

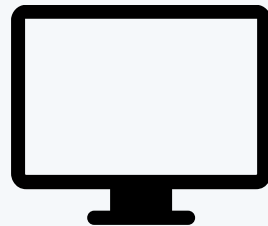
# Efficient Hosted Interpreter for Dynamic Languages

PhD Defense by Wei Zhang

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Prof. Kwei-Jay Lin  
Prof. Guoqing Xu

# A Modern Web Service

client side



JS, Coffee...

server side



Python, PHP, Ruby...

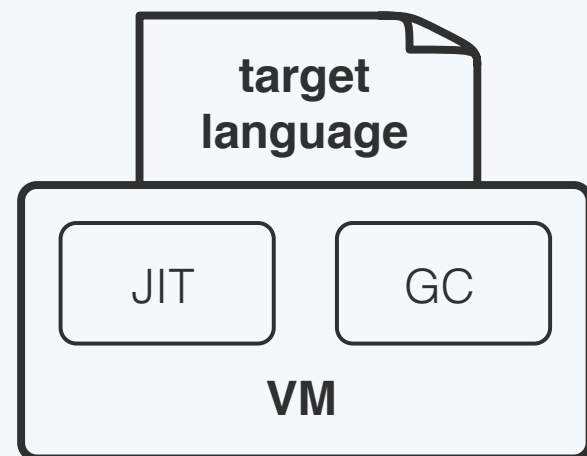
# Dynamic languages are no longer — “scripting languages”

- No longer simply used to accomplish small tasks
- Ubiquitous in multiple domains
- Appealing to programmers; offer higher “productivity”
- Suffer from suboptimal performance

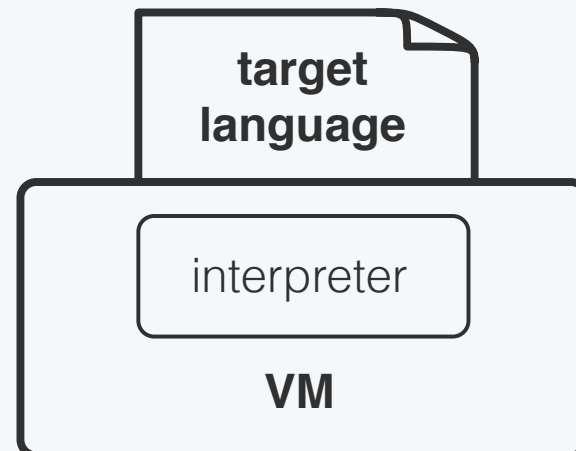
# Brief history of dynamic language VMs

1. 1980s: early academic work on Smalltalk & SELF as full-custom VMs
2. Early 90s: interpreters written in C (Python, Ruby)
3. Late 90s: more powerful and popular VM for statically typed OO languages like JVM and CLR (Java & C#)
4. Early 00s: hosted dynamic language VMs (Rhino, Jython, JRuby)
5. Late 00s: second coming of full-custom VMs for dynamic languages (V8)

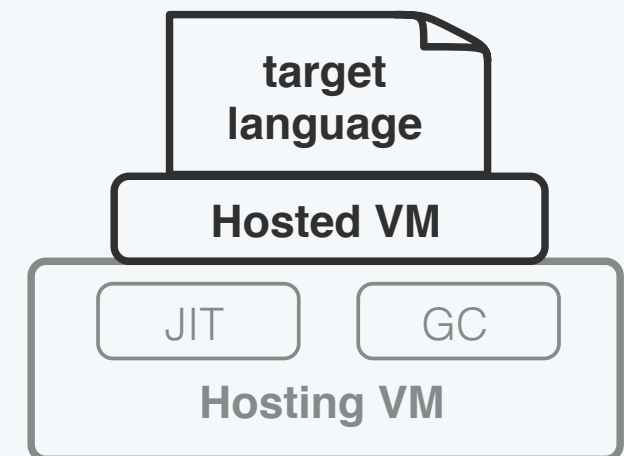
# Architectural choice of dynamic language VMs



full-custom



interpreter-based



hosted

# Hosted VM / interpreter for dynamic languages

- Full-custom VMs are costly to build and maintain
- Existing VMs offer mature and powerful components (JIT, GC)
- Interpreters are more cost-effective
- **Existing hosted VMs do not offer competitive performance**

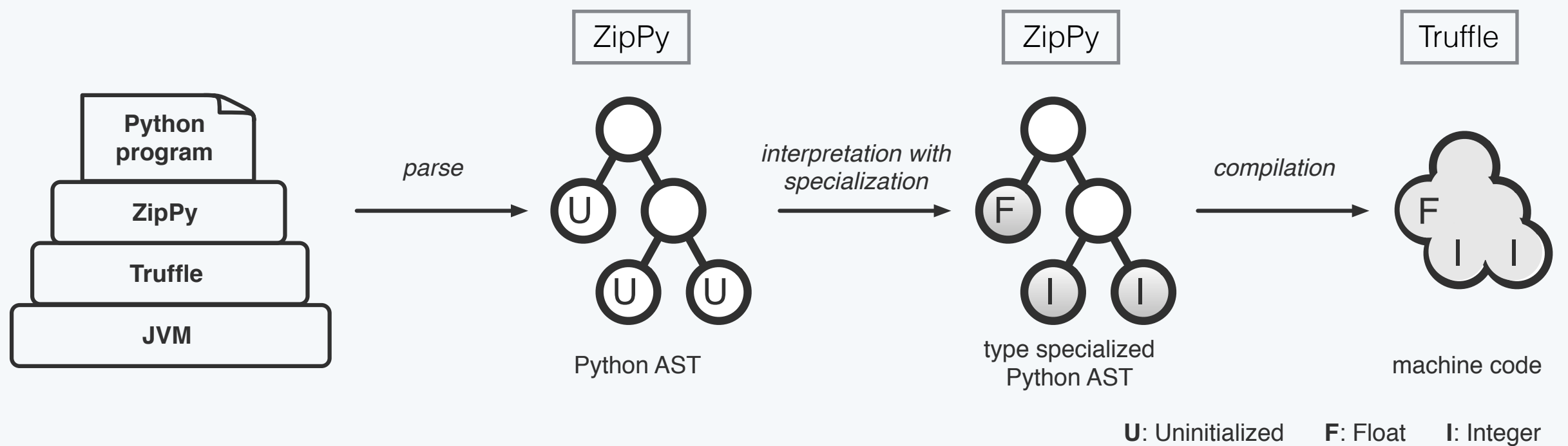
# ZipPy is a hosted interpreter for Python3

- Built atop Truffle framework
- Supports the common feature of the language
- Open sourced at <https://bitbucket.org/ssllab/zippy>

# Truffle is a multi-language framework

- Facilitates AST interpreter construction
- Streamlines type specialization via AST node rewriting
- Bridges the guest interpreter with the underlying JIT compiler

# ZipPy on Truffle





# Agenda

- *Trufflization*
- ★ Generators optimizations
- ★ Efficient object model for Python
  - ★ *our contributions*

## A for range loop example in Python

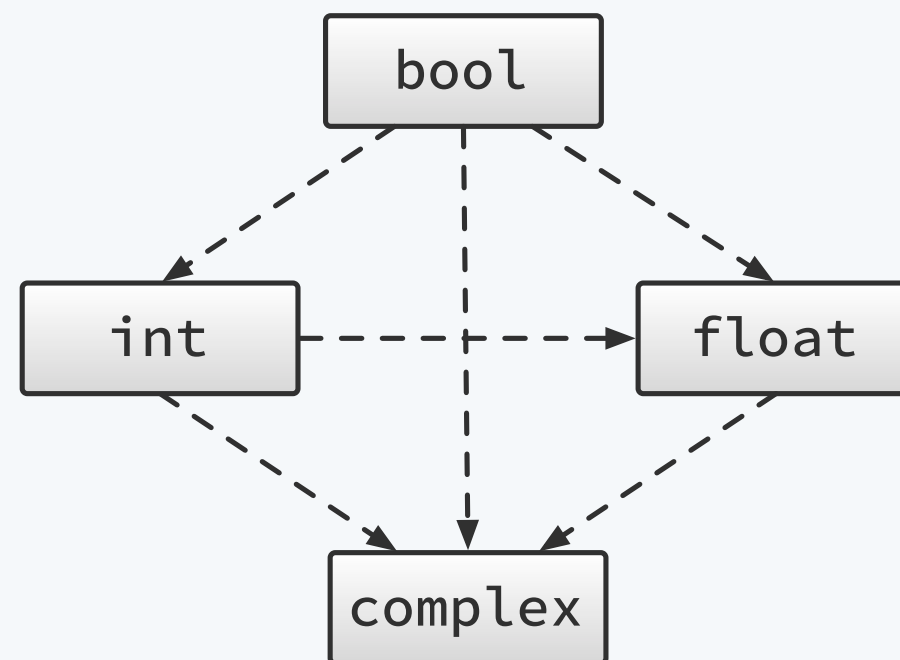
```
def sum(n):  
    ttl = 0  
    for i in range(n):  
        ttl += i  
    return ttl
```

for range loop

```
print(sum(1000))
```

addition

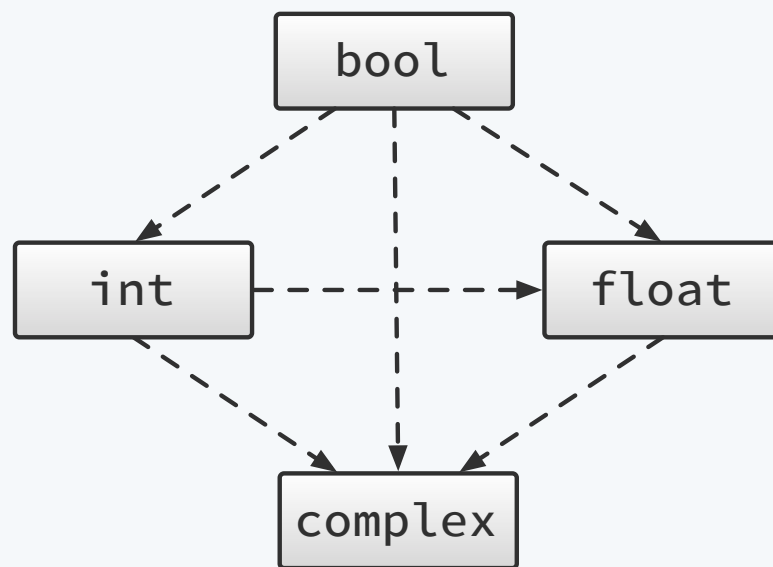
# Numeric types in Python



**int** has arbitrary precision

- - - -> type coercion

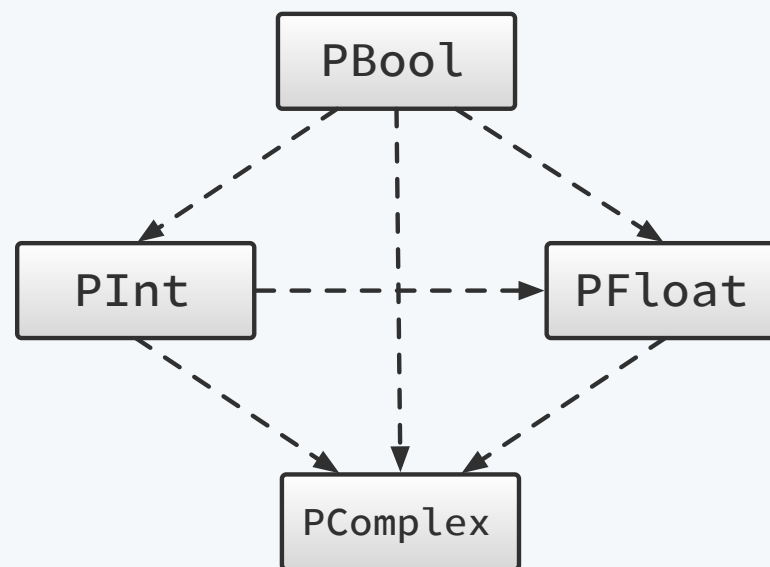
# Numeric types in ZipPy



**int** has arbitrary precision

-----> type coercion

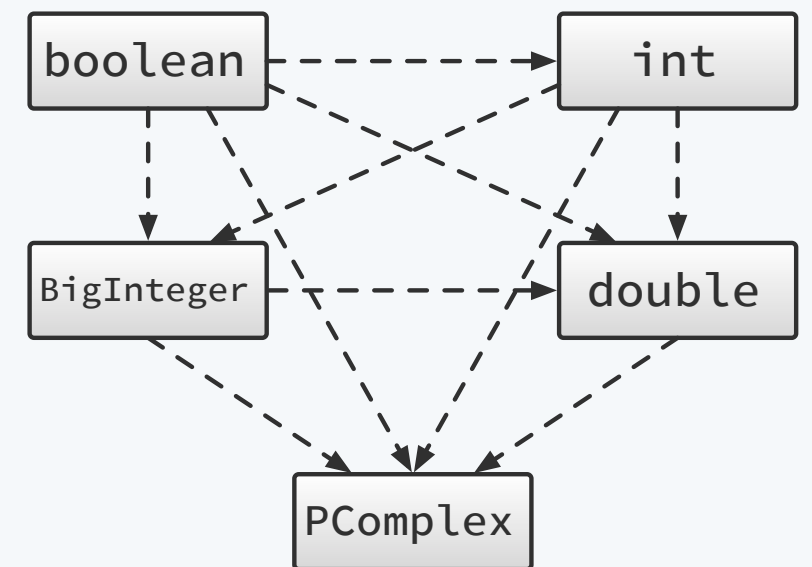
numeric types



**PInt** has arbitrary precision

-----> type coercion

boxed representation



-----> type coercion

unboxed representation

## Type specialization for addition

```
abstract class AddNode extends BinaryArithmeticNode {

    @Specialization
    int doBoolean(boolean left, boolean right) {
        final int leftInt = left ? 1 : 0;
        final int rightInt = right ? 1 : 0;
        return leftInt + rightInt;
    }

    @Specialization(rewriteOn = ArithmeticException.class)
    int doInteger(int left, int right) {
        return ExactMath.addExact(left, right);
    }

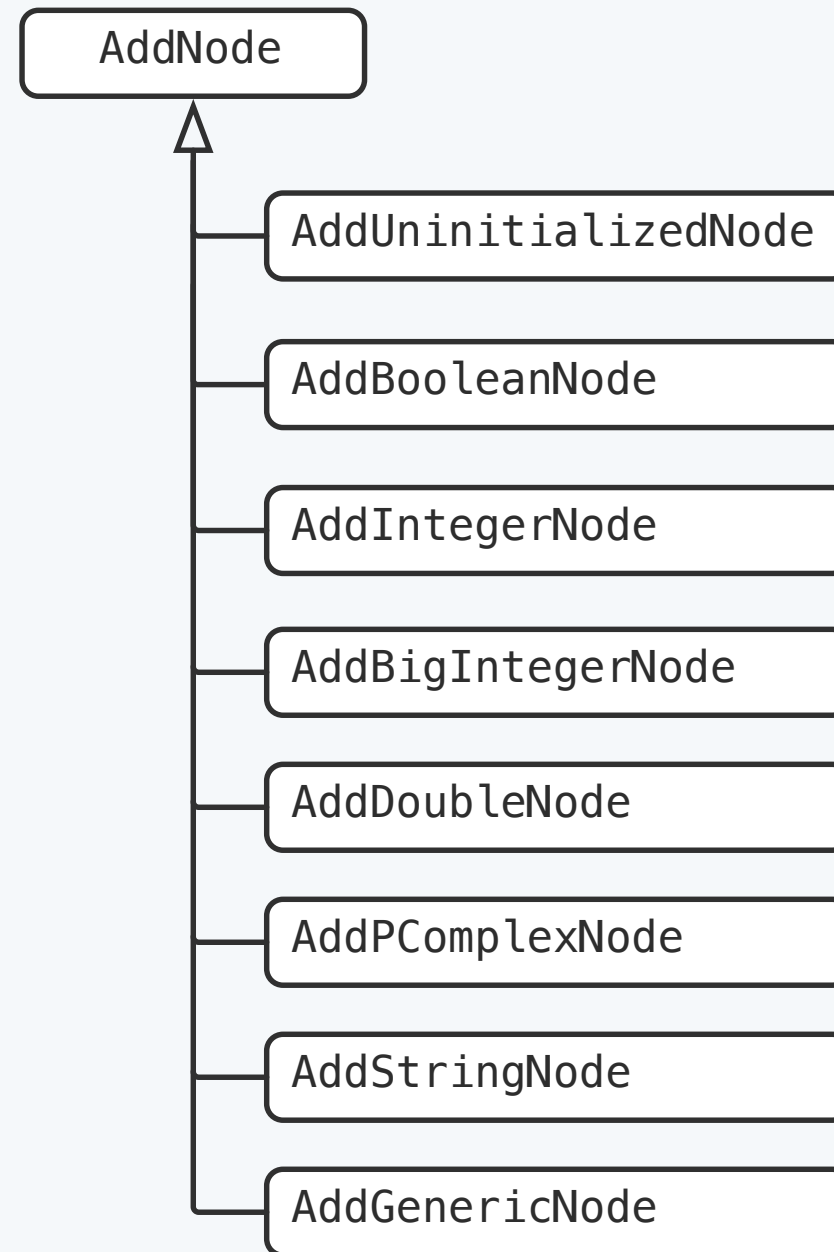
    @Specialization
    BigInteger doBigInteger(BigInteger left, BigInteger right) {
        return left.add(right);
    }

    @Specialization
    double doDouble(double left, double right) {
        return left + right;
    }

    @Specialization
    PComplex doComplex(PComplex left, PComplex right) {
        return left.add(right);
    }

    @Specialization
    String doString(String left, String right) {
        return left + right;
    }
    //...
}
```

# AddNode derivatives

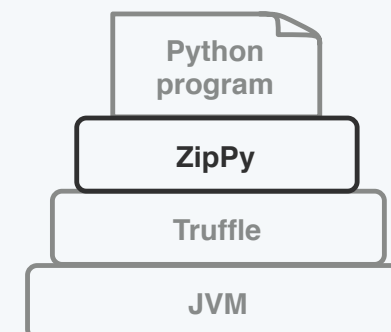
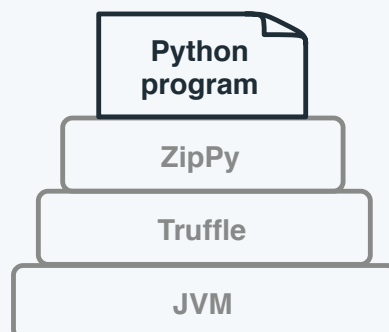


# ForNode specialization for range iterator

## for-range loop in Python

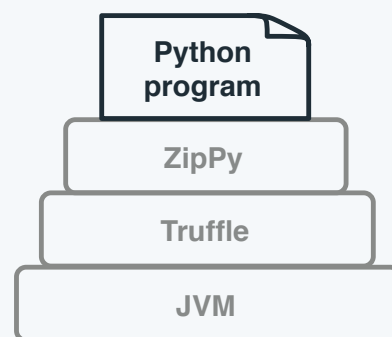
```
def sum(n):  
    ttl = 0  
    for i in range(n):  
        ttl += i  
    return ttl
```

```
class ForNode extends LoopNode {  
    @Specialization  
    public Object doPRange(VirtualFrame frame,  
                           PRangeIterator range) {  
        int start = range.getStart();  
        int stop = range.getStop();  
        int step = range.getStep();  
  
        for (int i = start; i < stop; i += step) {  
            ((WriteNode) target).executeWrite(frame, i);  
            body.executeVoid(frame);  
        }  
  
        return PNone.NONE;  
    }  
}
```



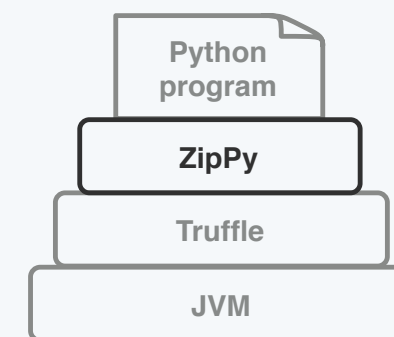
## for-range loop in Python

```
def sum(n):  
    ttl = 0  
    for i in range(n):  
        ttl += i  
    return ttl
```



## optimized for-range loop

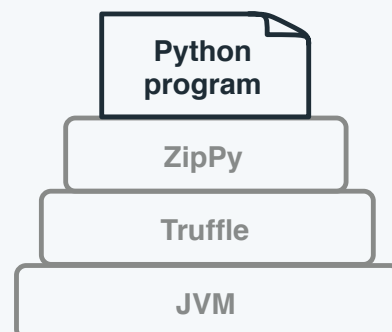
```
public int sum(int n) {  
    int ttl = 0;  
  
    for (int i = 0; i < n; i++) {  
        ttl += i;  
    }  
  
    return ttl;  
}
```





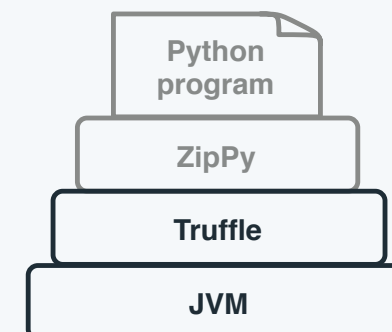
## for-range loop in Python

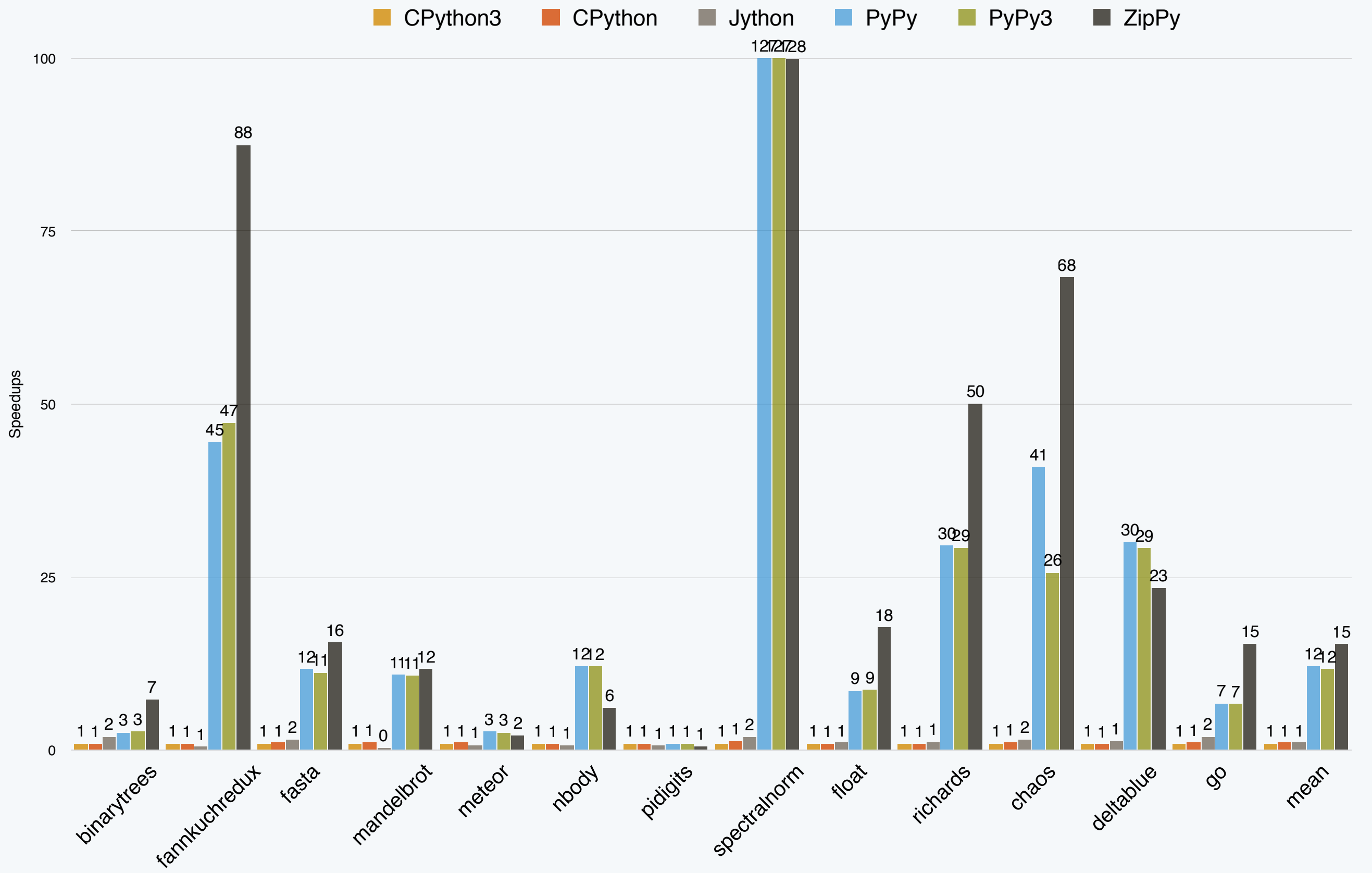
```
def sum(n):  
    ttl = 0  
    for i in range(n):  
        ttl += i  
    return ttl
```



## JIT compiled for range loop

```
                                jmp L7  
  
L6:    mov     ecx, edx  
        add     ecx, ebp  
        jo      L8  
        mov     edx, ebp  
        incl    edx  
        mov     esi, ebp  
        mov     ebp, edx  
        mov     edx, ecx  
  
L7:    cmp     eax, ebp  
        jle     L9  
        jmp     L6  
  
L8:    call    deoptimize()  
  
L9:
```



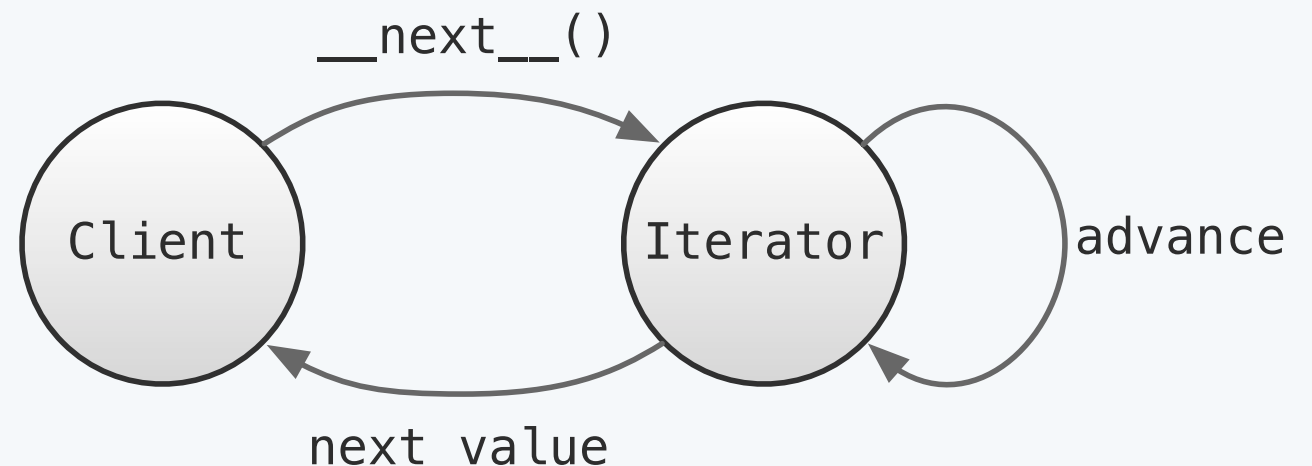


benchmark	CPython3	CPython	Jython	PyPy	PyPy3	ZipPy
binarytrees	1.00	0.94	1.99	2.60	2.70	7.31
fannkuchredux	1.00	0.97	0.51	44.53	47.29	87.50
fasta	1.00	1.04	1.55	11.73	11.24	15.57
mandelbrot	1.00	1.08	0.34	10.91	10.82	11.69
meteor	1.00	1.02	0.77	2.64	2.62	2.13
nbody	1.00	0.97	0.73	12.13	12.06	6.17
pidigits	1.00	1.00	0.62	0.98	0.95	0.60
spectralnorm	1.00	1.33	1.89	127.33	127.25	128.10
float	1.00	0.95	1.05	8.64	8.67	17.71
richards	1.00	0.94	1.21	29.53	29.25	50.13
chaos	1.00	1.17	1.55	40.88	25.69	68.28
deltablue	1.00	0.85	1.33	30.08	29.14	23.46
go	1.00	1.08	1.99	6.79	6.66	15.41
mean	1.00	1.02	1.05	12.15	11.68	15.34

ZipPy is competitive with PyPy and a fast Python3  
on the JVM

# Python iterators

- Iterators are ubiquitous
  - Implement iterator protocol
  - Built-in iterators
  - User-defined iterators
- **Generators** are user-defined iterators using special control-flow construct (yield)
- **Generators** exist in other languages too, like C#, PHP,...



# Python generators

```
l = []  
for i in fib(10):  
    if i % 2 == 0:  
        l.append(i)
```

# [2, 8, ..]

*consumer loop*

```
def fib(n):  
    a, b = 0, 1  
    for i in range(n):  
        a, b = b, a+b  
        yield a
```

# 1, 1, 2, 3, 5, 8..

*generator function*

# Python generators

- We surveyed the use of generators in Python programs
- 90% of the top 50 Python projects on PyPI and GitHub use generators
- Given its popularity the performance of generators are critical to Python programs

Jinja2  
Django  
Flask  
LXML  
Requests  
Pandas  
Fabric  
pip  
Reddit





Python generators are slow...



# Generator Execution

```
l = []  
for i in fib(10):  
    if i % 2 == 0:  
        l.append(i)  
  
    consumer loop
```

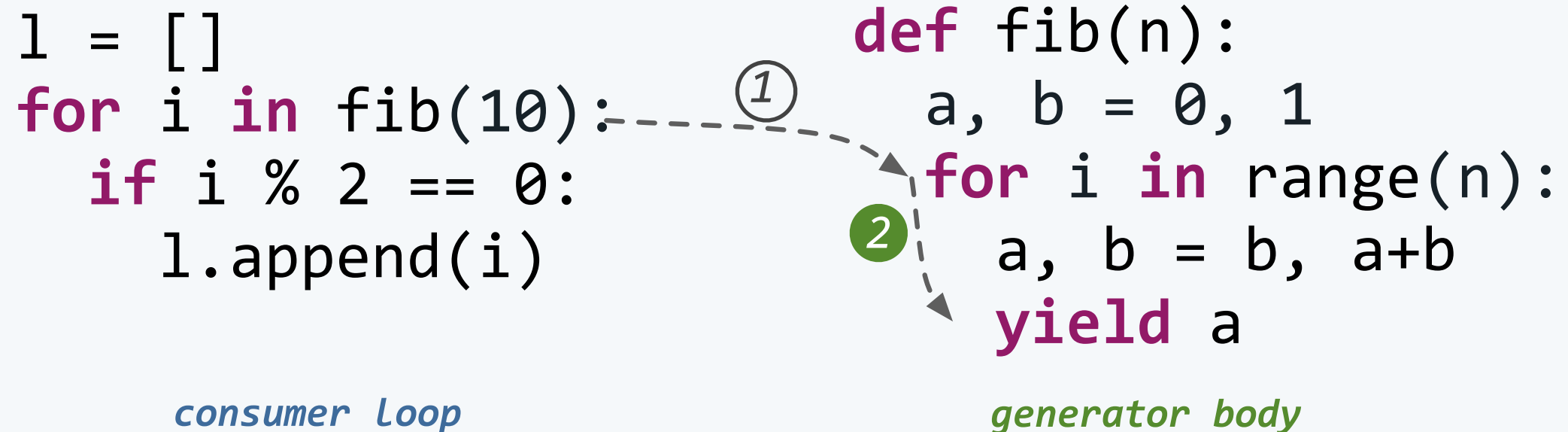
①

```
def fib(n):  
    a, b = 0, 1  
    for i in range(n):  
        a, b = b, a+b  
        yield a  
  
    generator body
```

1. The implicit call to `__next__` and resume execution

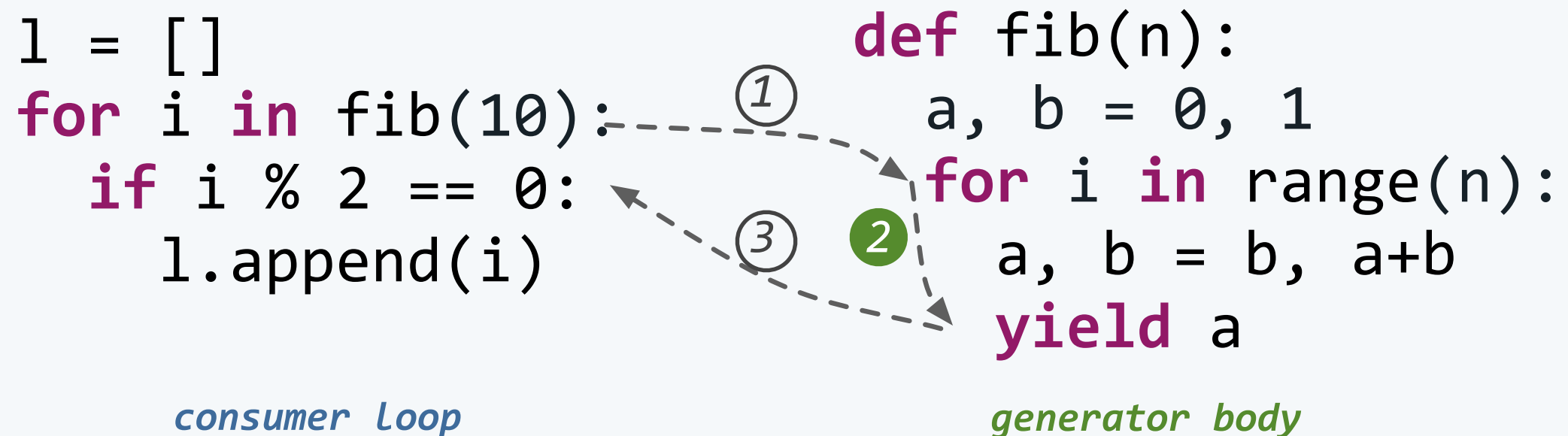


# Generator Execution



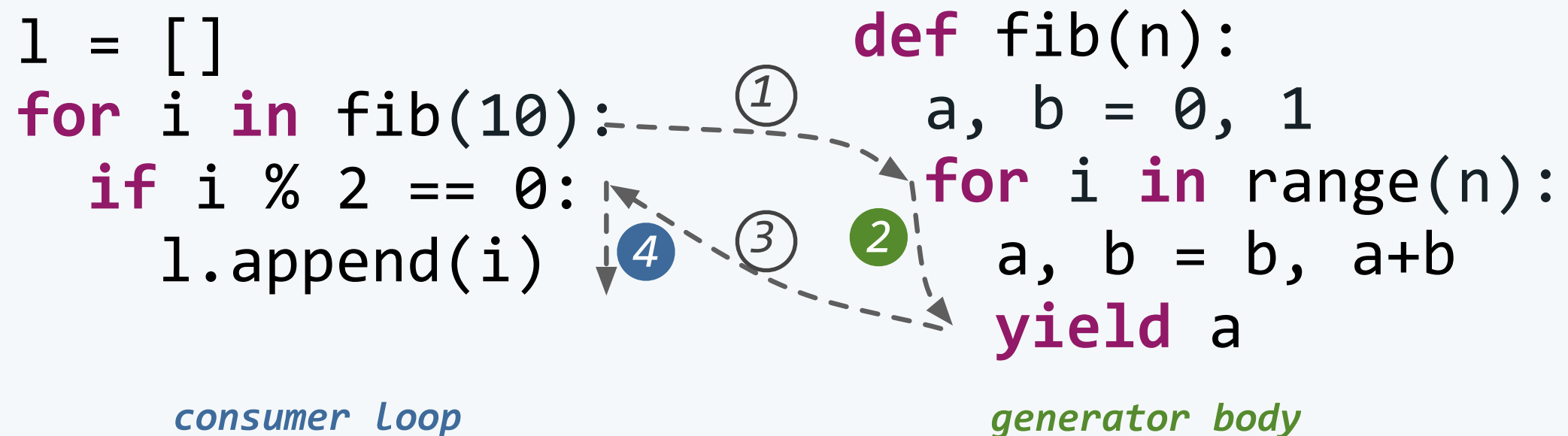
1. The implicit call to `__next__` and resume execution
2. Evaluate the next value in generator body

# Generator Execution



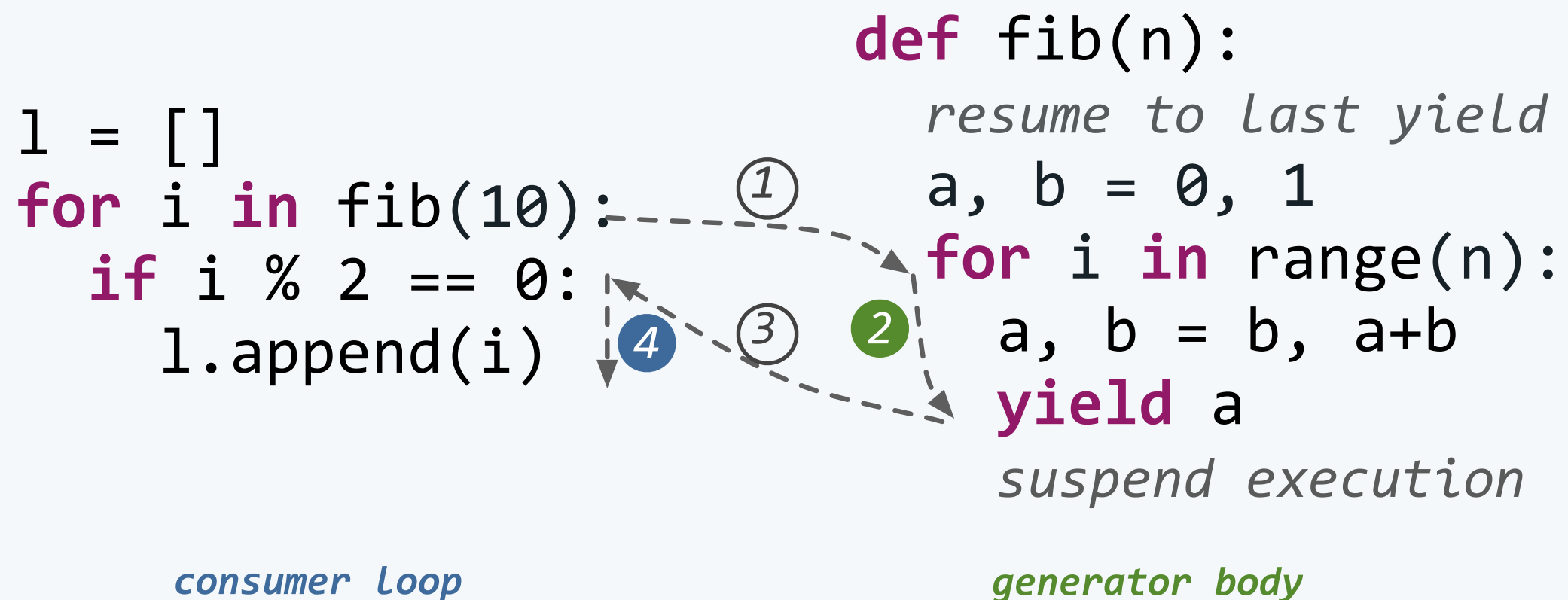
- 1.The implicit call to `__next__` and resume execution
- 2.Evaluate the next value in generator body
- 3.Suspend execution and return to the caller

# Generator Execution



- 1.The implicit call to `__next__` and resume execution
- 2.Evaluate the next value in generator body
- 3.Suspend execution and return to the caller
- 4.Consume the generated value

# Generator Overheads



- Only step 2 and 4 do the real work
- Python call is expensive
- Resume and suspend add additional costs and prevent frame optimizations

# Naive Inlining

```
l = []  
g = fib(10)  
while True:
```

```
resume to last yield  
a, b = 0, 1  
for i in range(n):  
    a, b = b, a+b  
    yield a  
suspend execution
```

```
i = a
```

```
if i % 2 == 0:  
    l.append(i)
```

```
except StopIter:
```

*generator body*

*generator frame*

0:	n
1:	a
2:	b
3:	i

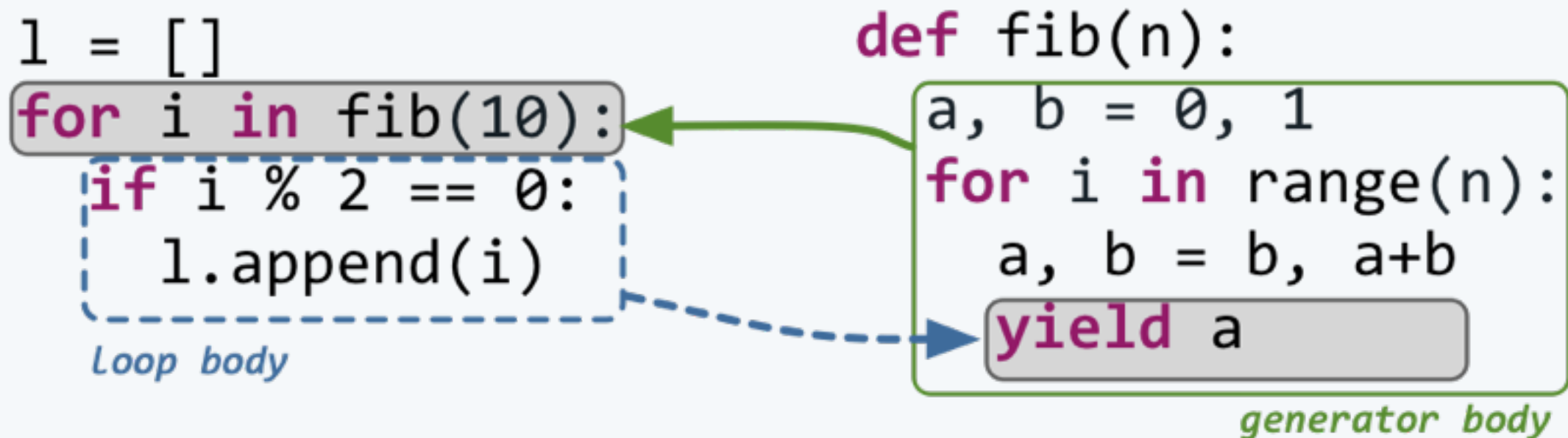
*caller frame*

0:	l
1:	i

*consumer loop*

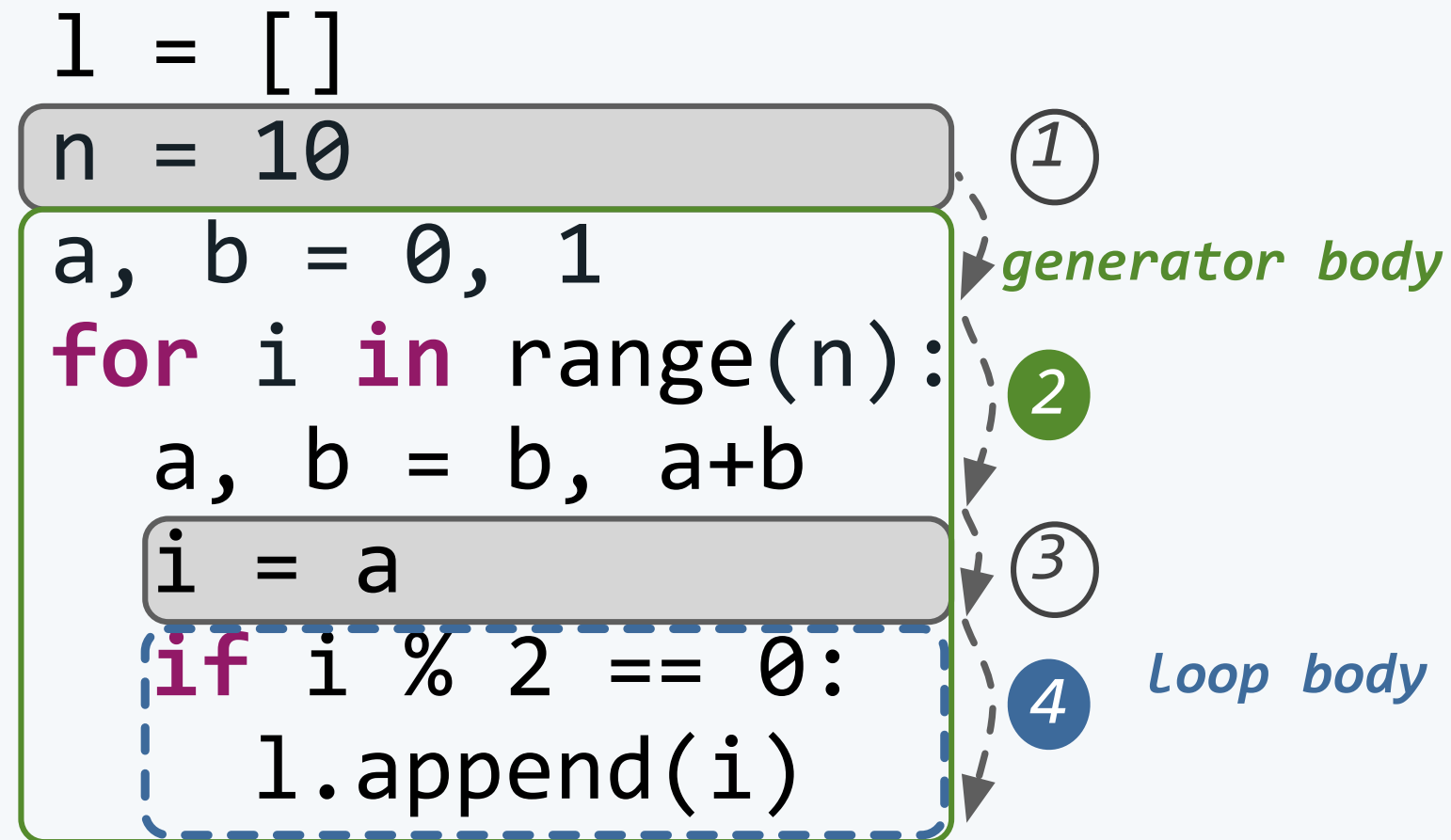
- Desugar the consumer loop and inline `__next__` directly
- The suspend and resume handling still persists

# Generator Peeling



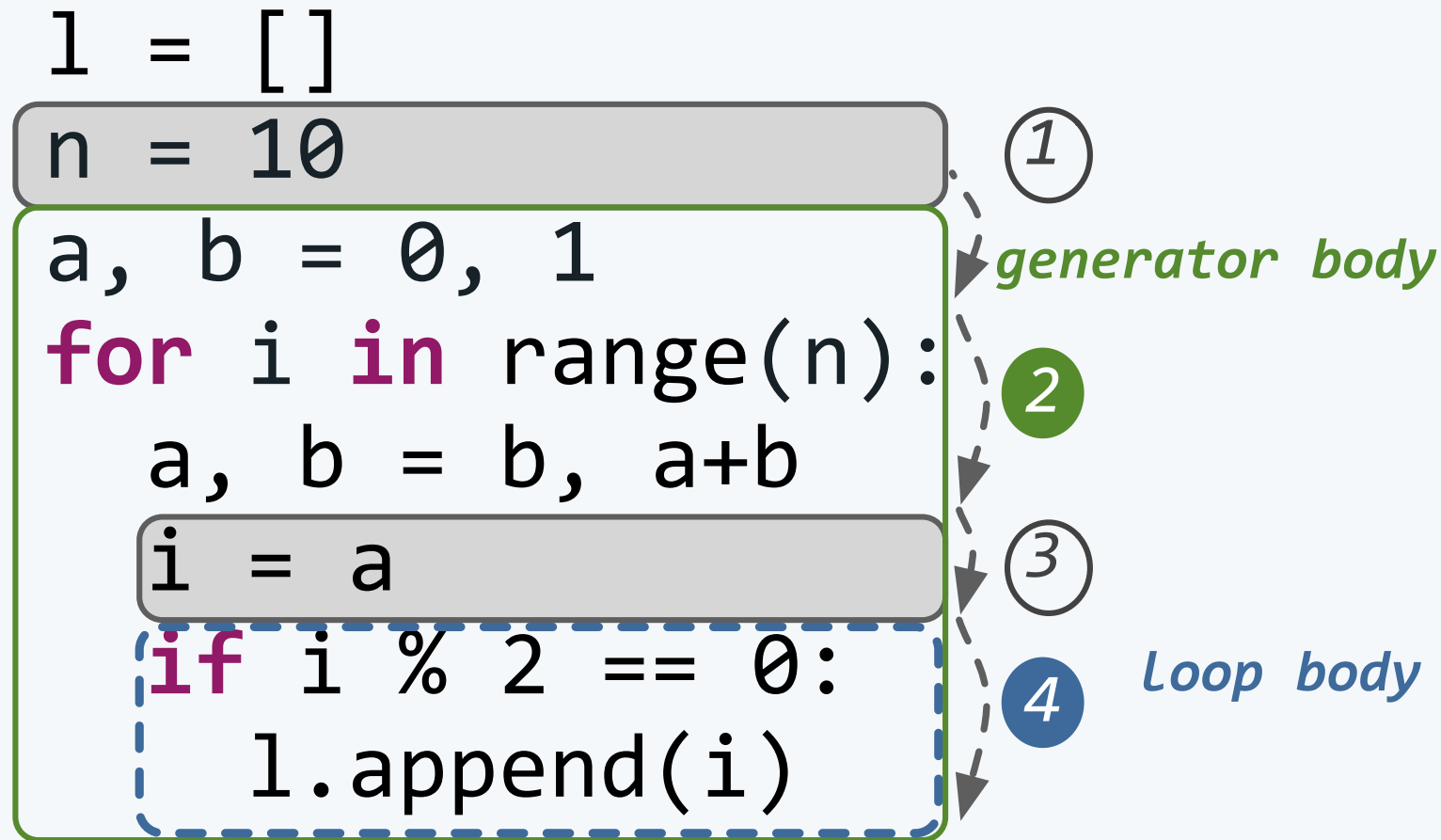
- Specialize the loop over generator at runtime
- Merge yield with consumer loop body

# Generator Peeling



- Specialize the loop over generator at runtime
- Remove suspend and resume handling

# Generator Peeling



*generator frame*

0:	n
1:	a
2:	b
3:	i

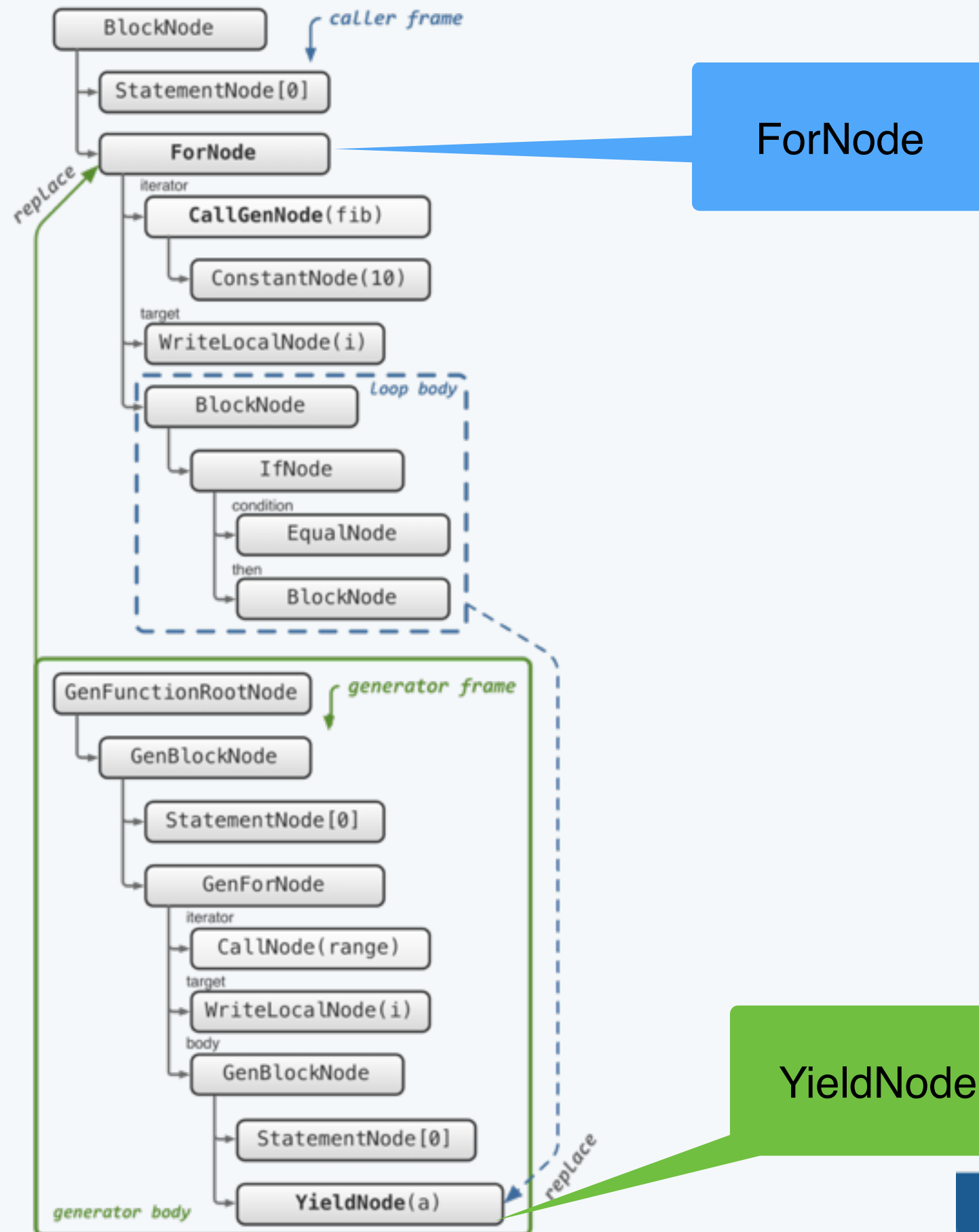
*caller frame*

0:	l
1:	i

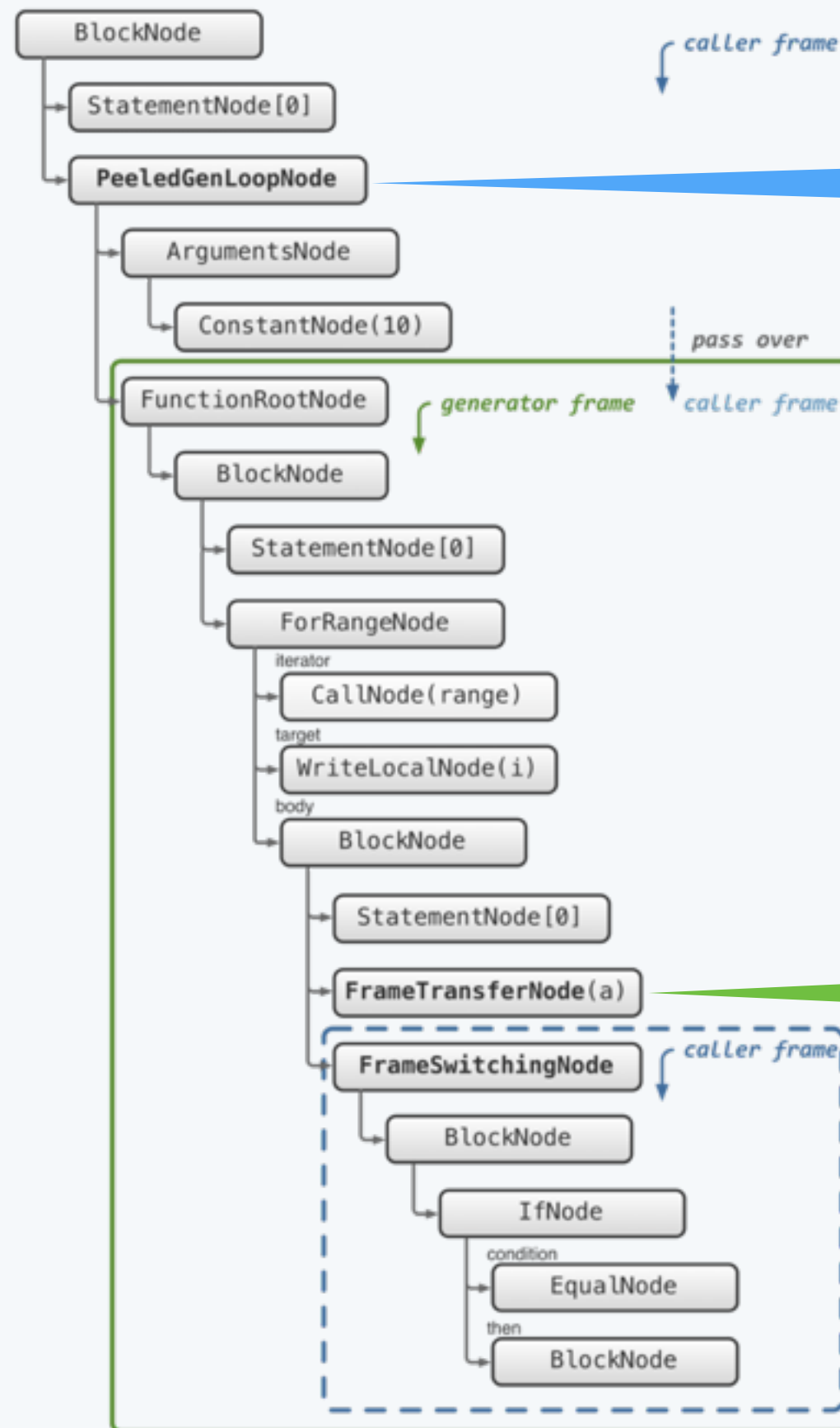
- Frames can be optimized during compilation



# Before



# After



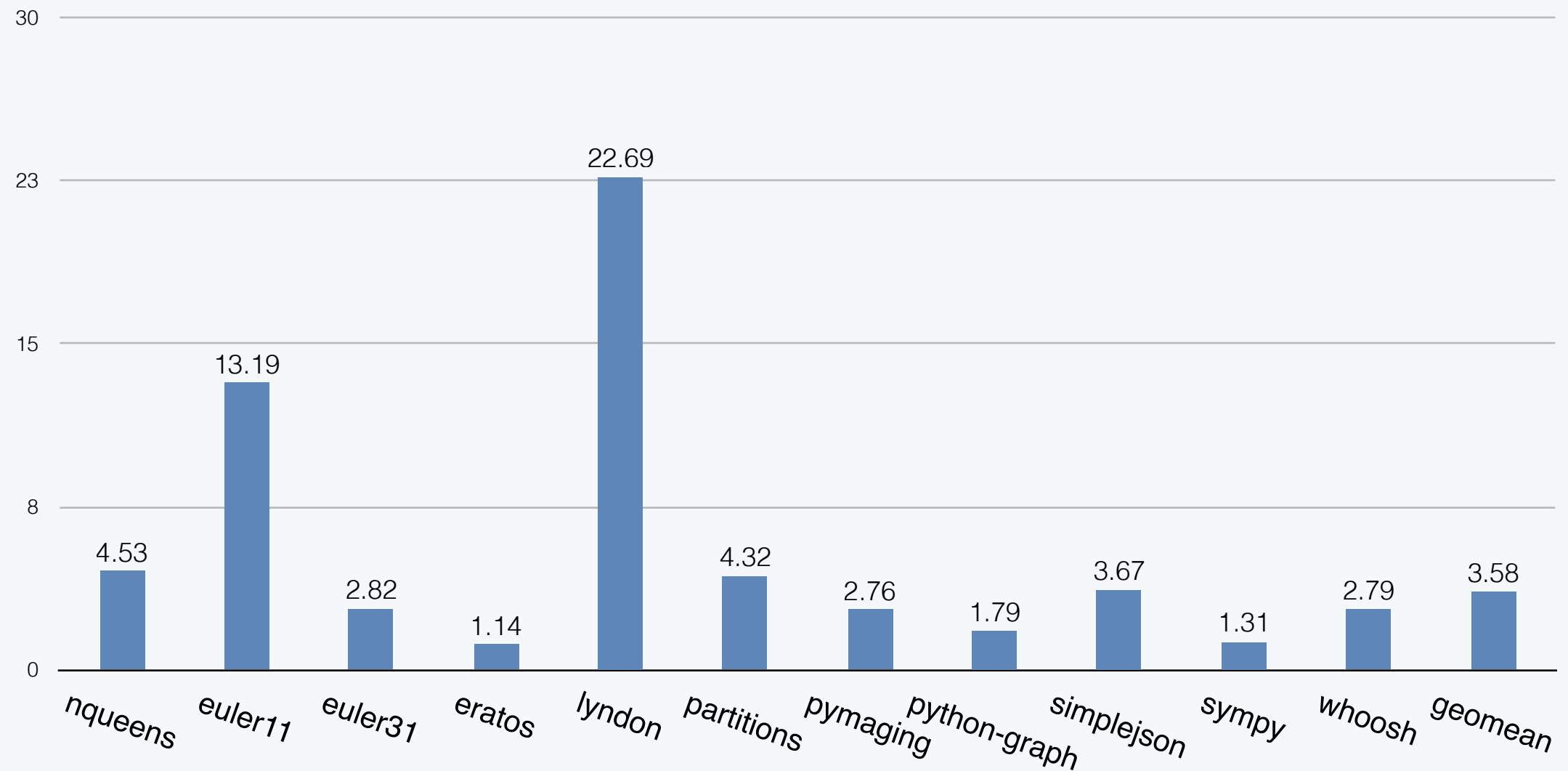
PeeledLoopNode

FrameTransferNode

# The End Result

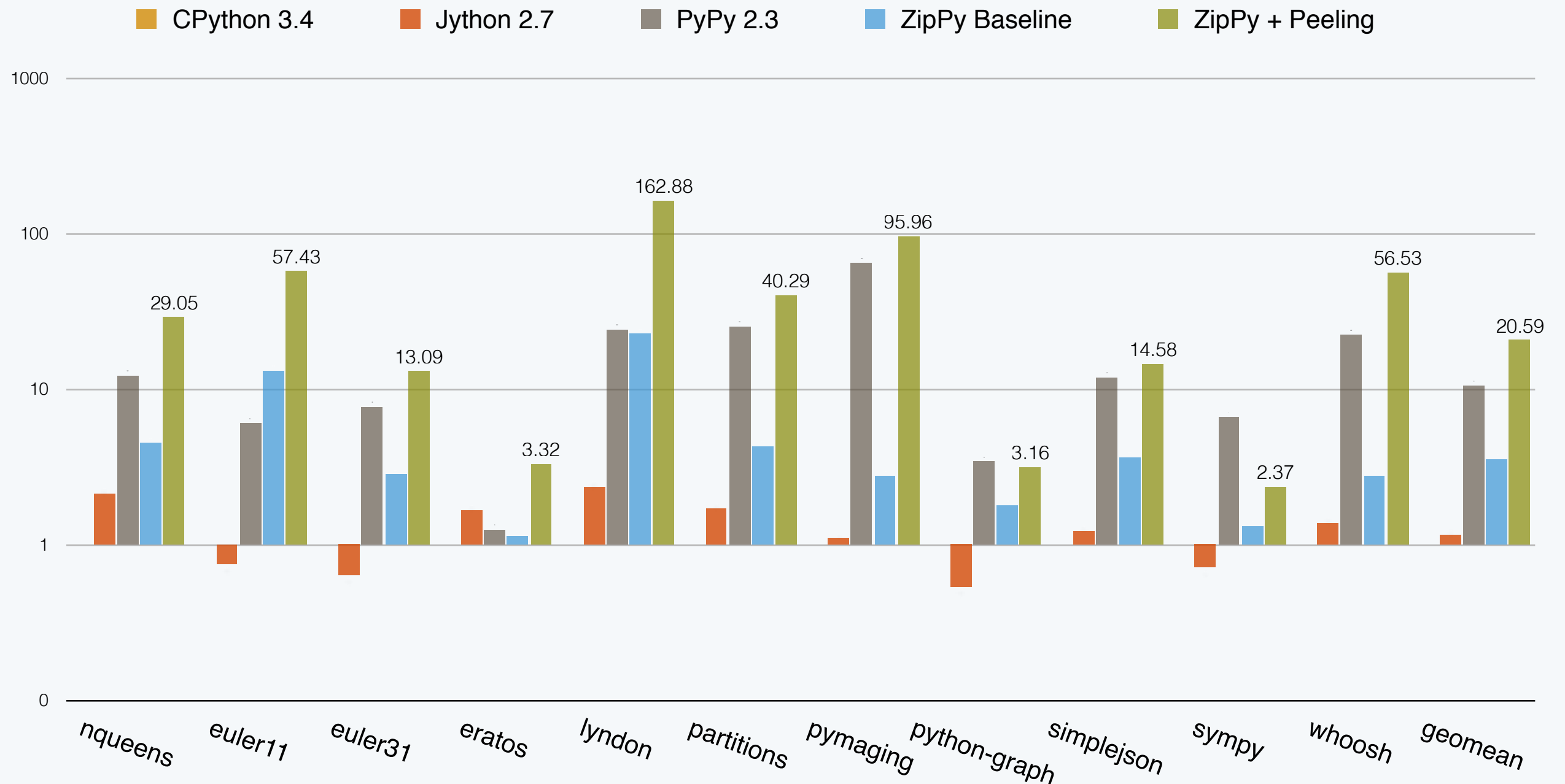
- Caller frame and generator frame can be optimized
- Peeling inlines the call to `__next__`
- No suspend and resume handling
- AST level transformation, independent from compilation

# Speedups of Generator Peeling



Measuring peak performance of ZipPy with and without Generator Peeling

# The Performance of ZipPy



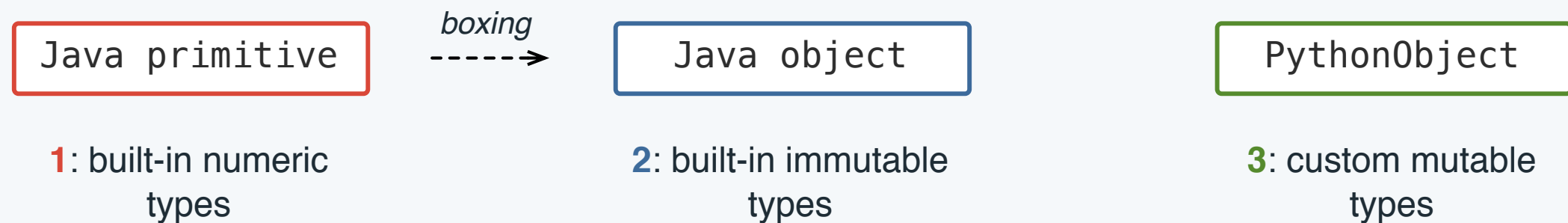
Measuring peak performance of ZipPy with Generator Peeling

# Generator peeling conclusions

- We present a dynamic program transformation that optimizes generators for optimizing AST interpreters
- Not restricted to ZipPy or Python
- As a result, programmers are free to enjoy generators' upsides

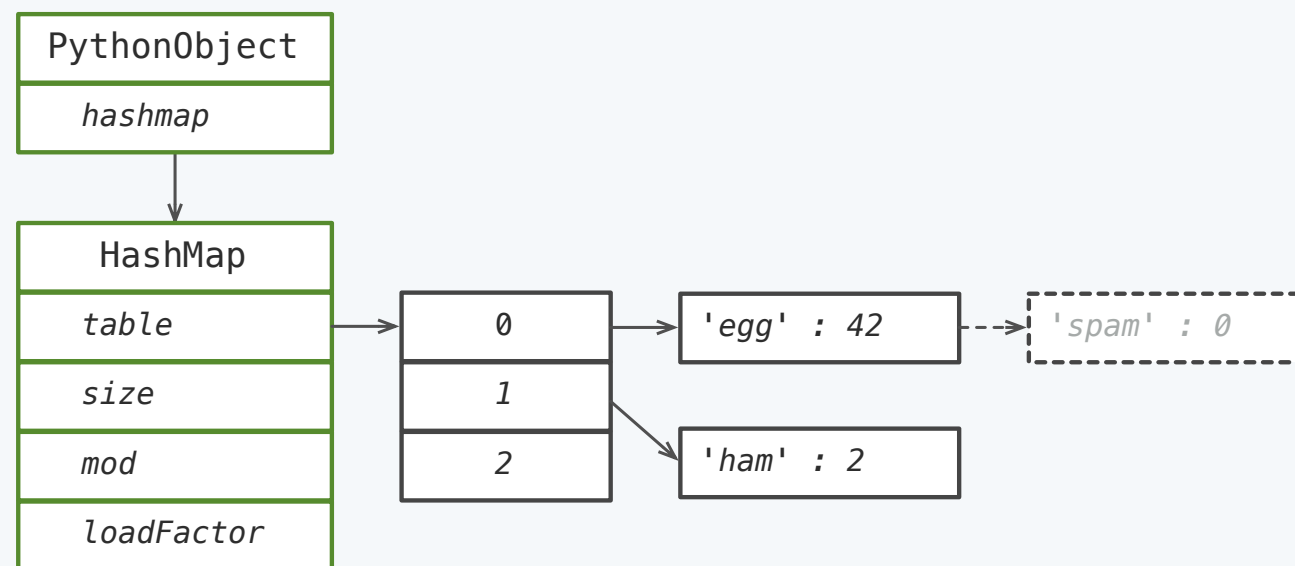


# Object model for dynamic languages

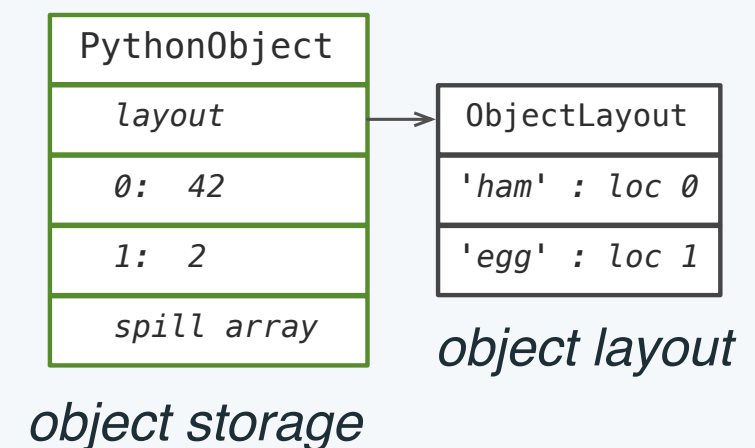


Multiple data representations for built-in and custom types

# Modeling mutable object in Python



HashMap based approach



Hidden class approach



# Implementation of object storage class

```
class FixedPythonObjectStorage extends PyObject {

    static final int INT_LOCATIONS_COUNT = 5;
    protected int primitiveInt0;
    protected int primitiveInt1;
    protected int primitiveInt2;
    protected int primitiveInt3;
    protected int primitiveInt4;

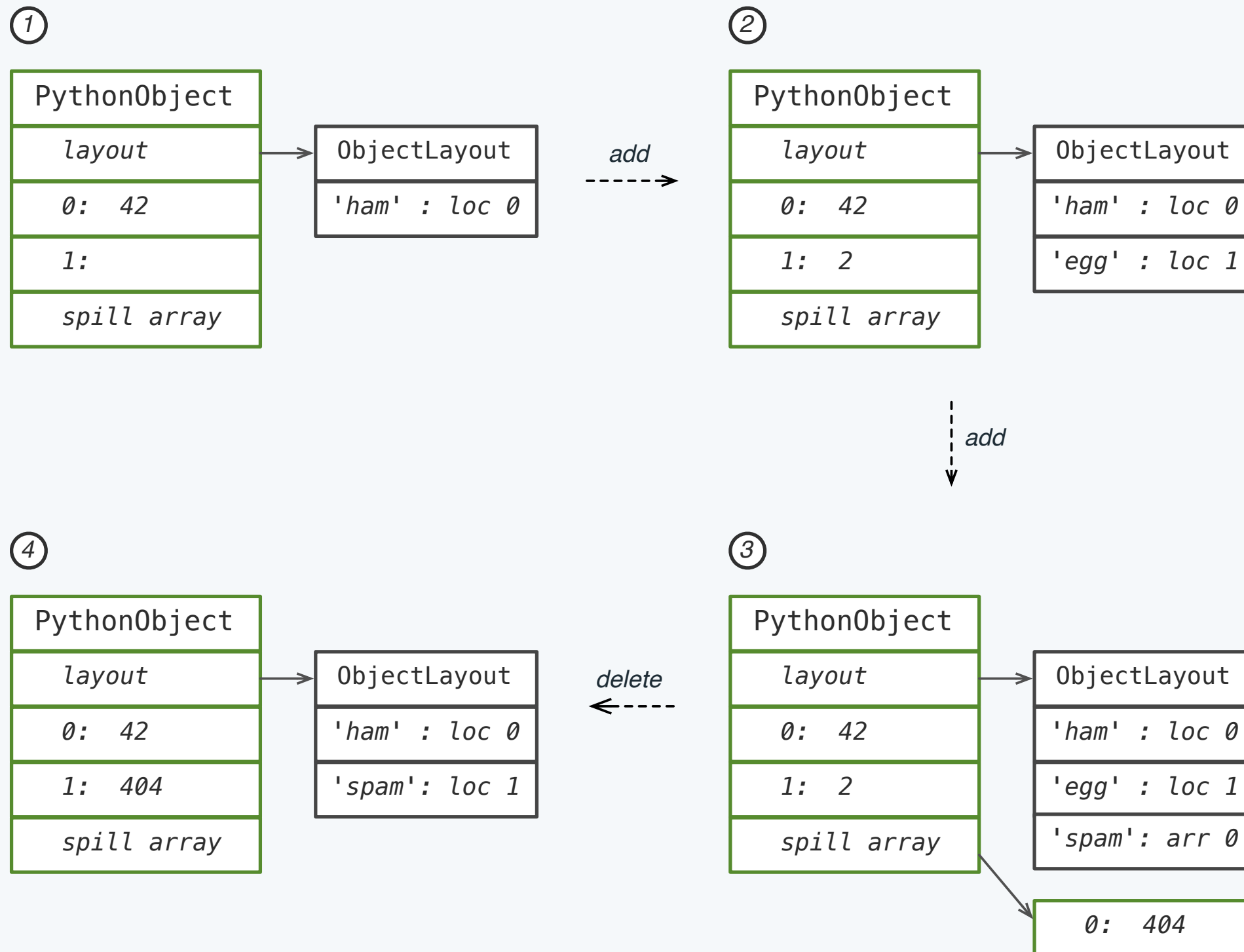
    static final int DOUBLE_LOCATIONS_COUNT = 5;
    protected double primitiveDouble0;
    protected double primitiveDouble1;
    protected double primitiveDouble2;
    protected double primitiveDouble3;
    protected double primitiveDouble4;

    static final int OBJECT_LOCATIONS_COUNT = 5;
    protected Object fieldObject0;
    protected Object fieldObject1;
    protected Object fieldObject2;
    protected Object fieldObject3;
    protected Object fieldObject4;

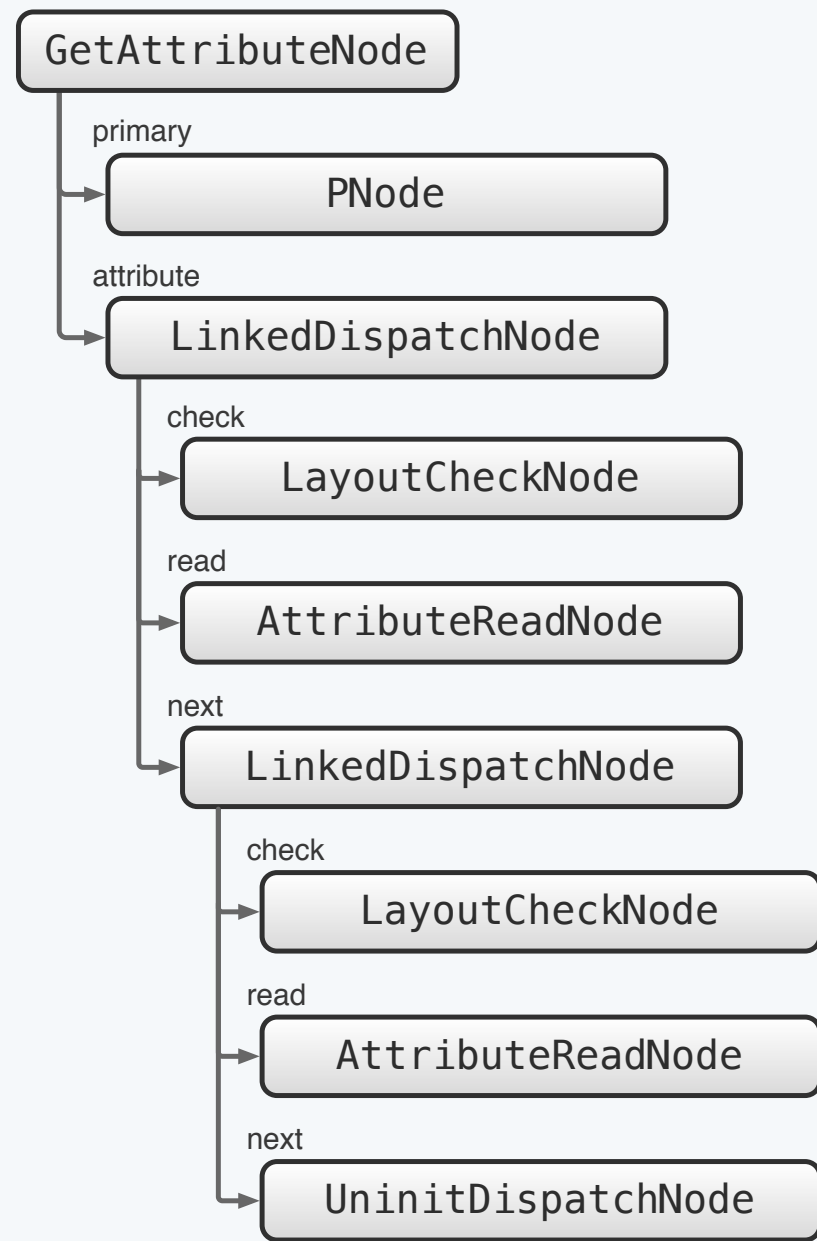
    protected Object[] objectsArray = null;

    public FixedPythonObjectStorage(PythonClass pythonClass) {
        super(pythonClass);
    }
}
```


# Implementation of object storage class



# Inline caching for object accesses



dispatch chain



```
cmp $0xe830f77b,r11d ; ObjectLayout
jne 0x000000001102e8ee9 ; next dispatch
mov rdi,0x640(%rsp)
```

JIT compiled dispatch node

# Flexible storage class generation

```
class Point:
    def __init__(self, x, y):
        self.x = x
        self.y = y
```

```
p = Point(1.2, 0.3)
# p.x == 1.2; p.y == 0.3
```

Python class Point

```
class Point extends FlexiblePythonObjectStorage {
    protected double x;
    protected double y;

    protected Object[] objectsArray = null;

    public Point(PythonClass pythonClass) {
        super(pythonClass);
    }
}
```

generated storage class for Point

# Python object layout change

```
class Point:
    def __init__(self, x, y):
        self.x = x
        self.y = y

    def addNeighbor(self, n):
        self.neighbors = n
```

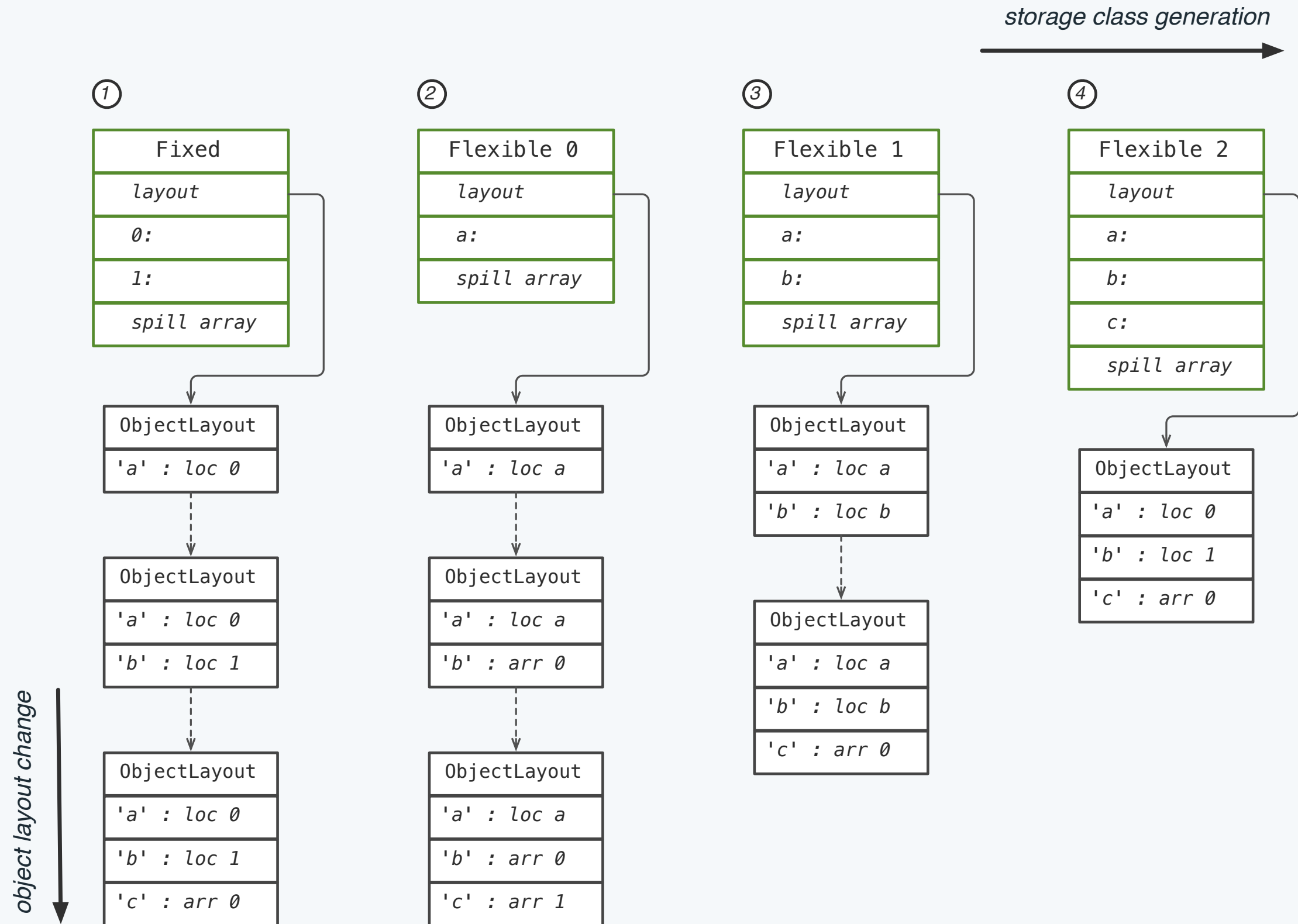
Python class Point

```
n = []

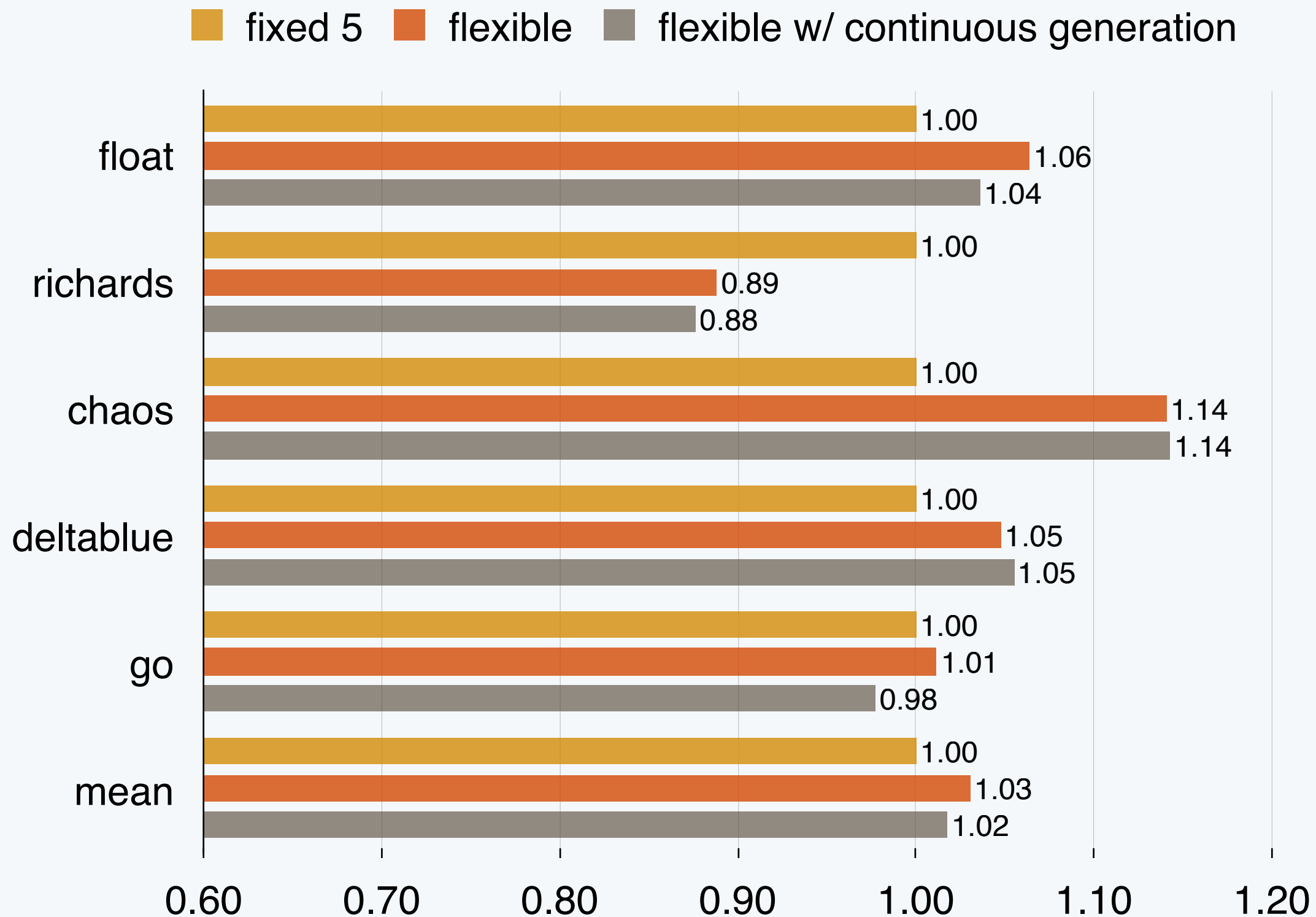
for i in range(5):
    p = Point(i*1.0, i*0.5)
    p.addNeighbors(n)
    n.append(p)
```

client code

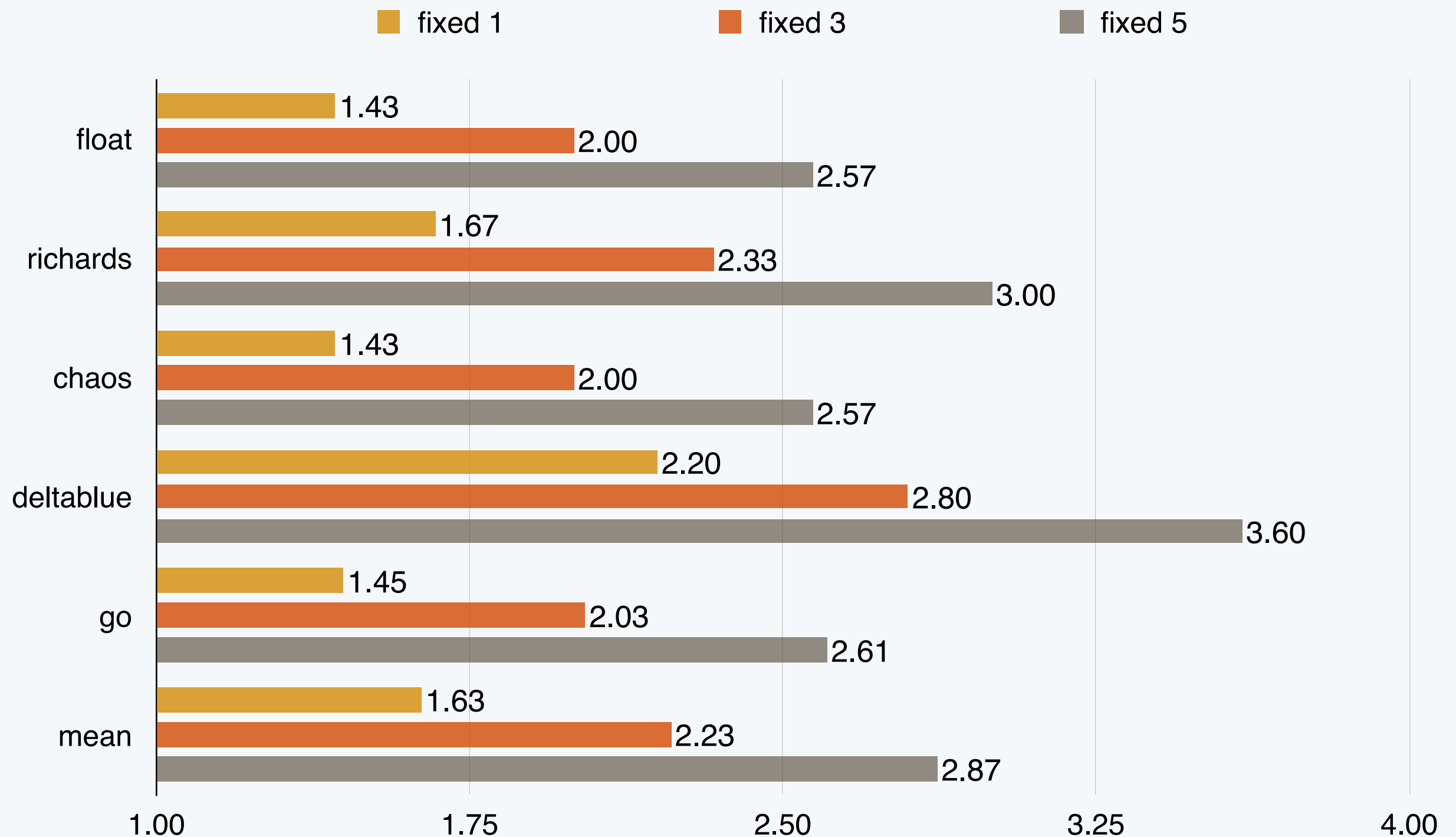
# Continuous storage class generation



# Performance of different object storage configurations

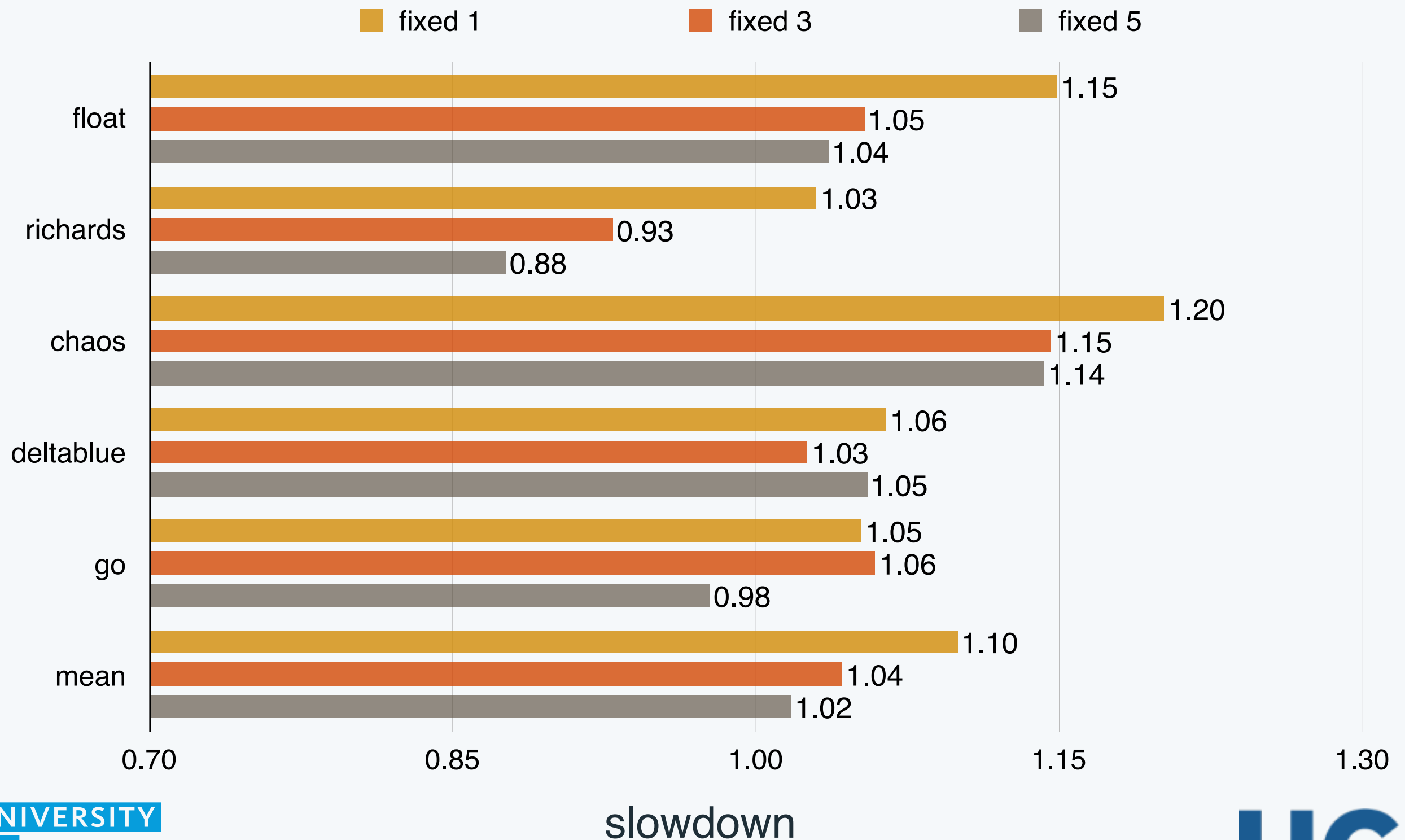


# Memory usage of fixed object storages normalized to flexible object storage





# Slowdown of fixed object storages normalized to flexible object storage



# Flexible object storage conclusions

- There is always a trade-off when using fixed object storage
- Fixed object storage leads up to 20% loss on performance or 3.6x more memory usage
- Flexible object storage always optimizes the current state of the target Python class
- The coexistence of multiple storage classes can introduce overhead

# Our contributions

- Generator peeling: a runtime optimization targeting hosted interpreters
- It is not restricted to Python or the implementation of ZipPy/Truffle
- Flexible object storage: a space efficient object model technique for class-based dynamic languages
- Can be reused by other languages hosted on the JVM

# Publications

- Wei Zhang, Per Larsen, Stefan Brunthaler, Michael Franz. **Accelerating Iterators in Optimizing AST Interpreters**. In *Proceedings of the 29th ACM SIGPLAN Conference on Object Oriented Programming: Systems, Languages, and Applications, Portland, OR, USA, October 20-24, 2014 (OOPSLA '14), 2014*.
- Gülfem Savrun-Yeniçeri, Wei Zhang, Huahan Zhang, Eric Seckler, Chen Li, Stefan Brunthaler, Per Larsen, Michael Franz. **Efficient Hosted Interpreters on the JVM**. In *ACM Transactions on Architecture and Code Optimization, volume 11(1) pages 9:1–9:24, 2014*.
- Gülfem Savrun-Yeniçeri, Wei Zhang, Huahan Zhang, Chen Li, Stefan Brunthaler, Per Larsen, Michael Franz. **Efficient Interpreter Optimizations for the JVM**. In *Proceedings of the 10th International Conference on Principles and Practice of Programming in Java, Stuttgart, Germany, September 11-13, 2013 (PPPJ '13), 2013*.

# Question Please?