Fastlife

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CONTENTS

Fast Life is an experiment in Python simulation performance. Python has many excellent simulation frameworks including SimPy and MESA, which make it easy to conduct simulations for research and experimental purposes. Fast Life is not intended to be a simulation framework in the same way, instead Fast Life is designed to answer the question: "Can Python be used to create extremely large scale simulations"? To this end, Fast Life implements a seemingly simple simulation: Conway's Game of Life – but scales it up to massive proportions. We then explore several different implementations including:

1. Pure Python Sequential
2. Pure Python Multiprocessing
3. C-bindings Sequential
4. C-bindings Parallel

And run benchmarks to see what is the simplest mechanism to combine the ease of Python programming with the performance required to generate massive worlds. All implementations are designed with the best effort in mind, using numpy where possible and where it enhances performance, and details matter with function profiling and more.

This work is still in progress and is a bit of a journey. If you're reading this, stay tuned, there is more coming! If you're interested in contributing, we'd also be happy to have you join, let us know how you'd like to participate!

CHAPTER

ONE

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1.1 Implementation Notes

Where possible, the implementation has been revised several times using profiling techniques in order to create the best performing simulation. In this section we describe in detail some of the choices we've made, and the impact that these choices have had on the performance of the overall simulation.

1.1.1 Neighborhoods

Most of the computational complexity from the Game of Life Cellular Automata comes from computing the next step in the simulation. This requires looping over all cells in the current frame and updating their state based on their *neighborhood*. In order to determine the neighborhood, another small loop is required to find the values of all cells surrounding the current cell and to sum their results. Each frame is a numpy 2-dimensional array wrapped with some helper utilities using a `Grid` object. This object exposes three methods to access the neighborhood:

- `neighborhood()`: uses Python generators
- `neighborhood_array()`: creates and returns a numpy array
- `neighborhood_sum()`: computes the sum directly

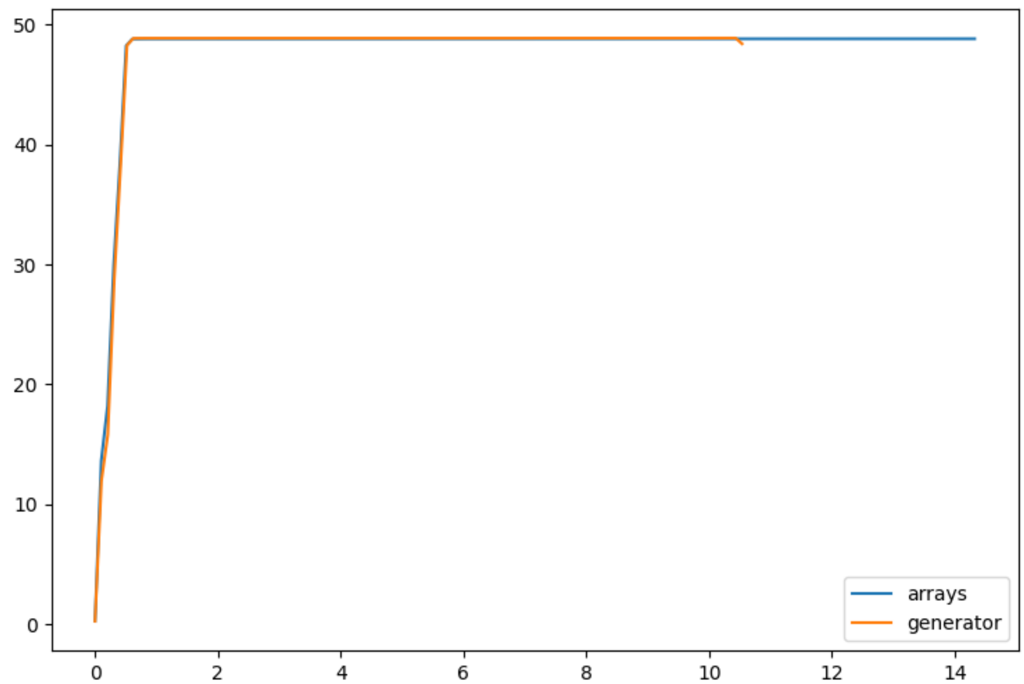
Note: We found that the `neighborhood_sum()` method was the fastest performing mechanism and this is the Grid method that the simulation currently uses.

The `neighborhood` method returns the value of the cells surrounding the cell at the `i,j` coordinates using either a Von Neumann or Moore (default) neighborhood. This method must return the values in a specific order, namely, starting from the top at the 12 o'clock position in clockwise order. We wanted to keep the order static so that callers could infer which position each returned value was, therefore rather than range from `(-1, 1)`, the index positions were statically stored as follows:

```
VNIP = np.asarray([-1, 0, 1, 0])
VNJP = np.asarray([0, 1, 0, -1])
MRIP = np.asarray([-1, -1, 0, 1, 1, 1, 0, -1])
MRJP = np.asarray([0, 1, 1, 1, 0, -1, -1, -1])
```

Here the `"VN"` prefix refers to the Von Neumann neighborhood and the `"MR"` prefix refers to the Moore neighborhood. At their core, each of the methods simply loops over the `i,j` indices of the neighborhood values using the deltas in these arrays to find the values and returns them.

Comparing the memory usage of generators (the `neighborhood` and `neighborhood_sum` methods) to arrays (`neighborhood_array`) showed that they used equivalent amounts of memory for decently sized programs:



Therefore we turned to `cProfile` to determine the stack performance of the methods instead. The below sections describe each method in detail and their results.

Generators

The generator method loops through the positions in the neighborhood and attempts to fetch their value, catching an `IndexError` if it is out of bounds. The function yields the result, which causes Python to return a `generator` which can be looped over by callers.

```
def neighborhood(self, i, j):
    ip, jp = (MRIP, MRJP) if self.adjacency == MOORE else (VNIP, VNJP)

    for id, jd in zip(ip, jp):
        try:
            yield self._world[i+id,j+jd]
        except IndexError:
            yield 0
```

The simulation must sum all of the values yielded by the generator and can do so by using the built-in `sum` function:

```
ngbrs = sum(cframe.neighborhood(i,j))
```

Resulted in the following profile:

```
        168826452 function calls (168826408 primitive calls) in 185.587 seconds

  Ordered by: cumulative time
```

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```
  List reduced from 345 to 20 due to restriction <20>

  ncalls  tottime  percall  cumtime  percall filename:lineno(function)
       1    0.000    0.000  185.586  185.586 sequential.py:106(run)
     150   30.499    0.203  185.543    1.237 sequential.py:75(step)
 9375304   49.018    0.000  133.994    0.000 {built-in method builtins.sum}
84375000   83.697    0.000   84.966    0.000 grid.py:72(neighborhood)
 9375055    9.608    0.000   12.357    0.000 grid.py:118(__setitem__)
 9375000    6.620    0.000    8.705    0.000 grid.py:113(__getitem__)
28125453    3.168    0.000    3.168    0.000 {built-in method builtins.isinstance}
18750560    1.666    0.000    1.666    0.000 {built-in method builtins.len}
 9375000    1.270    0.000    1.270    0.000 grid.py:57(adjacency)
```

Approximately 26% of the time of this program was spent in the `builtins.sum` method, and 45% of the time spent in the *neighborhood* function. This was an interesting result in that it balanced the summation and the loops fairly well.

Arrays

The goal of the arrays method was to save memory or increase performance by using numpy instead of a pure Python solution. In this implementation, a numpy array of the correct size is created with the neighborhood and then returned. Instead of catching exceptions, the function checks boundaries before data access.

```
def neighborhood_array(self, i, j):
    if self.adjacency == MOORE:
        ip, jp = MRIP, MRJP
        vals= np.zeros(8)
    else:
        ip, jp = VNIP, VNJP
        vals = np.zeros(4)

    im, jm = self._world.shape
    for v, (id, jd) in enumerate(zip(ip, jp)):
        ic, jc = i+id, j+jd
        if ic >= 0 and jc >=0 and ic < im and jc < jm:
            vals[v] = self._world[ic,jc]

    return vals
```

Callers have to compute the sum, but they can use a numpy method instead of the builtin as follows:

```
ngbrs = cframe.neighborhood_array(i, j).sum()
```

Resulted in the following profile:

```
      121951451 function calls (121951407 primitive calls) in 261.210 seconds

  Ordered by: cumulative time
  List reduced from 348 to 20 due to restriction <20>

  ncalls  tottime  percall  cumtime  percall filename:lineno(function)
       1    0.000    0.000  261.209  261.209 sequential.py:106(run)
     150   39.191    0.261  261.161    1.741 sequential.py:75(step)
 9375000  154.458    0.000  165.727    0.000 grid.py:85(neighborhood_array)
 9375000    3.690    0.000   34.852    0.000 {method 'sum' of 'numpy.ndarray' objects}
```

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```
 9375000    2.506    0.000   31.162    0.000 _methods.py:45(_sum)
 9375000   28.656    0.000   28.656    0.000 {method 'reduce' of 'numpy.ufunc'␣
↪objects}
 9375055    9.748    0.000   12.510    0.000 grid.py:118(__setitem__)
 9375002    9.881    0.000    9.881    0.000 {built-in method numpy.zeros}
 9375000    6.615    0.000    8.880    0.000 grid.py:113(__getitem__)
28125453    3.171    0.000    3.171    0.000 {built-in method builtins.isinstance}
18750560    1.856    0.000    1.856    0.000 {built-in method builtins.len}
 9375000    1.388    0.000    1.388    0.000 grid.py:57(adjacency)
```

The summation function in this version is dramatically increased, however it does so at the cost of the performance of the `neighborhood_array` method which takes 59% of the computation. Other numpy methods such as reduce and the alloc caused by numpy.zeros also take relatively significant time, as a result, this method is almost 1.5x slower than the generator method.

Iterated Sum

Noting the performance of the generators method but the poor use of the built-in `sum` method, we created a third function that does not return a neighborhood, but rather returns the sum of the neighborhood, which is what is needed anyway. This function does not yield zeros and keeps track of the running sum without an additional call on the stack. As a result it is more lightweight and is slightly faster than the generator method by itself.

```python
def neighborhood_sum(self, i, j):
    total = 0
    ip, jp = (MRIP, MRJP) if self.adjacency == MOORE else (VNIP, VNJP)

    for id, jd in zip(ip, jp):
        try:
            total += self._world[i+id,j+jd]
        except IndexError:
            continue
    return total
```

No extra work is needed by the caller, they can get the result directly:

```
ngbrs = cframe.neighborhood_sum(i,j)
```

Resulted in the following profile:

```
       84451452 function calls (84451408 primitive calls) in 162.208 seconds

  Ordered by: cumulative time
  List reduced from 345 to 20 due to restriction <20>

  ncalls  tottime  percall  cumtime  percall filename:lineno(function)
       1    0.000    0.000  162.208  162.208 sequential.py:107(run)
     150   29.307    0.195  162.165    1.081 sequential.py:75(step)
 9375000  111.495    0.000  112.871    0.000 grid.py:72(neighborhood_sum)
 9375055    8.961    0.000   11.508    0.000 grid.py:129(__setitem__)
 9375000    6.505    0.000    8.478    0.000 grid.py:124(__getitem__)
28125453    3.025    0.000    3.025    0.000 {built-in method builtins.isinstance}
18750560    1.495    0.000    1.495    0.000 {built-in method builtins.len}
 9375000    1.376    0.000    1.376    0.000 grid.py:57(adjacency)
```

This implementation is the fastest mechanism implemented so far, with the majority of the time spent in the `neighborhood_sum` method, and very few other stack calls required.

1.2 API Reference

In this section, we describe in detail the API and implementations of the `fastlife` module. The transparency of this section is critical to ensure that user's understand the best effort made to enhance the performance of all implementations. Much of the documentation here is generated from the docstrings in the code as a result.

1.2.1 Grid

1.2.2 Sequential

1.2.3 Utilities

Utility functions and helpers for the fastlife module

`fastlife.utils.`**`load_mprofile`**(*path*, *name=None*)
    Load a memory profile from disk for plotting and comparison.

`fastlife.utils.`**`sprofile`**(*func*)
    Decorator that performs a speed/stack profile of the time spent in each function call from the stack below the wrapped function. Prints the results when done.

1.2.4 Exceptions

Exception and warnings hierarchy for use with fastlife.

exception `fastlife.exceptions.`**`ConsoleError`**
    Bases: *`fastlife.exceptions.FastlifeError`*

exception `fastlife.exceptions.`**`FastlifeError`**
    Bases: `Exception`

exception `fastlife.exceptions.`**`FastlifeTypeError`**
    Bases: *`fastlife.exceptions.FastlifeError`*, `TypeError`

exception `fastlife.exceptions.`**`FastlifeValueError`**
    Bases: *`fastlife.exceptions.FastlifeError`*, `ValueError`

exception `fastlife.exceptions.`**`FastlifeWarning`**
    Bases: `UserWarning`

CHAPTER TWO

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