

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

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# 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

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## Goals

Reconciling:

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

# Outline

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  - Technical Factors
  - Requirements

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  - Implementing VMs in C/C++
  - Method-Based JIT Compilers
  - Tracing JIT Compilers
  - Building on Top of an OO VM

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- 3 PyPy's Approach to VM Construction
  - PyPy's Meta-Tracing JIT Compiler

# 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



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- 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"

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- the class of objects
- class hierarchy

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- 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

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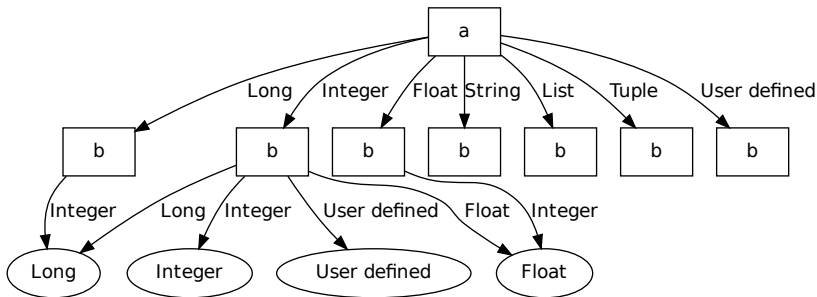
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- raise an `AttributeError`

## 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

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- ...

## Building on top of a general-purpose OO VM

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

# Implementing VMs in C

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## 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?

	<b>Interpreter</b>	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
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### Python Case

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

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  - type profiling
  - inlining based on that
  - general optimizations
  - complex backends
- very hard to pull off for a volunteer team

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## 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

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## 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

```
if isinstance(a, Integer):
    if isinstance(b, Integer):
        x = Integer(<perform int addition>)
    else:
        x = Float(<perform float addition>)
else:
    x = Float(<perform float addition>)
# x can be Float or Integer here
if isinstance(x, Integer):
    if isinstance(c, Integer):
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- turned out to be well-suited for dynamic languages

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## Examples

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

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## 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

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## 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

# 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



# 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

# 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?

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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
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## 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

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## 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
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- 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

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- IronPython misses reified frames

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- 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

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### Ruby Case

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

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# 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."
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## 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)

# 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

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# PyPy

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## 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

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## Examples

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

# Good Points of the Approach

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

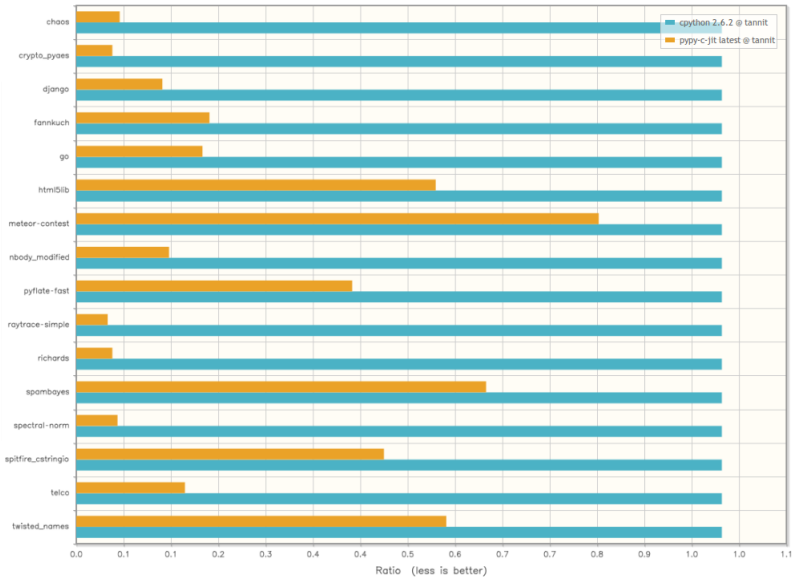
# Good Points of the Approach

**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



# Meta-Tracing

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- specific to one language's bytecode
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## 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
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- 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
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## 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

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- 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 very 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

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- 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