PyPy's Approach to Implementing Dynamic Languages Using a Tracing JIT Compiler

Carl Friedrich Bolz

Institut für Informatik
Heinrich-Heine-Universität Düsseldorf

IBM Watson Research Center, February 8th, 2011

Scope

This talk is about:

- implementing dynamic languages
  (with a focus on complicated ones)
- in a context of limited resources
  (academic, open source, or domain-specific)
- imperative, object-oriented languages
- single-threaded implementations

Scope

This talk is about:

- implementing dynamic languages
  (with a focus on complicated ones)
- in a context of limited resources
  (academic, open source, or domain-specific)
- imperative, object-oriented languages
- single-threaded implementations

Goals

Reconciling:

- flexibility, maintainability (because languages evolve)
- simplicity (because teams are small)
- performance

Outline

1. The Difficulties of Implementing Dynamic Languages
   - Technical Factors
   - Requirements

Outline

Outline

What is Needed Anyway

A lot of things are not really different from other languages:

- lexer, parser
- (bytecode) compiler
- garbage collector
- object system

Control Flow

- every language implementation needs a way to implement the control flow of the language
- trivially and slowly done in interpreters with AST or bytecode
- technically very well understood
- sometimes small difficulties, like generators in Python

Control Flow

- every language implementation needs a way to implement the control flow of the language
- trivially and slowly done in interpreters with AST or bytecode
- technically very well understood
- sometimes small difficulties, like generators in Python
- some languages have more complex demands
  but this is rare
- examples: Prolog

Late Binding

- lookups can be done only at runtime
- historically, dynamic languages have moved to ever later binding times
- a large variety of mechanisms exist in various languages
- mechanism are often very ad-hoc because
  "it was easy to do in an interpreter"

Late Binding in Python

In Python, the following things are late bound

- global names
- modules
- instance variables
- methods

Late Binding in Python

In Python, the following things are late bound

- global names
- modules
- instance variables
- methods
- the class of objects
- class hierarchy

Dispatching

- dispatching is a very important special case of late binding
- how are the operations on objects implemented?
- this is usually very complex, and different between languages

Dispatching

- dispatching is a very important special case of late binding
- how are the operations on objects implemented?
- this is usually very complex, and different between languages
- operations are internally split up into one or several lookup and call steps
- a huge space of paths ensues
- most of the paths are uncommon

Example: Attribute Reads in Python

What happens when an attribute `x.m` is read? (simplified)

- check for the presence of `x.__getattribute__`, if there, call it

Example: Attribute Reads in Python

What happens when an attribute `x.m` is read? (simplified)

- check for the presence of `x.__getattribute__`, if there, call it
- look for the name of the attribute in the object's dictionary, if it's there, return it

Example: Attribute Reads in Python

What happens when an attribute `x.m` is read? (simplified)

- check for the presence of `x.__getattribute__`, if there, call it
- look for the name of the attribute in the object's dictionary, if it's there, return it
- walk up the MRO of the object and look in each class' dictionary for the attribute

Example: Attribute Reads in Python

What happens when an attribute `x.m` is read? (simplified)

- check for the presence of `x.__getattribute__`, if there, call it
- look for the name of the attribute in the object's dictionary, if it's there, return it
- walk up the MRO of the object and look in each class' dictionary for the attribute
- if the attribute is found, call its `__get__` attribute and return the result

Example: Attribute Reads in Python

What happens when an attribute `x.m` is read? (simplified)

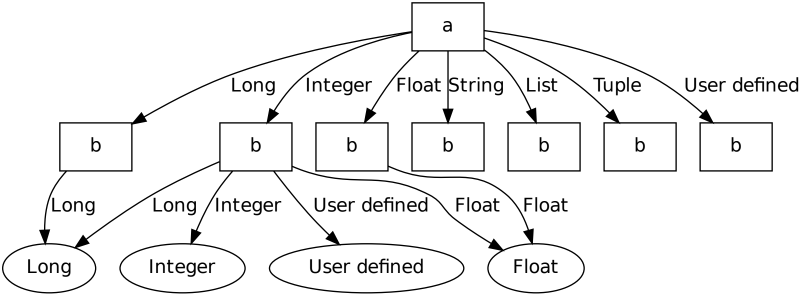
- check for the presence of `x.__getattribute__`, if there, call it
- look for the name of the attribute in the object's dictionary, if it's there, return it
- walk up the MRO of the object and look in each class' dictionary for the attribute
- if the attribute is found, call its `__get__` attribute and return the result
- if the attribute is not found, look for `x.__getattr__`, if there, call it

Example: Attribute Reads in Python

What happens when an attribute `x.m` is read? (simplified)

- check for the presence of `x.__getattribute__`, if there, call it
- look for the name of the attribute in the object's dictionary, if it's there, return it
- walk up the MRO of the object and look in each class' dictionary for the attribute
- if the attribute is found, call its `__get__` attribute and return the result
- if the attribute is not found, look for `x.__getattr__`, if there, call it
- raise an `AttributeError`

Example: Addition in Python



Dependencies Between Subsequent Dispatches

- one dispatch operation is complex
- many in a sequence are worse
- take `(a + b) + c`
- the dispatch decision of the first operation influences the second

Boxing of Primitive Values

- primitive values often need to be boxed,
  to ensure uniform access
- a lot of pressure is put on the GC by arithmetic
- need a good GC (clear anyway)
- in arithmetic, lifetime of boxes is known

Escaping Paths

- considering again `(a + b) + c`
- assume `a` and `b` are ints
- then the result should not be allocated
- escaping path: if `c` has a user-defined class

(Frames)

- side problem:
- many languages have reified frame access
- e.g. Python, Smalltalk, Ruby, ...
- support for in-language debuggers
- in an interpreter these are trivial,
  because the interpreter needs them anyway
- how should reified frames work efficiently when a compiler is used?

Summarizing the Requirements

1. control flow
2. late binding
3. **dispatching**
4. **dependencies between subsequent dispatches**
5. boxing
6. (reified frames)

Common Approaches to Language Implementation

- Using C/C++
  - for an interpreter
  - for a static compiler
  - for a method-based JIT
  - for a tracing JIT
- Building on top of a general-purpose OO VM

Common Approaches to Language Implementation

Using C/C++

- CPython (interpreter)
- Ruby (interpreter)
- V8 (method-based JIT)
- TraceMonkey (tracing JIT)
- ...

Common Approaches to Language Implementation

Using C/C++

- CPython (interpreter)
- Ruby (interpreter)
- V8 (method-based JIT)
- TraceMonkey (tracing JIT)
- ...

Building on top of a general-purpose OO VM

- Jython, IronPython
- JRuby, IronRuby
- various Prolog, Lisp, even Smalltalk implementations

Implementing VMs in C

When writing a VM in C it is hard to reconcile our goals

- flexibility, maintainability
- simplicity
- performance

Implementing VMs in C

When writing a VM in C it is hard to reconcile our goals

- flexibility, maintainability
- simplicity
- performance

Python Case

- CPython is a very simple bytecode VM, performance not great
- Psyco is a just-in-time-specializer, very complex, hard to maintain, but good performance
- Stackless is a fork of CPython adding microthreads. It was never incorporated into CPython for complexity reasons

Interpreters in C/C++

- mostly very easy
- well understood problem
- portable, maintainable
- slow

How do Interpreters Meet the Requirements?

	Interpreter	Static Compiler	Method Compiler	Tracing JIT	OO VMs
Control Flow	-				
Late Binding	-				
Dispatching	-				
Dependencies	-				
Boxing	-				
(Reified Frames)	-				

Static Compilers to C/C++

- first reflex of many people is to blame it all on bytecode dispatch overhead
- thus static compilers are implemented that reuse the object model of an interpreter
- gets rid of interpretation overhead only
- seems to give about 2x speedup

Static Compilers to C/C++

- first reflex of many people is to blame it all on bytecode dispatch overhead
- thus static compilers are implemented that reuse the object model of an interpreter
- gets rid of interpretation overhead only
- seems to give about 2x speedup
- dispatch, late-binding and boxing only marginally improved
- static analysis mostly never works

Static Compilers to C/C++

- first reflex of many people is to blame it all on bytecode dispatch overhead
- thus static compilers are implemented that reuse the object model of an interpreter
- gets rid of interpretation overhead only
- seems to give about 2x speedup
- dispatch, late-binding and boxing only marginally improved
- static analysis mostly never works

Python Case

- Cython, Pyrex are compilers
  from large subsets of Python to C
- lots of older experiments, most discontinued

How do Static Compilers Meet the Requirements?

	Interpreter	**Static Compiler**	Method Compiler	Tracing JIT	OO VMs
Control Flow	-	+			
Late Binding	-	-			
Dispatching	-	-			
Dependencies	-	-			
Boxing	-	-			
(Reified Frames)	-	--			

Method-Based JIT Compilers

- to fundamentally attack some of the problems, a dynamic compiler is needed
- a whole new can of worms

Method-Based JIT Compilers

- to fundamentally attack some of the problems, a dynamic compiler is needed
- a whole new can of worms
  - type profiling
  - inlining based on that
  - general optimizations
  - complex backends
- very hard to pull off for a volunteer team

Method-Based JIT Compilers

- to fundamentally attack some of the problems, a dynamic compiler is needed
- a whole new can of worms
  - type profiling
  - inlining based on that
  - general optimizations
  - complex backends
- very hard to pull off for a volunteer team

Examples

- Smalltalk and SELF JITs
- V8 and JägerMonkey
- Psyco, sort of

Compilers are a bad encoding of Semantics

- to improve all complex corner cases of the language, a huge effort is needed
- often needs a big "bag of tricks"
- the interactions between all tricks is hard to foresee
- the encoding of language semantics in the compiler is thus often obscure and hard to change

Compilers are a bad encoding of Semantics

- to improve all complex corner cases of the language, a huge effort is needed
- often needs a big "bag of tricks"
- the interactions between all tricks is hard to foresee
- the encoding of language semantics in the compiler is thus often obscure and hard to change

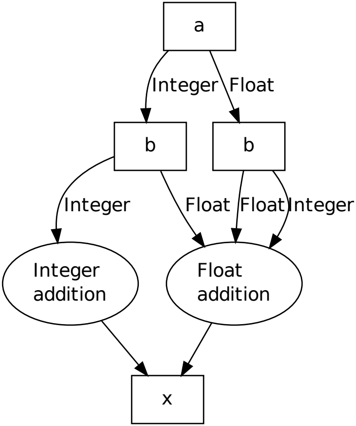
Python Case

- Psyco is a dynamic compiler for Python
- synchronizing with CPython's development is a lot of effort
- many of CPython's new features not supported well
- not ported to 64-bit machines, and probably never will

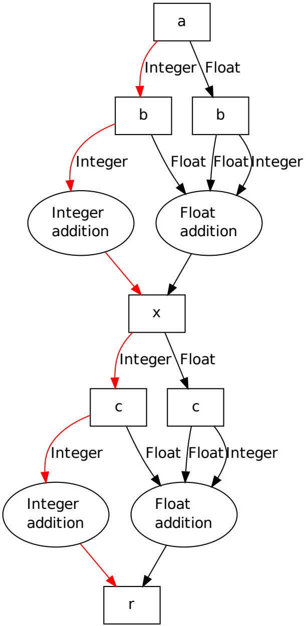
Method-Based JITs and Dispatching Dependencies

```
x = add(a, b)
r = add(x, c)
```

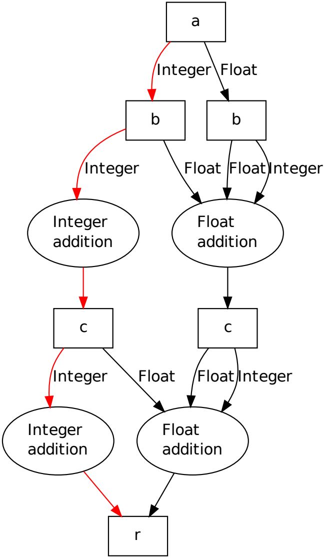
Method-Based JITs and Dispatching Dependencies



Method-Based JITs and Dispatching Dependencies



Method-Based JITs and Dispatching Dependencies



How do Method-Based JIT Compilers Meet the Requirements?

	Interpreter	Static Compiler	**Method Compiler**	Tracing JIT	OO VMs
Control Flow	-	+	+		
Late Binding	-	-	+		
Dispatching	-	-	+		
Dependencies	-	-	?		
Boxing	-	-	?		
(Reified Frames)	-	--	?		

Tracing JIT Compilers

- relatively recent approach to JIT compilers
- pioneered by Michael Franz and Andreas Gal for Java
- turned out to be well-suited for dynamic languages

Tracing JIT Compilers

- relatively recent approach to JIT compilers
- pioneered by Michael Franz and Andreas Gal for Java
- turned out to be well-suited for dynamic languages

Examples

- TraceMonkey
- LuaJIT
- SPUR, sort of
- PyPy, sort of

Tracing JIT Compilers

- idea from Dynamo project:
  dynamic rewriting of machine code
- conceptually simpler than type profiling

Tracing JIT Compilers

- idea from Dynamo project:
  dynamic rewriting of machine code
- conceptually simpler than type profiling

Basic Assumption of a Tracing JIT

- programs spend most of their time executing loops
- several iterations of a loop are likely to take similar code paths

Tracing VMs

- mixed-mode execution environment
- at first, everything is interpreted
- lightweight profiling to discover hot loops
- code generation only for common paths of hot loops
- when a hot loop is discovered, start to produce a trace

Tracing

- a trace is a sequential list of operations
- a trace is produced by recording every operation the interpreter executes
- tracing ends when the tracer sees a position in the program it has seen before
- a trace thus corresponds to exactly one loop
- that means it ends with a jump to its beginning

Tracing

- a trace is a sequential list of operations
- a trace is produced by recording every operation the interpreter executes
- tracing ends when the tracer sees a position in the program it has seen before
- a trace thus corresponds to exactly one loop
- that means it ends with a jump to its beginning

Guards

- the trace is only one of the possible code paths through the loop
- at places where the path could diverge, a guard is placed

Code Generation and Execution

- being linear, the trace can easily be turned into machine code
- execution stops when a guard fails
- after a guard failure, go back to interpreting program

Dealing With Control Flow

- an if statement in a loop is turned into a guard
- if that guard fails often, things are inefficient
- solution: attach a new trace to a guard, if it fails often enough
- new trace can lead back to same loop
- or to some other loop

Dispatching in a Tracing JIT

- trace contains bytecode operations
- bytecodes often have complex semantics
- optimizer often type-specializes the bytecodes
- according to the concrete types seen during tracing
- need to duplicate language semantics in optimizer for that

Example: Dispatching in a Tracing JIT

```
x = ADD(a : Integer, b : Integer)
```

Example: Dispatching in a Tracing JIT

```
guard_class(a, Integer)
guard_class(b, Integer)
u_a = unbox(a)
u_b = unbox(b)
u_x = int_add(a, b)
x = new(Integer, u_x)
```

Dispatching Dependencies in a Tracing JIT

- one consequence of the tracing approach:
- paths are split aggressively
- control flow merging happens at beginning of loop only
- after a type check, the rest of the trace can assume that type
- only deal with paths that are actually seen

Example: Dependencies in a Tracing JIT

```
guard_class(a, Integer)
guard_class(b, Integer)
u_a = unbox(a)
u_b = unbox(b)
u_x = int_add(u_a, u_b)
x = new(Integer, u_x)

guard_class(x, Integer)
guard_class(c, Integer)
u_x2 = unbox(x)
u_c = unbox(c)
u_r = int_add(u_x2, u_c)
r = new(Integer, u_r)
```

Example: Dependencies in a Tracing JIT

```
guard_class(a, Integer)
guard_class(b, Integer)
u_a = unbox(a)
u_b = unbox(b)
u_x = int_add(u_a, u_b)
x = new(Integer, u_x)

guard_class(x, Integer)
guard_class(c, Integer)
u_x2 = unbox(x)
u_c = unbox(c)
u_r = int_add(u_x2, u_c)
r = new(Integer, u_r)
```

Boxing Optimizations in a Tracing JIT

- possibility to do escape analysis within the trace
- only optimize common path
- i.e. the one where the object doesn't escape

Example: Boxing in a Tracing JIT

```
guard_class(a, Integer)
guard_class(b, Integer)
u_a = unbox(a)
u_b = unbox(b)
u_x = int_add(u_a, u_b)
x = new(Integer, u_x)

guard_class(c, Integer)
u_x2 = unbox(x)
u_c = unbox(c)
u_r = int_add(u_x2, u_c)
r = new(Integer, u_r)
```

Example: Boxing in a Tracing JIT

```
guard_class(a, Integer)
guard_class(b, Integer)
u_a = unbox(a)
u_b = unbox(b)
u_x = int_add(u_a, u_b)
x = new(Integer, u_x)

guard_class(c, Integer)
u_x2 = unbox(x)
u_c = unbox(c)
u_r = int_add(u_x, u_c)
r = new(Integer, u_r)
```

Advantages of Tracing JITs

- can be added to an existing interpreter unobtrusively
- interpreter does most of the work
- automatic inlining
- deals well with finding the few common paths through the large space

Bad Points of the Approach

- switching between interpretation and machine code execution takes time
- problems with really complex control flow
- granularity issues: often interpreter bytecode is too coarse
- if this is the case, the optimizer needs to carefully re-add the decision tree

How do Tracing JITs Meet the Requirements?

	Interpreter	Static Compiler	Method Compiler	**Tracing JIT**	OO VMs
Control Flow	-	+	+	+	
Late Binding	-	-	+	+	
Dispatching	-	-	+	+	
Dependencies	-	-	?	++	
Boxing	-	-	?	+	
(Reified Frames)	-	--	?	+	

Implementing Languages on Top of OO VMs

- approach: implement on top of the JVM or the CLR
- usually by compiling to the target bytecode
- plus an object model implementation
- brings its own set of benefits of problems

Implementing Languages on Top of OO VMs

- approach: implement on top of the JVM or the CLR
- usually by compiling to the target bytecode
- plus an object model implementation
- brings its own set of benefits of problems

Python Case

- Jython is a Python-to-Java-bytecode compiler
- IronPython is a Python-to-CLR-bytecode compiler

Benefits of Implementing on Top of OO VMs

- higher level of implementation
- the VM supplies a GC and a JIT
- better interoperability than what the C level provides

Benefits of Implementing on Top of OO VMs

- higher level of implementation
- the VM supplies a GC and a JIT
- better interoperability than what the C level provides

Python Case

- both Jython and IronPython integrate well with their host OO VM
- both have proper threading

The Problems of OO VMs

- often hard to map concepts of the dynamic language
- performance not improved because of the semantic mismatch
- untypical code in most object models
- object model typically has many megamorphic call sites

The Problems of OO VMs

- often hard to map concepts of the dynamic language
- performance not improved because of the semantic mismatch
- untypical code in most object models
- object model typically has many megamorphic call sites
- escape analysis cannot help with boxing, due to escaping paths
- to improve, very careful manual tuning is needed
- VM does not provide enough customization/feedback

Examples of Problems

- both Jython and IronPython are quite a bit slower than CPython
- IronPython misses reified frames

Examples of Problems

- both Jython and IronPython are quite a bit slower than CPython
- IronPython misses reified frames
- for languages like Prolog it is even harder to map the concepts

The Future of OO VMs?

- the problems described might improve in the future
- JVM will add extra support for more languages
- i.e. tail calls, `InvokeDynamic`, ...
- has not really landed yet
- good performance needs a huge amount of tweaking
- controlling the VM's behaviour is brittle:
  VMs not meant for people who care about exact shape of assembler

The Future of OO VMs?

- the problems described might improve in the future
- JVM will add extra support for more languages
- i.e. tail calls, `InvokeDynamic`, ...
- has not really landed yet
- good performance needs a huge amount of tweaking
- controlling the VM's behaviour is brittle:
  VMs not meant for people who care about exact shape of assembler

Ruby Case

- JRuby tries really hard to be a very good implementations
- took an enormous amount of effort
- tweaking is essentially Hotspot-specific

How do OO VMs Meet the Requirements?

	Interpreter	Static Compiler	Method Compiler	Tracing JIT	**OO VMs**
Control Flow	-	+	+	+	+
Late Binding	-	-	+	+	+
Dispatching	-	-	+	+	+
Dependencies	-	-	?	++	?
Boxing	-	-	?	+	?
(Reified Frames)	-	--	?	+	?

The PyPy Project

- started in 2003, received funding from the EU, Google, Nokia and some smaller companies
- goal: "The PyPy project aims at producing a flexible and fast Python implementation."
- technology should be reusable for other dynamic languages

The PyPy Project

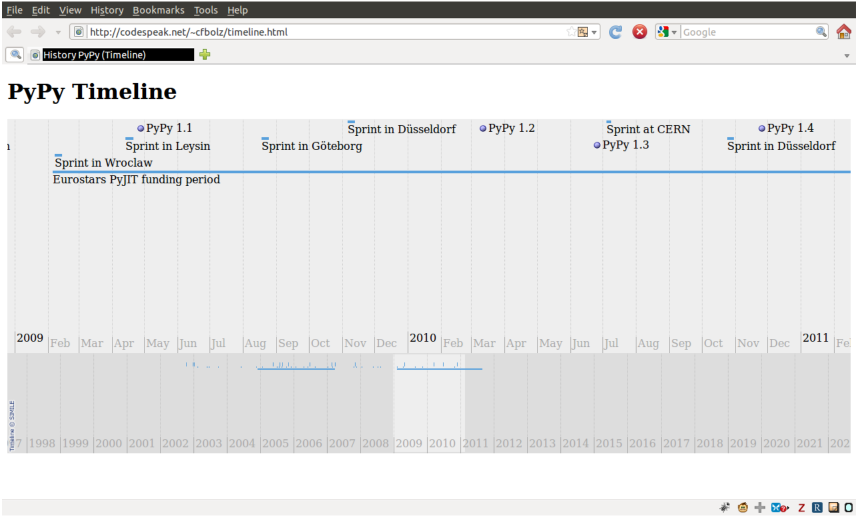
- started in 2003, received funding from the EU, Google, Nokia and some smaller companies
- goal: "The PyPy project aims at producing a flexible and fast Python implementation."
- technology should be reusable for other dynamic languages

Language Status

- the fastest Python implementation, very complete
- contains a reasonably good Prolog
- full Squeak, but no JIT for that yet
- various smaller experiments (JavaScript, Scheme, Haskell)

Project Status

- about two people work on it full-time
- sizeable open source community
- one-week development sprints several times per year
- about 20-30 person-years so far
- heavily dedicated to testing and quality


File Edit View History Bookmarks Tools Help
http://codespeak.net/~cfbolz/timeline.html
Google
History PyPy (Timeline)
PyPy Timeline
PyPy 1.1
Sprint in Leysin
Sprint in Wroclaw
Sprint in Düsseldorf
Sprint in Göteborg
PyPy 1.2
Sprint at CERN
PyPy 1.3
PyPy 1.4
Sprint in Düsseldorf
Eurostars PyJIT funding period
2009 Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec 2010 Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec 2011
1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021
Timeline © SIMILE

PyPy's Approach to VM Construction

Goal: achieve flexibility, simplicity and performance together

- Approach: auto-generate VMs from high-level descriptions of the language
- ... using meta-programming techniques and aspects
- high-level description: an interpreter written in a high-level language
- ... which we translate (i.e. compile) to a VM running in various target environments, like C/Posix

PyPy's Approach to VM Construction

Goal: achieve flexibility, simplicity and performance together

- Approach: auto-generate VMs from high-level descriptions of the language
- ... using meta-programming techniques and aspects
- high-level description: an interpreter written in a high-level language
- ... which we translate (i.e. compile) to a VM running in various target environments, like C/Posix, CLR, JVM

PyPy

- PyPy = Python interpreter written in RPython + translation toolchain for RPython

PyPy

- PyPy = Python interpreter written in RPython + translation toolchain for RPython

What is RPython

- RPython is a (large) subset of Python
- subset chosen in such a way that type-inference can be performed
- still a high-level language (unlike SLang or PreScheme)

Auto-generating VMs

- we need a custom translation toolchain to compile the interpreter to a full VM
- many aspects of the final VM are orthogonal from the interpreter source: they are inserted during translation

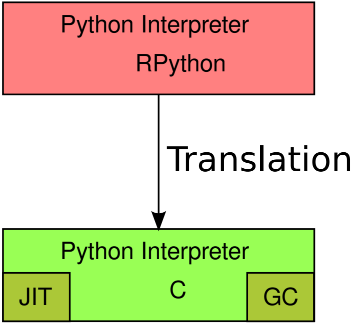
Auto-generating VMs

- we need a custom translation toolchain to compile the interpreter to a full VM
- many aspects of the final VM are orthogonal from the interpreter source: they are inserted during translation

Examples

- Garbage Collection strategy
- non-trivial translation aspect: auto-generating a tracing JIT compiler from the interpreter

Architecture



Good Points of the Approach

Simplicity: separation of language semantics from low-level details

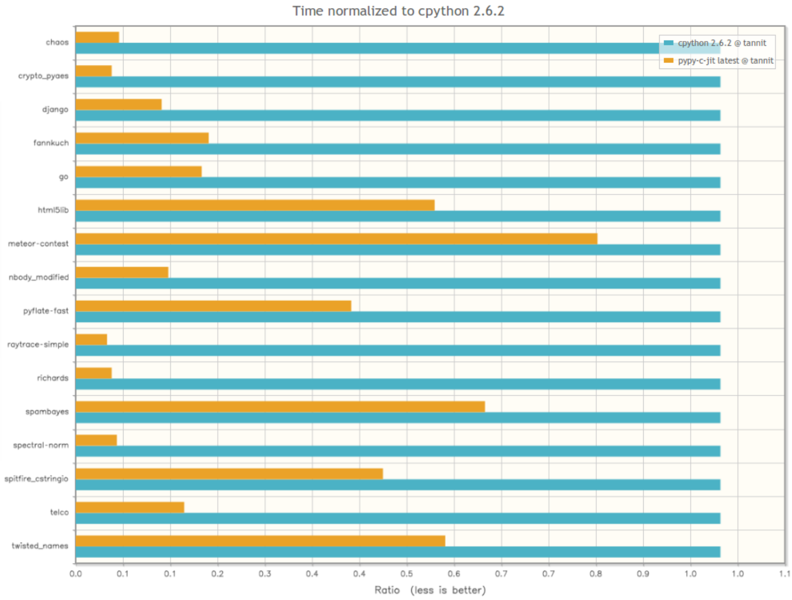
Good Points of the Approach

Simplicity: separation of language semantics from low-level details

Flexibility high-level implementation language eases things (meta-programming)

Good Points of the Approach

Simplicity: separation of language semantics from low-level details
Flexibility high-level implementation language eases things (meta-programming)
Performance: "reasonable" baseline performance, can be very good with JIT


Time normalized to cpython 2.6.2
cpython 2.6.2 @ tannit
pypy-c-jit latest @ tannit
chaos
crypto_pyaes
django
fannkuch
go
html5lib
meteor-contest
nbody_modified
pyflate-fast
raytrace-simple
richards
spambayes
spectral-norm
spitfire_cstringio
telco
twisted_names
0.0 0.1 0.1 0.2 0.3 0.4 0.4 0.5 0.6 0.7 0.7 0.8 0.9 1.0 1.0 1.1
Ratio (less is better)

Meta-Tracing

Problems of Tracing JITs:

- specific to one language's bytecode
- bytecode has wrong granularity
- internals of an operation not visible in trace

Meta-Tracing

Problems of Tracing JITs:

- specific to one language's bytecode
- bytecode has wrong granularity
- internals of an operation not visible in trace

PyPy's Idea:

- write interpreters in RPython
- trace the execution of the RPython code
- using one generic RPython tracer
- the process is customized via hints in the interpreter
- no language-specific bugs

Interpreter Overhead

- most immediate problem with meta-tracing
- interpreter typically has a bytecode dispatch loop
- not a good idea to trace that

Interpreter Overhead

- most immediate problem with meta-tracing
- interpreter typically has a bytecode dispatch loop
- not a good idea to trace that
- solved by a simple trick:
- unroll the bytecode dispatch loop
- control flow then taken care of

Optimizing Late Binding and Dispatching

- late binding and dispatching code in the interpreter is traced
- as in a normal tracing JIT, the meta-tracer is good at picking common paths
- a number of hints to fine-tune the process

Optimizing Boxing Overhead

- boxing optimized by a powerful general optimization on traces
- tries to defer allocations for as long as possible
- allocations only happen in those (rare) paths where they are needed

Optimizing Boxing Overhead

- boxing optimized by a powerful general optimization on traces
- tries to defer allocations for as long as possible
- allocations only happen in those (rare) paths where they are needed

Use Cases

- arithmetic
- argument holder objects
- frames of inlined functions

Dealing With Reified Frames

- interpreter needs a frame object to store its data anyway
- those frame objects are specially marked
- JIT special-cases them
- their attributes can live in CPU registers/stack
- on reflective access, machine code is left, interpreter continues

Dealing With Reified Frames

- interpreter needs a frame object to store its data anyway
- those frame objects are specially marked
- JIT special-cases them
- their attributes can live in CPU registers/stack
- on reflective access, machine code is left, interpreter continues
- nothing deep, but a lot of engineering

Feedback from the VM

- in the beginning the hints are often not optimal yet
- to understand how to improve them, the traces must be read
- traces are in a machine-level intermediate representation
- not machine code
- corresponds quite closely to RPython interpreter code
- visualization and profiling tools

Drawbacks / Open Issues / Further Work

- writing the translation toolchain in the first place takes lots of effort (but it can be reused)
- writing a good GC was still necessary, not perfect yet
- dynamic compiler generation seems to work now, but took <u>very</u> long to get right
- granularity of tracing is sometimes not optimal, very low level

Conclusion

- PyPy solves many of the problems of dynamic language implementations
- it uses a high-level language
    - to ease implementation
    - for better analyzability
- it gives good feedback to the language implementor
- and provides various mechanisms to express deeply different language semantics

Conclusion

- PyPy solves many of the problems of dynamic language implementations
- it uses a high-level language
  - to ease implementation
  - for better analyzability
- it gives good feedback to the language implementor
- and provides various mechanisms to express deeply different language semantics
- only one solution in this design space (SPUR is another)
- more experiments needed