Python and PyPy performance (not) for dummies

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About us

- PyPy core devs
- `vmprof`, `cffi`, `pdb++`, `fancycompleter`, ...
- Consultants
- `http://baroquesoftware.com/`

Optimization for dummies

- Obligatory citation
  - *premature optimization is the root of all evil* (D. Knuth)
- Pareto principle, or 80-20 rule
  - 80% of the time will be spent in 20% of the program
  - 20% of 1 mln is 200 000
- Two golden rules:
  1. Identify the slow spots
  2. Optimize them

This talk

- Two parts
    1. How to identify the slow spots
    2. How to address the problems

Part 1

- identifying the slow spots

What is performance?

- something quantifiable by numbers
- usually, time spent doing task X
- number of requests, latency, etc.
- statistical properties about that metric

Do you have a performance problem?

- what you're trying to measure
- means to measure it (production, benchmarks, etc.)
- is Python is the cause here?
- environment to quickly measure and check the results
  - same as for debugging

When Python is the problem

- tools, timers etc.
- systems are too complicated to **guess** which will be faster
- find your bottlenecks
- 20/80 (but 20% of million lines is 200 000 lines, remember that)

Profilers landscape

- cProfile, runSnakeRun (high overhead) - event based profiler
- plop, vmprof - statistical profilers
- cProfile & vmprof work on pypy

vmprof

- inspired by `gperftools`
- statistical profiler run by an interrupt (~300Hz on modern linux)
- sampling the C stack
- CPython, PyPy, possibly more virtual machines

why not gperftools?

- C stack does not contain python-level frames
- 90% `PyEval_EvalFrame` and other internals
- we want python-level functions
- picture is even more confusing in the presence of the JIT

using vmprof

- demo
- `http://vmprof.readthedocs.org`

using vmprof in production

- low overhead (5-10%), possibly lower in the future
- possibility of realtime monitoring (coming)

vmprof future

- profiler as a service
- realtime advanced visualization

Part 2

Make it fast

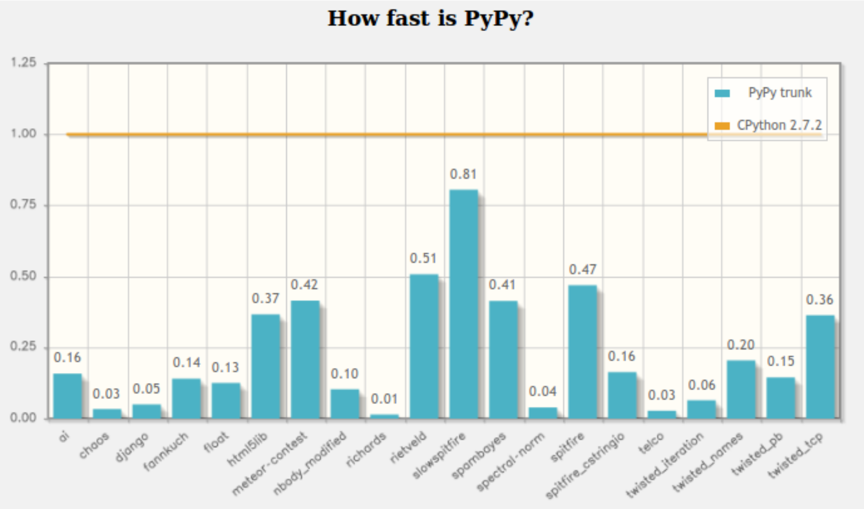
Tools

- Endless list of tools/techniques to increment speed
- C extension
- Cython
- numba
- "performance tricks"
- **PyPy**
  - We'll concentrate on it
  - WARNING: we wrote it, we are biased :)
  - gives you most wins for free (*)

What is PyPy

- Alternative, fast Python implementation
- Performance: JIT compiler, advanced GC
- PyPy 2.6.0 (Python version 2.7.9)
- Py3k as usual in progress (3.2.5 out, 3.3 in development)
- `http://pypy.org`
- EP Talks:
  - The GIL is dead: PyPy-STM
    (July 23, 16:45 by Armin Rigo)
  - PyPy ecosystem: CFFI, numpy, scipy, etc
    (July 24, 15:15 by Romain Guillebert)

Speed: 7x faster than CPython

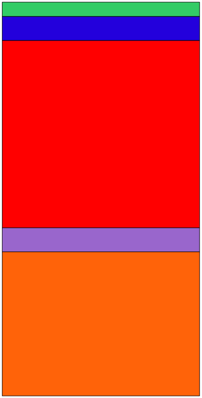


The JIT

```
def main():
    init()
    some_quick_code()
    for x in large_list:
        do_something(x)
    some_other_code()
    while condition():
        expensive_computation()
```

The JIT

NO JIT



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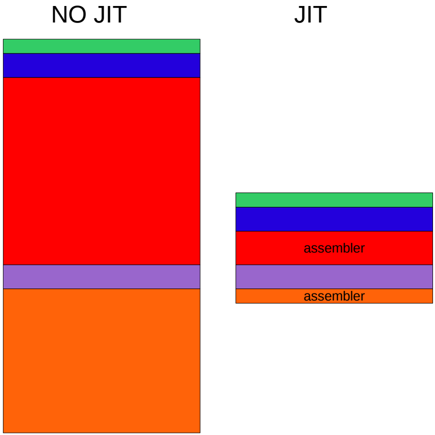

JIT overview

- Tracing JIT
  - detect and compile "hot" code
- **Specialization**
- Precompute as much as possible
- Constant propagation
- Aggressive inlining

Specialization (1)

- `obj.foo()`
- which code is executed? (SIMPLIFIED)
  - lookup `foo` in obj.__dict__
  - lookup `foo` in obj.__class__
  - lookup `foo` in obj.__bases__[0], etc.
  - finally, execute `foo`
- without JIT, you need to do these steps again and again
- Precompute the lookup?

Specialization (2)

- pretend and assume that `obj.__class__` IS constant
  - "promotion"
- guard
  - check our assumption: if it's false, bail out
- now we can directly jump to `foo` code
  - ...unless `foo` is in `obj.__dict__`: GUARD!
  - ...unless `foo.__class__.__dict__` changed: GUARD!
- Too many guard failures?
  - Compile some more assembler!
- guards are cheap
  - out-of-line guards even more

Specialization (3)

- who decides what to promote/specialize for?
  - we, the PyPy devs :)
  - heuristics
- instance attributes are never promoted
- class attributes are promoted by default (with some exceptions)
- module attributes (i.e., globals) as well
- bytecode constants

Specialization trade-offs

- Too much specialization
  - guards fails often
  - explosion of assembler
- Not enough specialization
  - inefficient code

Guidos points

Guido van Rossum
Shared publicly - Sep 10, 2012

Some patterns for fast Python. Know any others?

- Avoid overengineering datastructures. Tuples are better than objects (try namedtuple too though). Prefer simple fields over getter/setter functions.

- Built-in datatypes are your friends. Use more numbers, strings, tuples, lists, sets, dicts. Also check out the collections library, esp. deque.

- Be suspicious of function/method calls; creating a stack frame is expensive.

- Don't write Java (or C++, or Javascript, ...) in Python.

- Are you sure it's too slow? Profile before optimizing!

- The universal speed-up is rewriting small bits of code in C. Do this only when all else fails.

Don't do it on PyPy (or at all)

- simple is better than complicated
- avoid string concatenation in the loop
- avoid replacing simple loop with itertools monsters
- "move stuff to C" is (almost) never a good idea
- use `cffi` when calling C
- avoid C extensions using CPython C API
- avoid creating classes at runtime

Example

- `map(operator.attrgetter('x'), list)`

vs

- `[x.x for x in list]`

More about PyPy

- we are going to run a PyPy open space (tomorrow 18:00 @ A4)
- come ask more questions

Q&A?

- Thank you!
- `http://baroquesoftware.com`
- `http://pypy.org`
- `http://vmprof.readthedocs.org`