Bringing Performance and Scalability to Dynamic Languages

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Dynamic Languages

- Ruby
- JavaScript
- Python
- PHP
- Julia
- MATLAB
- R
- APL
- Smalltalk
- 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)

Goal:

- C gcc
- C++ g++
- Java 7
- JavaScript V8
- Perl
- PHP
- Python
- Ruby
- Smalltalk

Languages:

- fasta-r
- fannkuch-r
- regex-dna
- binary-trees
- mandelbrot
- pidigits
- reverse-c
- fasta
- spectra-norm
- n-body
- k-nucleotide
- mean
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).
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?
AST rewriting during interpretation to gather types

$$\text{eval}() \{ \text{..left.eval()} + \text{right.eval()} \ldots \}$$

$$\text{eval()} \{ \text{..left.evalInt()} + \text{right.evalInt()} \ldots \}$$

$\text{int} +$ throws Unexpected-Result exception
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
Compiling the specialized ASTs

eval() {... left.evalInt()
+right.evalInt() ...}

inline

eval() {... val("a") + val("b") ...}

compile

add Ra, Rb, Result
Rewritten node does less work in subsequent evaluations

After compilation:

• Check that the operation is applicable to the data types, throw error if not

• Invoke the operation
• Invoke the operation
• Invoke the operation
• ....
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.
Alphabet Soup HLVM architecture

Truffle Framework
- Parser → AST
- AST Interpreter
- Object Layout
- Class Metadata
- Runtime Calls
- Guest Language Implementation

Oracle Guest Languages:
- JavaScript, Array Language (J)
- R

Purdue + Dortmund universities: R

Main point for external contributions

Baseline Execution
- AST Rewriting
- Optimized Execution
- Compiled code
- Graal compiler

Compilation
- Maps
- AST Interpreter Framework
- Hosted on any JVM
  (slow, for testing and debugging)

Substrate VM
- Deoptimization
- Debug Information
- Object Layout
- GC
- Stack Walker
- Exception Handling
- Hosted on Graal VM
  (fast, but not self-hosted)

VM Bootstrapping
- Boot Image Generation using Graal AOT
- Java Bytecode Loader

Existing Libraries
- (mostly in C)

Hosted on any JVM
- (slow, for testing and debugging)

Pure Java Code
- (without some Java features that complicate AOT compilation)

Java and C code

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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