Compiled and interpreted languages

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Roughly two kinds of languages

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Pedantic disclaimer

Compilation/interpretation is strictly a property of *implementations*, not *languages*.

- You could have a C interpreter or Python compiler
- But most (not all!) languages are built with a specific implementation technique in mind
- A few languages (Lisp, JavaScript) have lots of *very* different implementations...

We teach you the big picture—the details are always more complicated in practice!

Tradeoffs

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  + Almost always faster
  - Require compilation after every change
  - Usually cannot run program fragments in isolation
  - Tend to have more restrictions (e.g. static typing)
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- Interpreted languages
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  - + Can run immediately
  - + Can easily run fragments (e.g. single functions) in isolation
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Let us look at the scale of the overhead.

The Collatz conjecture

$$f(n) = \left\{ \begin{array}{ll} \frac{n}{2} & \text{if } n \text{ is even} \\ 3n+1 & \text{if } n \text{ is odd} \end{array} \right\}$$

- **Conjecture:** if we apply this function to some number greater than 1, we will eventually reach 1
- To disprove this conjecture, we only need *a single counter-example* that goes into a cycle instead
- People write programs to investigate the behaviour of this sequence

Listing 1: collatz.py

```python
import sys

def collatz(n):
    i = 0
    while n != 1:
        if n % 2 == 0:
            n = n // 2
        else:
            n = 3 * n + 1
        i = i + 1
    return i

k = int(sys.argv[1])
for n in range(1, k):
    print(n, collatz(n))
```

Listing 2: collatz.c

```c
#include <stdio.h>
#include <stdlib.h>

int collatz(int n) {
  int i = 0;
  while (n != 1) {
    if (n % 2 == 0) {
      n = n / 2;
    } else {
      n = 3 * n + 1;
    }
    i++;
  }
  return i;
}

int main(int argc, char** argv) {
  int k = atoi(argv[1]);
  for (int n = 1; n < k; n++) {
    printf("%d %d\n", n, collatz(n));
  }
}
```

Benchmarking `collatz.py`

```
$ time python3 ./collatz.py 100000 >/dev/null

real    0m1.368s
user    0m1.361s
sys     0m0.007s
```

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$ gcc collatz.c -o collatz
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Speedup: $\frac{1.368}{0.032} = 42.75$

Combining interpretation and compilation

- Interpreted languages can be fast when
  - Most of the run-time is spent waiting data from files or network
  - They mostly call functions written in faster compiled languages
- **Best of both worlds:** flexibility of interpretation, and speed of C

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$ gcc collatz.c -c -o collatz.o
```

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- Can be processed further

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$ gcc collatz.c -o collatz
```

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To object file `collatz.o`

```
$ gcc collatz.c -c -o collatz.o
```

- Can be *linked* with other object files
- Can be processed further

To shared object file `libcollatz.so`

```
$ gcc collatz.c -fPIC -shared -o libcollatz.so
```

- Can be linked *at run-time* by a running program
- How compiled programs support dynamic “plug-ins”

All output files contain fully compiled machine code.

Calling C from Python

Compiling C program to shared library

```
$ gcc collatz.c -fPIC -shared -o libcollatz.so
```

Listing 3: `collatz-ffi.py`

```python
import ctypes
import sys

c_lib = ctypes.CDLL('./libcollatz.so')

k = int(sys.argv[1])
for n in range(1, k):
    print(n, c_lib.collatz(n))
```

```
$ time python3 ./collatz-ffi.py 100000 >/dev/null

real    0m0.165s
user    0m0.163s
sys     0m0.003s
```

Speedup: $\frac{1.368}{0.165} = 8.2$

```
$ time python3 ./collatz-ffi.py 100000 >/dev/null

real    0m0.165s
user    0m0.163s
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```

$$\textbf{Speedup:} \quad \frac{1.368}{0.165} = 8.2$$

- Slower than pure C by about $5\times$
- Faster if we made fewer "foreign" calls, but each took more time
- Ideal case is single foreign function call that operates on many values
- **This is exactly how NumPy works!**

NumPy performance

```
def f_python(v):
    for i in range(len(v)):
        v[i] = v[i]*2 + 3

def f_numpy(v):
    return v * 2 + 3
```

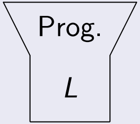
Size of v	f_python	f_numpy	Difference
1	0.01ms	0.01ms	0.9×
10	0.01ms	0.01ms	1.4×
100	0.1ms	0.01ms	13.3×
1000	0.98ms	0.01ms	95.3×
10000	9.96ms	0.05ms	190.7×
100000	98.59ms	0.41ms	240.7×

Now a high-level view

- We've looked at some technical details of compilers and interpreters
- Do we also have a high-level model?

Tombstone diagrams

A program written in L



Tombstone diagrams

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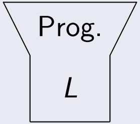
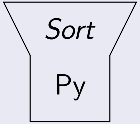
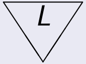


Example of program written in Python



A machine that runs L programs



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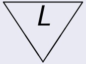
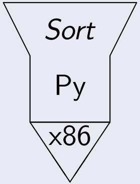


Example



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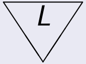

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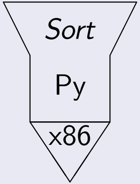
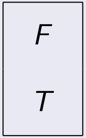


Incorrect! Languages (Python and x86) do not match!

An interpreter for F, written in T



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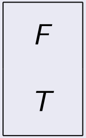

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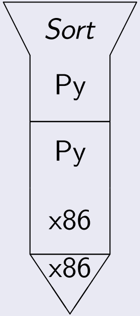
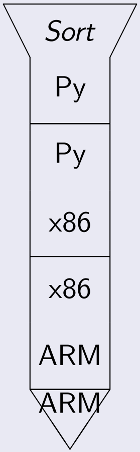
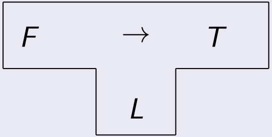


Stacking interpreters



A compiler from F to T, written in L



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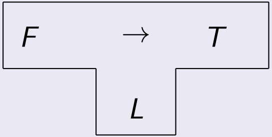

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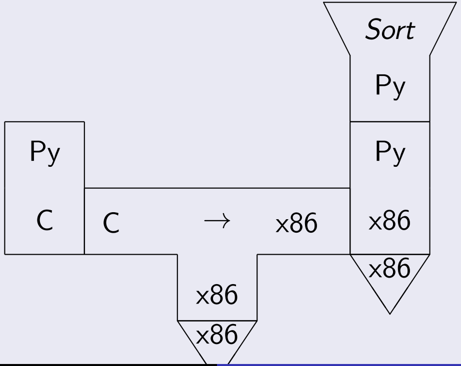

Compilers can be chained

Futhark $\rightarrow$ C $\rightarrow$ machine code

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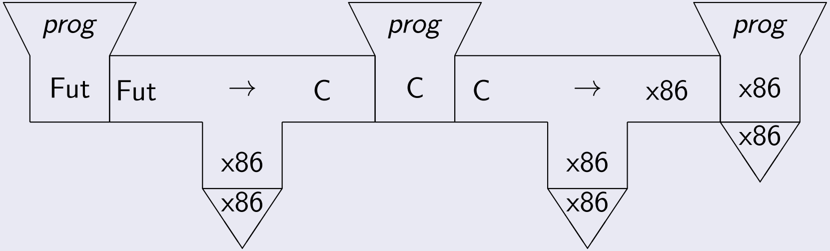
Futhark → C → machine code

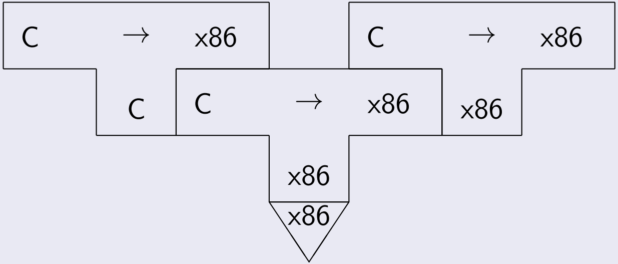
Example



Compilers are also programs

- A C compiler is usually written in a high-level language, not in machine code
- Use old version of the compiler to compile the new version of the compiler

Example



- All the way back to the first computers, where some primordial primitive compiler or assembler was written in machine code

Advantages and limitations of tombstone diagrams

- + Abstracts away technical details of object files, compilation modes etc
- - Cannot express more complex situations such as dynamic linking
- In practice mostly used for visualising **bootstrapping**—the process of writing compilers in the language they compile, or bringing up new hardware

Conclusions

- Compiled languages tend to be fast, but less flexible
- Interpreted languages tend to be slower, but more flexible
- **Best of both worlds:** write computational primitives in fast languages, call them from slow languages
  - NumPy works like this
- Tombstone diagrams make the relationship between compiler, interpreter, and machine clear
  - Although in day-to-day work, we only use simple compositions