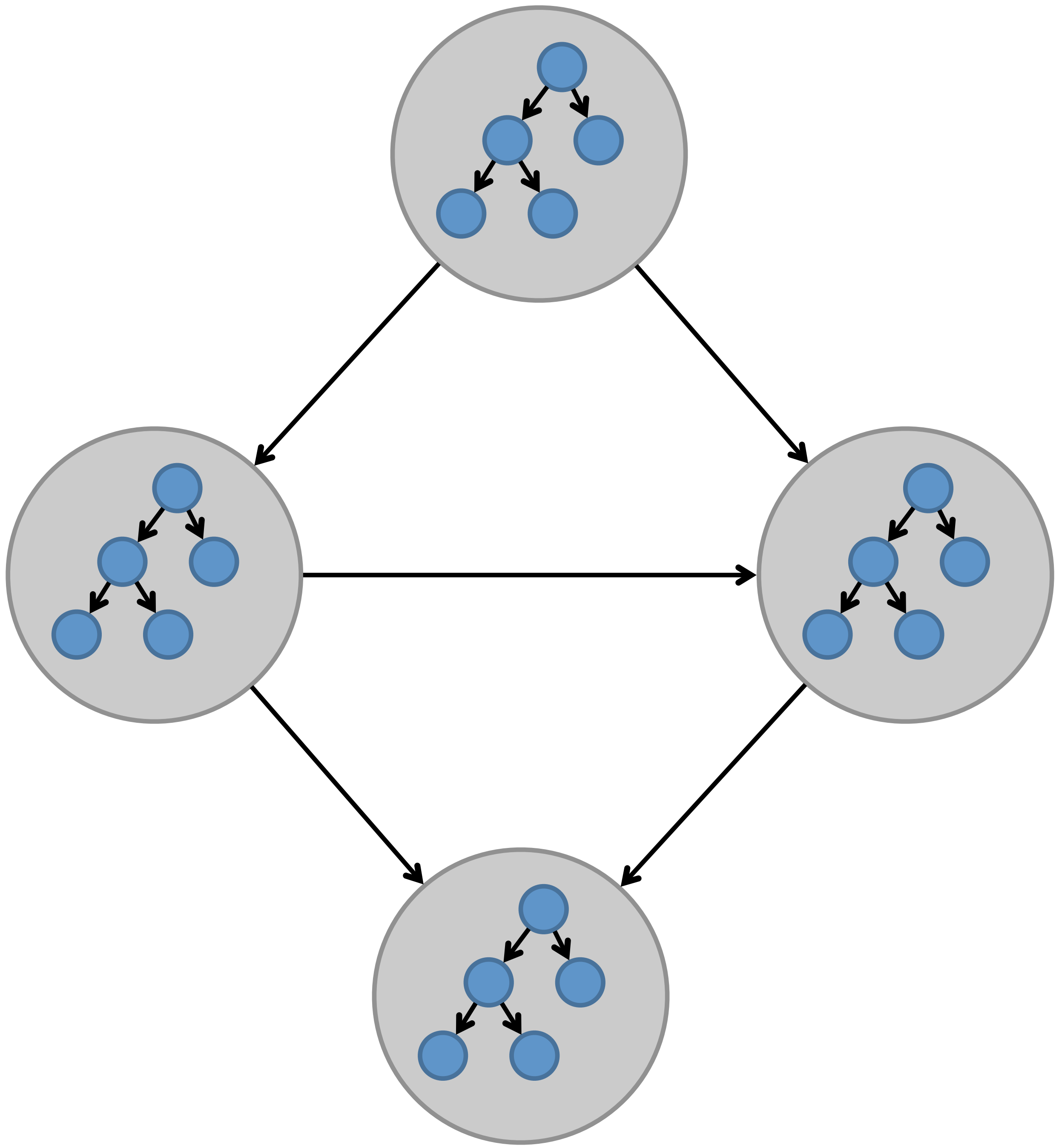
After:

- ~~Find out the type of `a`~~
- ~~Find out the type of `b`~~
- ~~Find out what + means~~
- Check that the operation is applicable to the data types, throw error if not
- ~~Prepare the data (e.g, strip tags)~~
- **Invoke the operation**
- ~~Convert the result to canonical form (add tags)~~

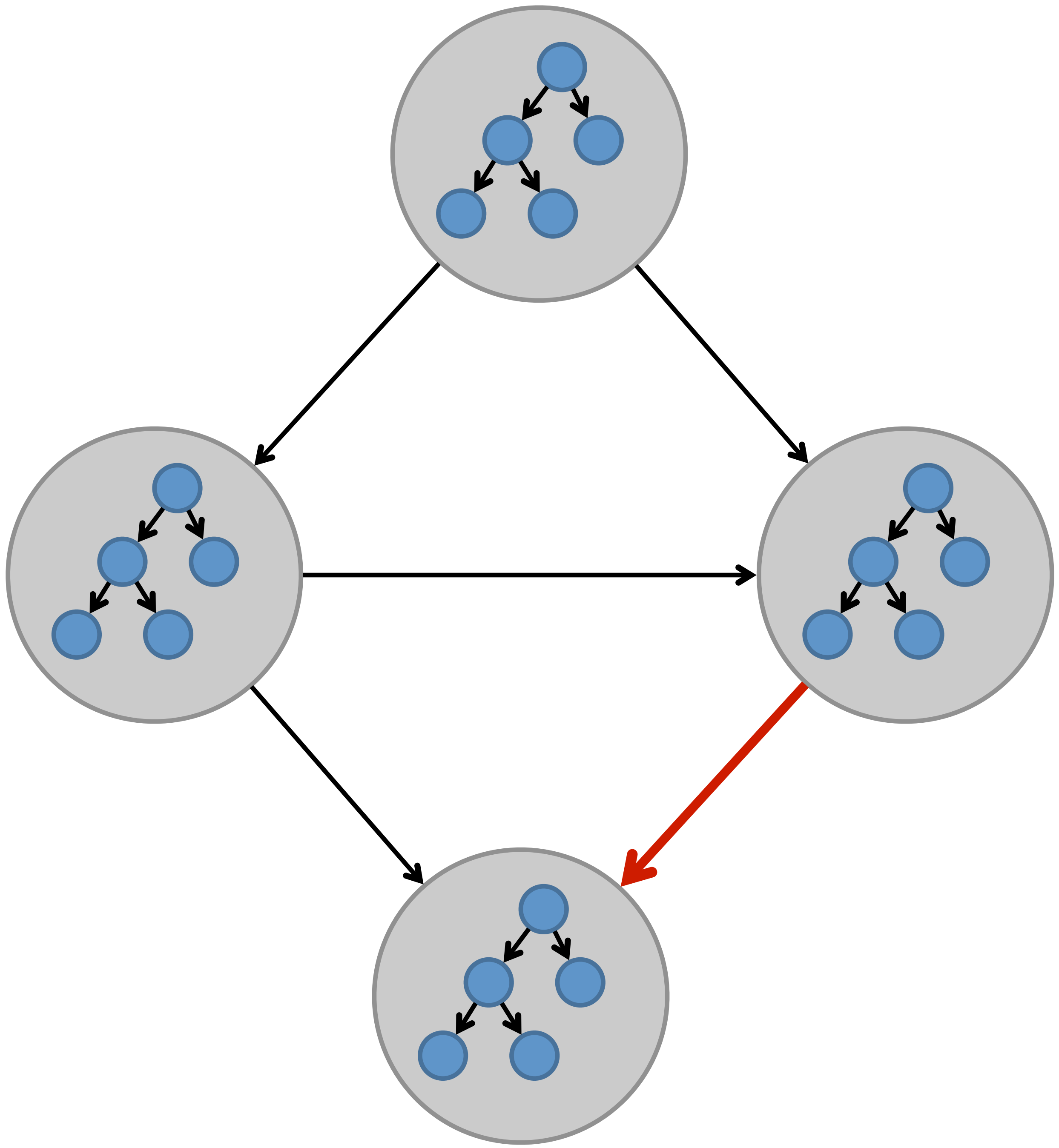
JavaScript Arithmetic Operations: Node State Graph



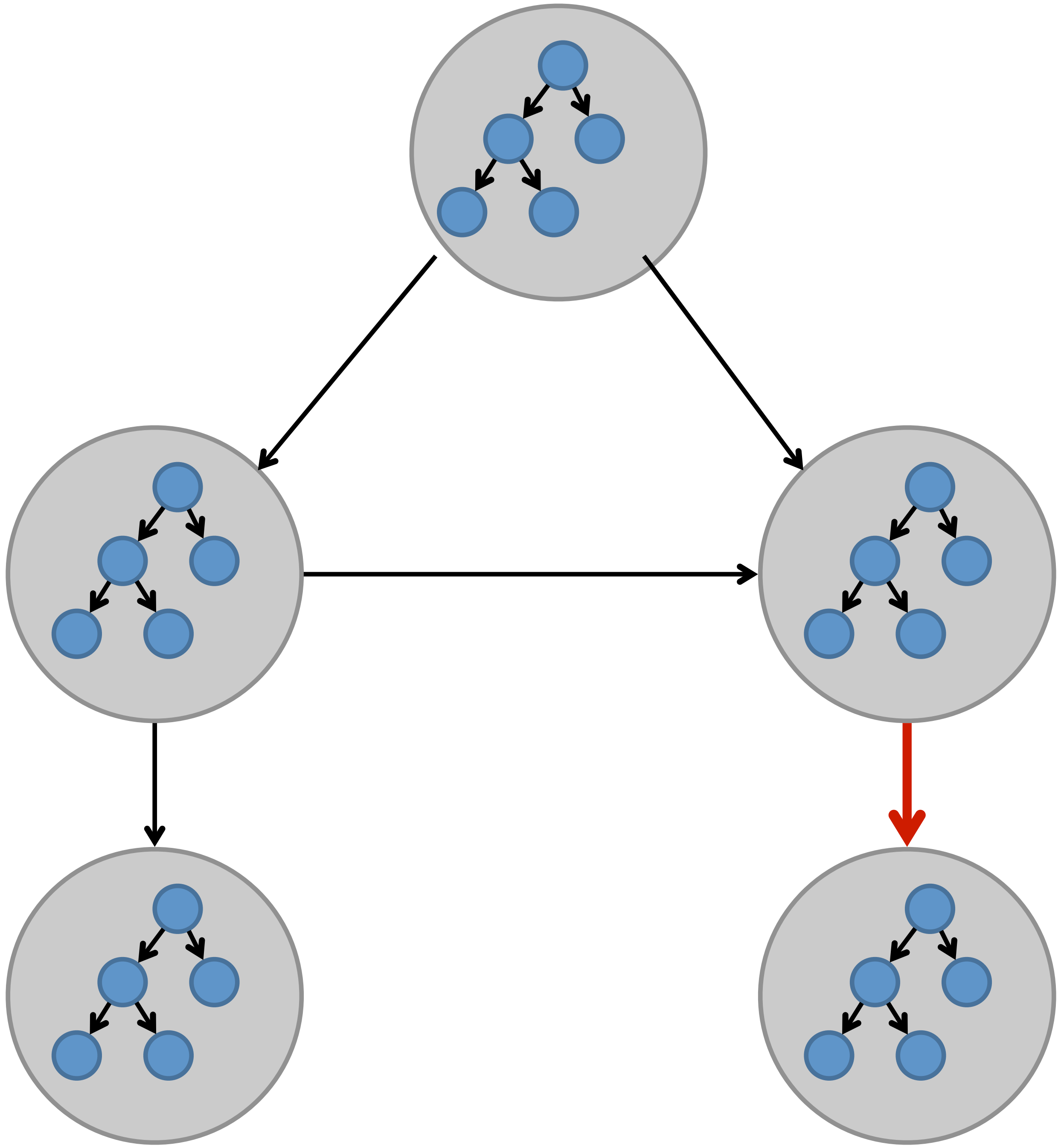
Optimization of programs during interpretation



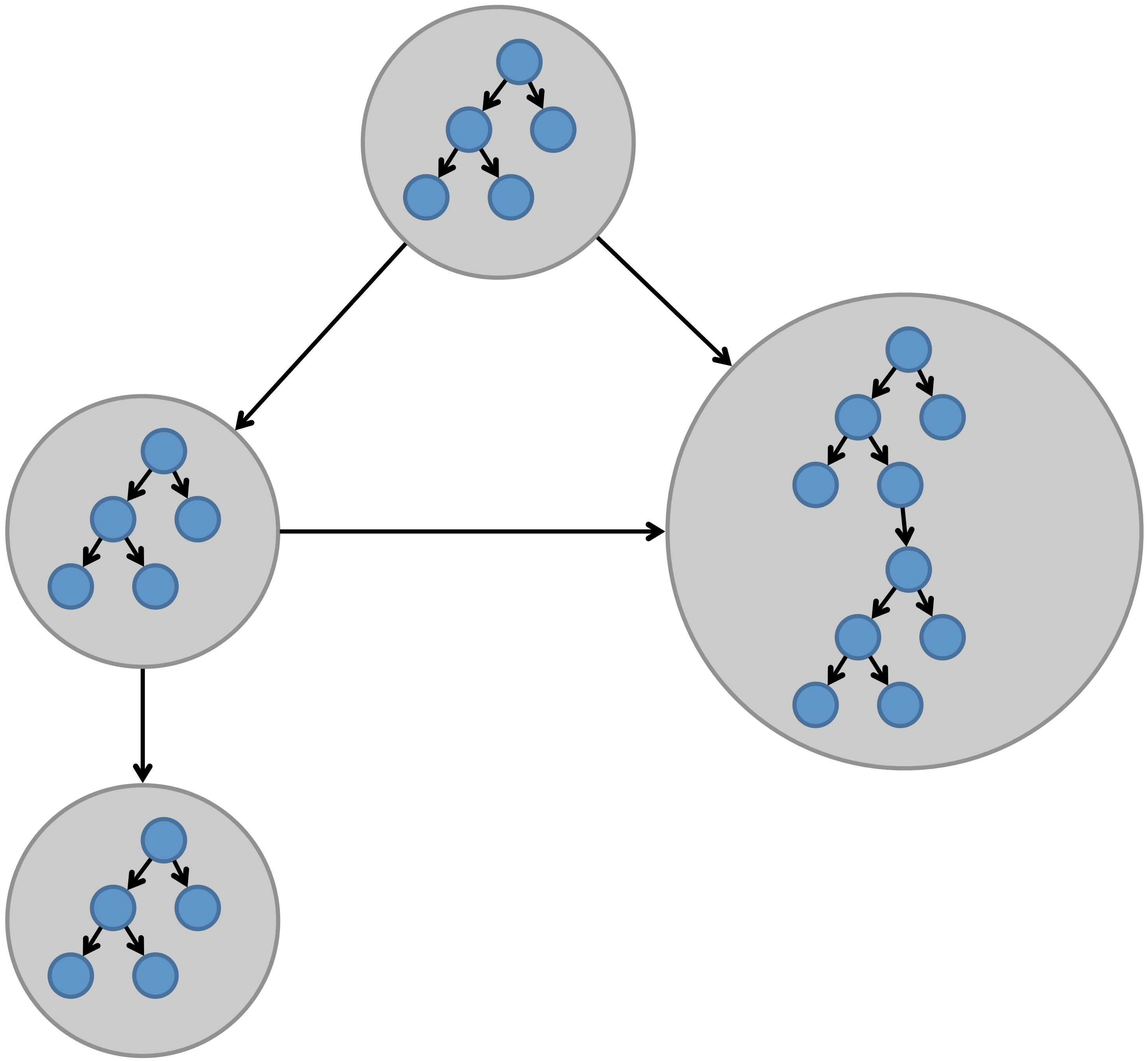
Call Graph: Hot Links



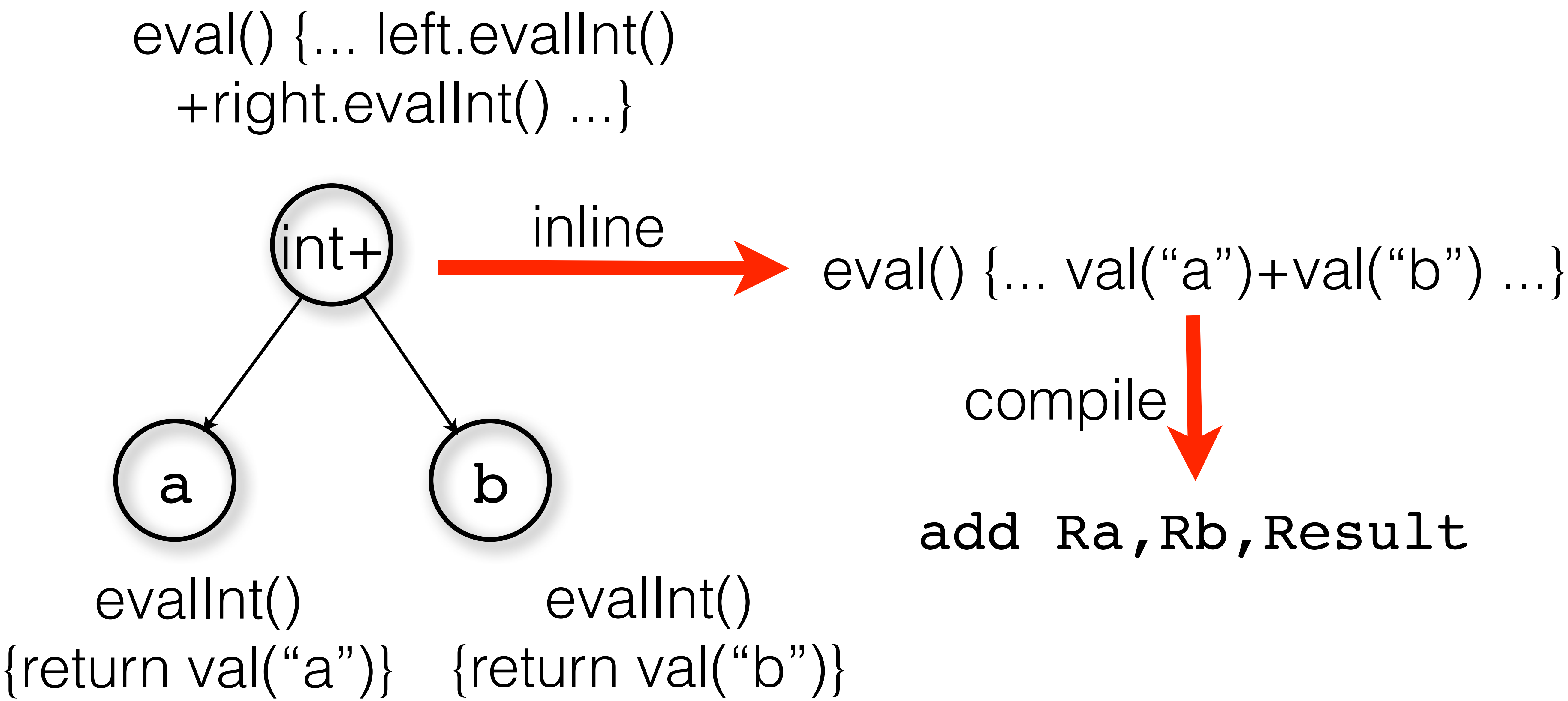
Call Graph: Duplication from hot call site



Call Graph: Inlining



Compiling the specialized ASTs



Rewritten node does less work in subsequent evaluations

After compilation:

checks
hoisted above all uses of
the data within the
compilation

- Check that the operation is applicable to the data types, throw error if not
- **Invoke the operation**
- **Invoke the operation**
- **Invoke the operation**
- **....**

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Putting it all together: repurposing the compiler

By traversing the recursive code of the interpreter, guided by the AST and the type information, we can compile the original expression/statement/method/region **without having written a compiler for that language.**

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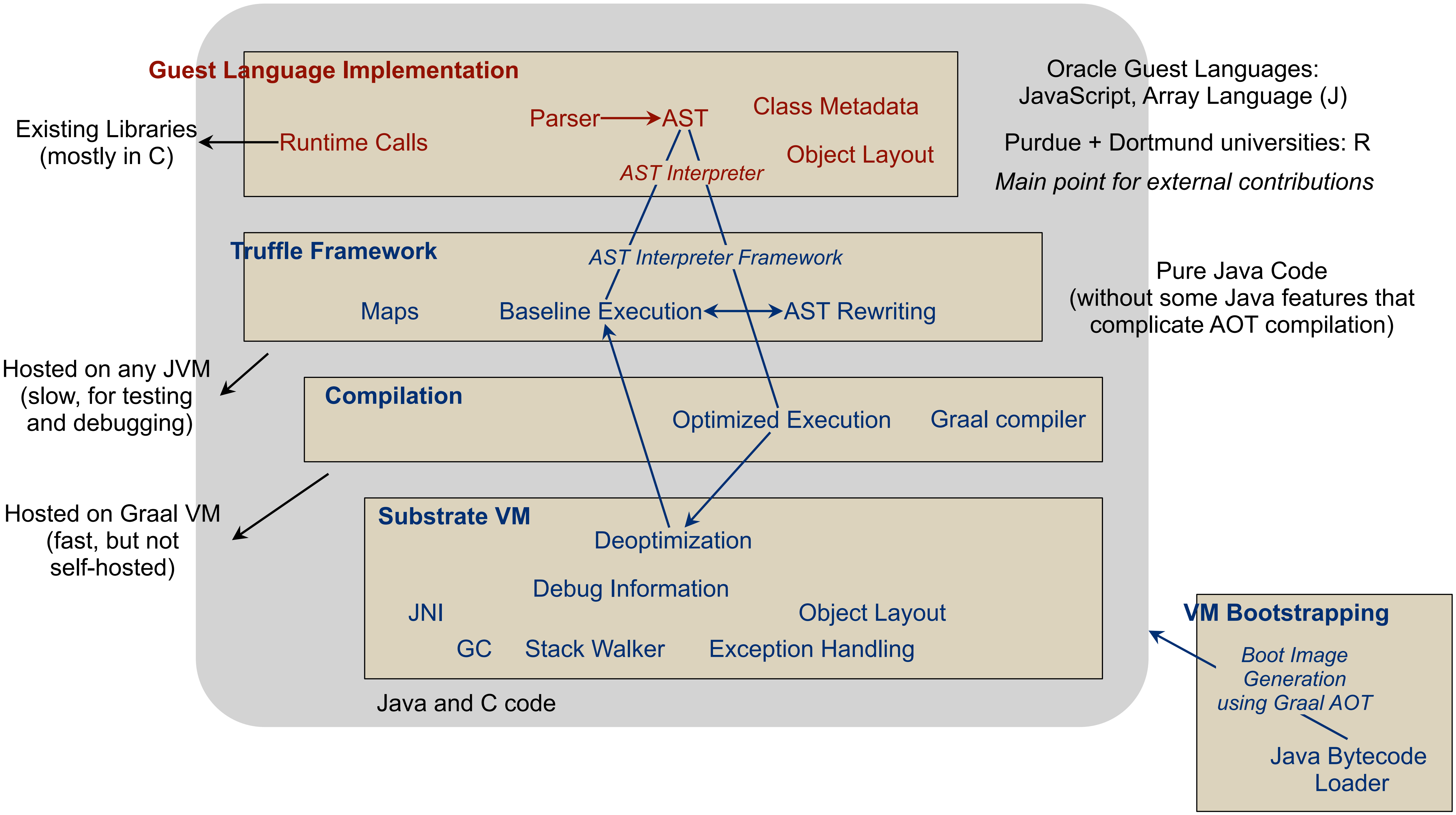
Alphabet Soup HLVM architecture



Parallelization opportunities in technical computing languages

- The technical computing languages have an array-processing core which is amenable to parallel execution:
  - Regular, bulk vector operations
  - Functional
- Once the interpretation overhead has been removed, these are attractive targets for further optimization when used on “big data”.
- High-level optimizations can remove intermediate computations.
- Vectorization and multi-core or GPU parallelism can exploit regularity.

Languages we are implementing

- To demonstrate the viability of the system for the “web” and “technical” languages we are implementing one of each: JavaScript and J.
- Longer term, we hope to build a community of language implementors via open source, and implement other languages. http://openjdk.java.net/projects/graal/

Status

- We are well along with interpreters for JavaScript and J (written in Java).
  - JS: 5x faster than Rhino interpreter
- We already have an extensible optimizing compiler, Graal, written in Java, for Java:
  - Compiles Java bytecode to machine code via a graph IR, for a JVM.
  - Extension in progress for AST inputs.
- To come:
  - Vectorization and parallelization
  - Design and implement a substrate VM (don’t need all the complexity of a full JVM)

Hardware and Software

Engineered to Work Together