

High Performance Computing Assignment 1

Task 1.1

```
In [1]: from timeit import default_timer as timer
import time
```

time.time()

```
In [2]: import numpy as np
def checktick1():
    M = 200
    timesfound = np.empty((M,))
    for i in range(M):
        t1 = time.time() # get timestamp from timer
        t2 = time.time() # get timestamp from timer
        while (t2 - t1) < 1e-16: # if zero then we are below clock granu
            t2 = time.time() # get timestamp from timer
        t1 = t2 # this is outside the loop
        timesfound[i] = t1 # record the time stamp
    minDelta = 1000000
    Delta = np.diff(timesfound) # it should be cast to int only when need
    minDelta = Delta.min()
    return minDelta
```

```
In [3]: checktick1()
```

```
Out[3]: np.float64(7.152557373046875e-07)
```

timeit()

```
In [4]: import numpy as np
def checktick2():
    M = 200
    timesfound = np.empty((M,))
    for i in range(M):
        t1 = timer() # get timestamp from timer
        t2 = timer() # get timestamp from timer
        while (t2 - t1) < 1e-16: # if zero then we are below clock granu
            t2 = timer() # get timestamp from timer
        t1 = t2 # this is outside the loop
        timesfound[i] = t1 # record the time stamp
    minDelta = 1000000
    Delta = np.diff(timesfound) # it should be cast to int only when need
    minDelta = Delta.min()
    return minDelta
```

```
In [5]: checktick2()
```

Out [5]: np.float64(2.0797597244381905e-07)

time.time_ns()

```
In [6]: import numpy as np
def checktick3():
    M = 200
    timesfound = np.empty((M,))
    for i in range(M):
        t1 = time.time_ns() # get timestamp from timer
        t2 = time.time_ns() # get timestamp from timer
        while (t2 - t1) < 1e-16: # if zero then we are below clock granu
            t2 = time.time_ns() # get timestamp from timer
        t1 = t2 # this is outside the loop
        timesfound[i] = t1 # record the time stamp
    minDelta = 1000000
    Delta = np.diff(timesfound) # it should be cast to int only when need
    minDelta = Delta.min()
    return minDelta
```

In [7]: checktick3()*1e-9

Out [7]: np.float64(7.6800000000000001e-07)

Task 1.2

Decorator

```
In [11]: from functools import wraps
import statistics
```

```
In [13]: """Julia set generator without optional PIL-based image drawing"""
import time
from functools import wraps

# area of complex space to investigate
x1, x2, y1, y2 = -1.8, 1.8, -1.8, 1.8
c_real, c_imag = -0.62772, -.42193

# decorator to time
def timefn(fn):
    times = []
    @wraps(fn)
    def measure_time(*args, **kwargs):
        t1 = timer()
        result = fn(*args, **kwargs)
        t2 = timer()
        time_elapsed = t2 - t1
        times.append(time_elapsed)
        print(f"@timefn: {fn.__name__} took {t2 - t1} seconds")
        return result

    def get_stats():
        if times:
```

```

        avg = statistics.mean(times)
        std_dev = statistics.stdev(times)
        return avg, std_dev
    else:
        return None, None

measure_time.get_stats = get_stats
return measure_time

@timefn
def calc_pure_python(desired_width, max_iterations):
    """Create a list of complex coordinates (zs) and complex parameters (cs) to build Julia set"""
    x_step = (x2 - x1) / desired_width
    y_step = (y1 - y2) / desired_width
    x = []
    y = []
    ycoord = y2
    while ycoord > y1:
        y.append(ycoord)
        ycoord += y_step
    xcoord = x1
    while xcoord < x2:
        x.append(xcoord)
        xcoord += x_step
    # build a list of coordinates and the initial condition for each cell
    # Note that our initial condition is a constant and could easily be replaced
    # we use it to simulate a real-world scenario with several inputs to the
    # function
    zs = []
    cs = []
    for ycoord in y:
        for xcoord in x:
            zs.append(complex(xcoord, ycoord))
            cs.append(complex(c_real, c_imag))

    print("Length of x:", len(x))
    print("Total elements:", len(zs))
    # start_time = timer()
    output = calculate_z_serial_purepython(max_iterations, zs, cs)
    # end_time = timer()
    # secs = end_time - start_time
    # print(calculate_z_serial_purepython.__name__ + " took", secs, "seconds")

    # This sum is expected for a 1000^2 grid with 300 iterations
    # It ensures that our code evolves exactly as we'd intended
    assert sum(output) == 33219980

@timefn
def calculate_z_serial_purepython(maxiter, zs, cs):
    """Calculate output list using Julia update rule"""
    output = [0] * len(zs)
    for i in range(len(zs)):
        n = 0
        z = zs[i]
        c = cs[i]
        while abs(z) < 2 and n < maxiter:
            z = z * z + c
            n += 1
        output[i] = n

```

```
    return output

if __name__ == "__main__":
    # Calculate the Julia set using a pure Python solution with
    # reasonable defaults for a laptop
    num_runs = 10
    for _ in range(num_runs):
        calc_pure_python(desired_width=1000, max_iterations=300) # Reduce

    calc_avg, calc_std = calc_pure_python.get_stats()
    z_avg, z_std = calculate_z_serial_purepython.get_stats()

    print("\n--- Statistics ---")
    if calc_avg:
        print(f"calc_pure_python: Average = {calc_avg:.4f} s, Standard De
    if z_avg:
        print(f"calculate_z_serial_purepython: Average = {z_avg:.4f} s, S
```

```

Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.6986198750091717 seconds
@timefn: calc_pure_python took 2.849360332998913 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.294878709013574 seconds
@timefn: calc_pure_python took 2.4328963329899125 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.240699832967948 seconds
@timefn: calc_pure_python took 2.3754435420269147 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.3812026670202613 seconds
@timefn: calc_pure_python took 2.515382374986075 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.2198940420057625 seconds
@timefn: calc_pure_python took 2.3566730829770677 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.2302856250316836 seconds
@timefn: calc_pure_python took 2.364553541992791 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.236042583012022 seconds
@timefn: calc_pure_python took 2.375761125003919 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.268640583031811 seconds
@timefn: calc_pure_python took 2.4037159999716096 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.338958750013262 seconds
@timefn: calc_pure_python took 2.475540583021939 seconds
Length of x: 1000
Total elements: 1000000
@timefn: calculate_z_serial_purepython took 2.2417154999566264 seconds
@timefn: calc_pure_python took 2.375050583970733 seconds

--- Statistics ---
calc_pure_python: Average = 2.4524 s, Standard Deviation = 0.1489 s
calculate_z_serial_purepython: Average = 2.3151 s, Standard Deviation = 0.1445 s

```

The standard deviation of the 10 attempts is 0.1489s and 0.1445 respectively, which are significantly larger than the granularity that we have calculated using the timeit module (2.079-07s). This suggests that our experiment is capturing real variations in execution time but not statistically affected by the physical limit of the timer (the granularity variation).

Task 1.3

Using cProfile

```
In [15]: !python -m cProfile -s cumulative JuliaSet.py
```

```
Length of x: 1000
Total elements: 1000000
calculate_z_serial_purepython took 3.8358170986175537 seconds
36221995 function calls in 4.067 seconds
```

Ordered by: cumulative time

	ncalls	tottime	percall	cumtime	percall	filename:lineno(function)
ec}	1	0.000	0.000	4.067	4.067	{built-in method builtins.ex
	1	0.010	0.010	4.067	4.067	JuliaSet.py:1(<module>)
hon)	1	0.177	0.177	4.057	4.057	JuliaSet.py:21(calc_pure_pyt
	1	3.057	3.057	3.836	3.836	JuliaSet.py:59(calculate_z_s
erial_purepython)	34219980	0.778	0.000	0.778	0.000	{built-in method builtins.ab
s}	2002000	0.042	0.000	0.042	0.000	{method 'append' of 'list' o
bjects}	1	0.003	0.003	0.003	0.003	{built-in method builtins.su
m}	3	0.000	0.000	0.000	0.000	{built-in method builtins.pr
int}	2	0.000	0.000	0.000	0.000	{built-in method time.time}
	1	0.000	0.000	0.000	0.000	{method 'disable' of '_lspro
f.Profiler' objects}	4	0.000	0.000	0.000	0.000	{built-in method builtins.le
n}						

Generate a profile.stats file

```
In [54]: !python -m cProfile -o profile.stats JuliaSet.py
```

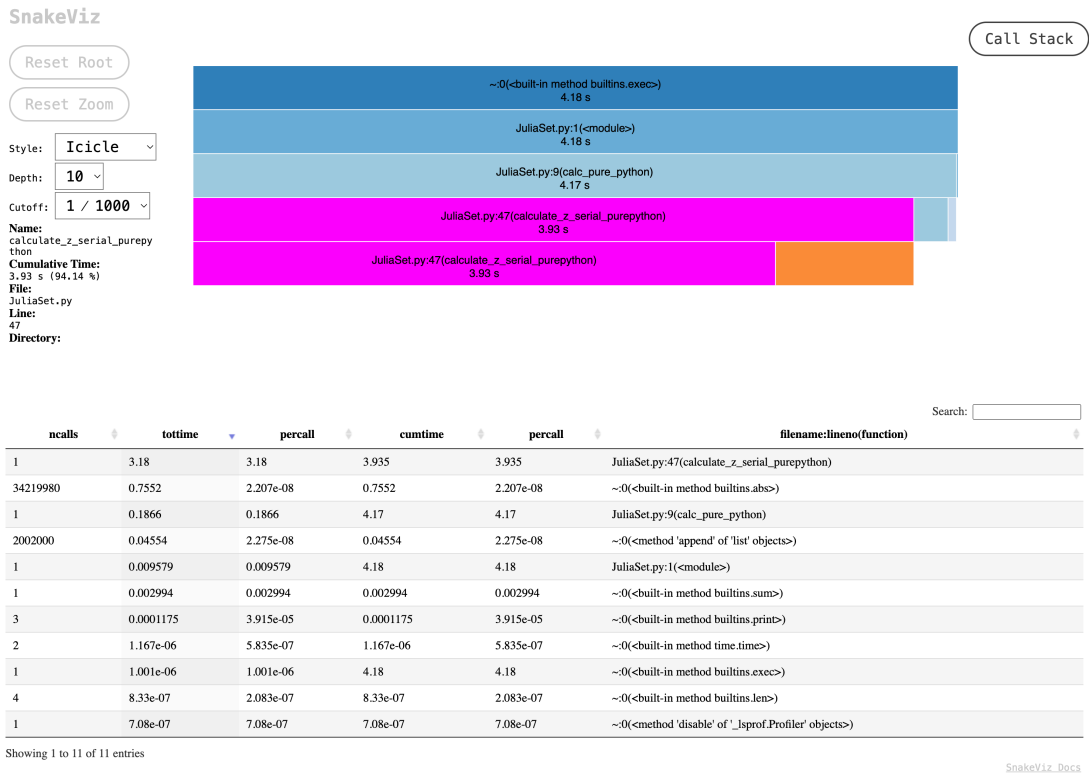
```
Length of x: 1000
Total elements: 1000000
calculate_z_serial_purepython took 3.934892177581787 seconds
```

Visualize using SnakeViz

```
In [55]: !python -m snakeviz profile.stats --server
```

```
snakeviz web server started on 127.0.0.1:8080; enter Ctrl-C to exit
http://127.0.0.1:8080/snakeviz/%2FUsers%2Ffranklin%2FCodes%2FCOMP%2FHigh%2
0Performance%20Computing%20%28KTH%29%2Fprofile.stats
^C
```

Bye!



Using line_profiler

```
In [26]: !python -m kernprof -l JuliaSet_profiler.py

Length of x: 1000
Total elements: 1000000
calculate_z_serial_purepython took 21.05274271965027 seconds
Wrote profile results to JuliaSet_profiler.py.lprof
Inspect results with:
python -m line_profiler -rmt "JuliaSet_profiler.py.lprof"

In [27]: !python -m line_profiler JuliaSet_profiler.py.lprof
```

Timer unit: 1e-06 s

Total time: 21.454 s

File: JuliaSet_profiler.py

Function: calc_pure_python at line 9

Line #	Hits	Time	Per Hit	% Time	Line Contents
9					@profile
10					def calc_pure_python(desired_width, max_iterations):
11					"""Create a list of complex coordinates (zs) and complex parameters (cs), build Julia set"""
12					"""
13	1	1.0	1.0	0.0	x_step = (x2 - x1) / desired_width
14	1	0.0	0.0	0.0	y_step = (y1 - y2) / desired_width
15	1	0.0	0.0	0.0	x = []
16	1	0.0	0.0	0.0	y = []
17	1	0.0	0.0	0.0	ycoord = y1
18	1001	108.0	0.1	0.0	while ycoord > y1:
19	1000	107.0	0.1	0.0	y.append(ycoord)
20	1000	86.0	0.1	0.0	ycoord += y_step
21	1	0.0	0.0	0.0	xcoord = x1
22	1001	122.0	0.1	0.0	while xcoord < x2:
23	1000	109.0	0.1	0.0	x.append(xcoord)
24	1000	87.0	0.1	0.0	xcoord += x_step
25					# build a list of coordinates and the initial condition for each cell.
26					# Note that our initial condition is a constant and could easily be removed,
27					# we use it to simulate a real-world scenario with several inputs to our
28					# function
29	1	0.0	0.0	0.0	zs = []
30	1	0.0	0.0	0.0	cs = []
31	1001	99.0	0.1	0.0	for ycoord in y:
32	1001000	79277.0	0.1	0.4	for xcoord in x:
33	1000000	149995.0	0.1	0.7	zs.append(complex(xcoord, ycoord))
34	1000000	168225.0	0.2	0.8	cs.append(complex(c_real, c_imag))
35					
36	1	33.0	33.0	0.0	print("Length of x:", len(x))
37	1	2.0	2.0	0.0	print("Total elements:", len(zs))
38	1	2.0	2.0	0.0	start_time = time.time()
39	1	21052741.0	2e+07	98.1	output = calculate_z_serial_purepython(max_iterations, zs, cs)
40	1	1.0	1.0	0.0	end_time = time.time()
41	1	1.0	1.0	0.0	secs = end_time - start_time
42	1	16.0	16.0	0.0	print(calculate_z_serial_purepython.__name__ + " took", secs, "seconds")
43					
44					# This sum is expected


```

d for a 1000^2 grid with 300 iterations
45                                     # It ensures that our
code evolves exactly as we'd intended
46          1          3007.0    3007.0    0.0    assert sum(output) ==
33219980

```

Total time: 11.5627 s
File: JuliaSet_profiler.py
Function: calculate_z_serial_purepython at line 48

Line #	Hits	Time	Per Hit	% Time	Line Contents
48					@profile
49					def calculate_z_serial_pu
repython(maxiter, zs, cs):					
50					"""Calculate output l
ist using Julia update rule"""					
51	1	500.0	500.0	0.0	output = [0] * len(z
s)					
52	1000001	98083.0	0.1	0.8	for i in range(len(z
s)):					
53	1000000	70791.0	0.1	0.6	n = 0
54	1000000	96073.0	0.1	0.8	z = zs[i]
55	1000000	75024.0	0.1	0.6	c = cs[i]
56	34219980	5293090.0	0.2	45.8	while abs(z) < 2
and n < maxiter:					
57	33219980	3074613.0	0.1	26.6	z = z * z + c
58	33219980	2746507.0	0.1	23.8	n += 1
59	1000000	108001.0	0.1	0.9	output[i] = n
60	1	1.0	1.0	0.0	return output

Without the Profiler

In [24]: !python JuliaSet.py

Length of x: 1000
Total elements: 1000000
calculate_z_serial_purepython took 2.179577112197876 seconds

With the cProfiler, calculate_z_serial_purepython took 3.83581s, with line_profiler, it took 11.9712 s. Without any profiler, it took 2.1796s, which is faster than both. It shows that two profiler have added a significant overhead to the function, while the overhead for line_profiler is more significant.

Task 1.4

In [30]: !python -m memory_profiler JuliaSet_memory.py

Length of x: 100

Total elements: 10000

calculate_z_serial_purepython took 10.960868120193481 seconds

Filename: JuliaSet_memory.py

Line #	Mem usage	Increment	Occurences	Line Contents
9	48.859 MiB	48.859 MiB	1	@profile
10				def calc_pure_python(desire
				d_width, max_iterations):
11				"""Create a list of com
				plex coordinates (zs) and complex parameters (cs),
12				build Julia set"""
13	48.859 MiB	0.000 MiB	1	x_step = (x2 - x1) / de
				sired_width
14	48.859 MiB	0.000 MiB	1	y_step = (y1 - y2) / de
				sired_width
15	48.859 MiB	0.000 MiB	1	x = []
16	48.859 MiB	0.000 MiB	1	y = []
17	48.859 MiB	0.000 MiB	1	ycoord = y2
18	48.859 MiB	0.000 MiB	101	while ycoord > y1:
19	48.859 MiB	0.000 MiB	100	y.append(ycoord)
20	48.859 MiB	0.000 MiB	100	ycoord += y_step
21	48.859 MiB	0.000 MiB	1	xcoord = x1
22	48.859 MiB	0.000 MiB	101	while xcoord < x2:
23	48.859 MiB	0.000 MiB	100	x.append(xcoord)
24	48.859 MiB	0.000 MiB	100	xcoord += x_step
25				# build a list of coord
				inates and the initial condition for each cell.
26				# Note that our initial
				condition is a constant and could easily be removed,
27				# we use it to simulate
				a real-world scenario with several inputs to our
28				# function
29	48.859 MiB	0.000 MiB	1	zs = []
30	48.859 MiB	0.000 MiB	1	cs = []
31	49.547 MiB	0.000 MiB	101	for ycoord in y:
32	49.547 MiB	0.000 MiB	10100	for xcoord in x:
33	49.547 MiB	0.047 MiB	10000	zs.append(compl
				ex(xcoord, ycoord))
34	49.547 MiB	0.641 MiB	10000	cs.append(compl
				ex(c_real, c_imag))
35				
36	49.547 MiB	0.000 MiB	1	print("Length of x:", l
				en(x))
37	49.547 MiB	0.000 MiB	1	print("Total element
				s:", len(zs))
38	49.547 MiB	0.000 MiB	1	start_time = time.time
				()
39	49.781 MiB	49.781 MiB	1	output = calculate_z_se
				rial_purepython(max_iterations, zs, cs)
40	49.781 MiB	0.000 MiB	1	end_time = time.time()
41	49.781 MiB	0.000 MiB	1	secs = end_time - start
				_time
42	49.781 MiB	0.000 MiB	1	print(calculate_z_seria
				l_purepython.__name__ + " took", secs, "seconds")
43				
44				# This sum is expected
				for a 1000^2 grid with 300 iterations
45				# It ensures that our c

ode evolves exactly as we'd intended

46
33219980

assert sum(output) ==

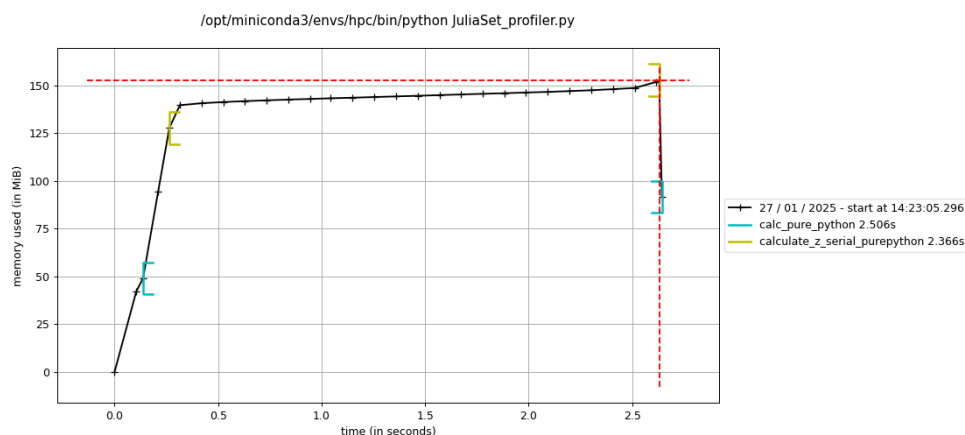
Filename: JuliaSet_memory.py

Line #	Mem usage	Increment	Occurrences	Line Contents
48	49.547 MiB	49.547 MiB	1	@profile
49				def calculate_z_serial_pure
				python(maxiter, zs, cs):
50				"""Calculate output lis
				t using Julia update rule"""
51	49.547 MiB	0.000 MiB	1	output = [0] * len(zs)
52	49.781 MiB	0.000 MiB	10001	for i in range(len(z
				s)):
53	49.781 MiB	0.000 MiB	10000	n = 0
54	49.781 MiB	0.000 MiB	10000	z = zs[i]
55	49.781 MiB	0.000 MiB	10000	c = cs[i]
56	49.781 MiB	0.031 MiB	344236	while abs(z) < 2 an
				d n < maxiter:
57	49.781 MiB	0.078 MiB	334236	z = z * z + c
58	49.781 MiB	0.125 MiB	334236	n += 1
59	49.781 MiB	0.000 MiB	10000	output[i] = n
60	49.781 MiB	0.000 MiB	1	return output

In [39]: !python -m mprof run JuliaSet_profiler.py

mprof.py: Sampling memory every 0.1s
running new process
running as a Python program...
Length of x: 1000
Total elements: 1000000
calculate_z_serial_purepython took 2.3665859699249268 seconds

In [40]: !python -m mprof plot -o memory_profile.png mprofile_20250127142305.dat



Overhead by memory_profiler and mprof

For memory profiler, it takes 10.96s for the calculate_z_serial_purepython function (100x100), the prof takes 2.37s for (1000x1000 grid), while the one without profiler

takes only 2.17s (for 1000x1000 grid). It shows that mprof samples by time but not by line and has a significantly low overhead that barely impacts the runtime of the code.

Task 2.1

In [43]: `!python -m cProfile -s cumulative diffusion.py`

205 function calls in 11.833 seconds

Ordered by: cumulative time

	ncalls	totttime	percall	cumtime	percall	filename:lineno(function)
ec}	1	0.000	0.000	11.833	11.833	{built-in method builtins.exec}
	1	0.002	0.002	11.833	11.833	diffusion.py:1(<module>)
nt)	1	0.131	0.131	11.831	11.831	diffusion.py:19(run_experiment)
	100	11.683	0.117	11.700	0.117	diffusion.py:4(evolve)
	100	0.016	0.000	0.016	0.000	diffusion.py:6(<listcomp>)
	1	0.000	0.000	0.000	0.000	diffusion.py:22(<listcomp>)
	1	0.000	0.000	0.000	0.000	{method 'disable' of '_lsprof.Profiler' objects}

In [45]: `!python -m cProfile -o profile_task2.stats diffusion.py`

In [56]: `!python -m snakeviz profile_task2.stats --server`

snakeviz web server started on 127.0.0.1:8080; enter Ctrl-C to exit
 http://127.0.0.1:8080/snakeviz/%2FUsers%2Ffranklin%2FCodes%2FCOMP%2FHigh%20Performance%20Computing%20%28KTH%29%2Fprofile_task2.stats
 ^C

Bye!

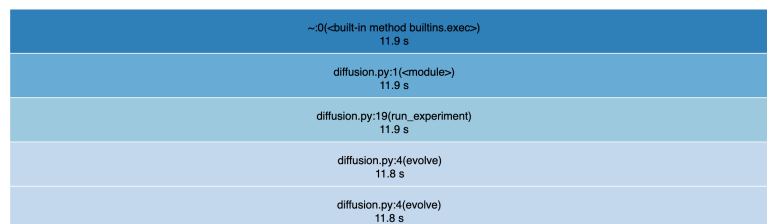
SnakeViz

Reset Root

Reset Zoom

Style: **Icicle** ▾
 Depth: **10** ▾
 Cutoff: **1 / 1000** ▾

Call Stack



ncalls	totttime	percall	cumtime	percall	filename:lineno(function)
100	11.74	0.1174	11.76	0.1176	diffusion.py:4(evolve)
1	0.1351	0.1351	11.89	11.89	diffusion.py:19(run_experiment)
100	0.0168	0.000168	0.0168	0.000168	diffusion.py:6(<listcomp>)
1	0.001636	0.001636	11.9	11.9	diffusion.py:1(<module>)
1	0.0003993	0.0003993	0.0003993	0.0003993	diffusion.py:22(<listcomp>)
1	1.833e-06	1.833e-06	11.9	11.9	~0(<built-in method builtins.exec>)
1	8.34e-07	8.34e-07	8.34e-07	8.34e-07	~0(<method 'disable' of '_lsprof.Profiler' objects>)

Showing 1 to 7 of 7 entries

SnakeViz Docs

line_profiler

```
In [48]: !python -m kernprof -l diffusion_profile.py
```

Wrote profile results to diffusion_profile.py.lprof

Inspect results with:

```
python -m line_profiler -rmt "diffusion_profile.py.lprof"
```

```
In [49]: !python -m line_profiler diffusion_profile.py.lprof
```

Timer unit: 1e-06 s

Total time: 41.1199 s

File: diffusion_profile.py

Function: evolve at line 3

Line #	Hits	Time	Per Hit	% Time	Line Contents
3					@profile
4					def evolve(grid, dt, D=1.
0):					
5	100	66.0	0.7	0.0	xmax, ymax = grid_shape
6	100	18153.0	181.5	0.0	new_grid = [[0.0] * y
max for x in range(xmax)]					
7	64100	6608.0	0.1	0.0	for i in range(xmax):
8	41024000	3728457.0	0.1	9.1	for j in range(ym
ax):					
9	40960000	2771096.0	0.1	6.7	grid_xx = (
10	40960000	11196951.0	0.3	27.2	grid[(i +
1) % xmax][j] + grid[(i - 1) % xmax][j] - 2.0 * grid[i][j])
11					
12	40960000	2765853.0	0.1	6.7	grid_yy = (
13	40960000	11774423.0	0.3	28.6	grid[i]
[(j + 1) % ymax] + grid[i][(j - 1) % ymax] - 2.0 * grid[i][j])
14					
15	40960000	8858266.0	0.2	21.5	new_grid[i]
[j] = grid[i][j] + D * (grid_xx + grid_yy) * dt					
16	100	33.0	0.3	0.0	return new_grid

Total time: 63.7211 s

File: diffusion_profile.py

Function: run_experiment at line 18

Line #	Hits	Time	Per Hit	% Time	Line Contents
18					@profile
19					def run_experiment(num_it
erations):					
20					# Setting up initial
conditions					
21	1	0.0	0.0	0.0	xmax, ymax = grid_shape
22	1	607.0	607.0	0.0	grid = [[0.0] * ymax
for x in range(xmax)]					
23					
24					# These initial condi
tions are simulating a drop of dye in the middle of our					
25					# simulated region
26	1	0.0	0.0	0.0	block_low = int(grid_
shape[0] * 0.4)					
27	1	0.0	0.0	0.0	block_high = int(grid
_shape[0] * 0.5)					
28	65	5.0	0.1	0.0	for i in range(block_
low, block_high):					
29	4160	337.0	0.1	0.0	for j in range(bl
ock_low, block_high):					
30	4096	390.0	0.1	0.0	grid[i][j] =
0.005					
31					

```
32                                     # Evolve the initial
conditions                             for i in range(num_it
33      101      17.0      0.2      0.0
erations):                             grid = evolve(gri
34      100      63719787.0 637197.9    100.0
d, 0.1)
```

Task 2.2

Memory_Profiler

```
In [50]: !python -m memory_profiler diffusion_profile.py
```

Filename: diffusion_profile.py

Line #	Mem usage	Increment	Occurences	Line Contents
3	91.344 MiB	5253.969 MiB	100	@profile
4				def evolve(grid, dt, D=1.
0):				
5	91.344 MiB	-3736.500 MiB	100	xmax, ymax = grid_shap
e				
6	91.344 MiB	-2340014.578 MiB	64300	new_grid = [[0.0] *
ymax for x in range(xmax)]				
7	96.344 MiB	-2741546.859 MiB	64100	for i in range(xma
x):				
8	96.344 MiB	-1754952840.828 MiB	41024000	for j in ran
ge(ymax):				
9	96.344 MiB	-1752214609.781 MiB	40960000	grid_xx
= (
10	96.344 MiB	-1752214725.219 MiB	40960000	grid
[(i + 1) % xmax][j] + grid[(i - 1) % xmax][j] - 2.0 * grid[i][j]				
11)
12	96.344 MiB	-1752214894.812 MiB	40960000	grid_yy
= (
13	96.344 MiB	-1752214772.141 MiB	40960000	grid
[i][(j + 1) % ymax] + grid[i][(j - 1) % ymax] - 2.0 * grid[i][j]				
14)
15	96.344 MiB	-1752215011.578 MiB	40960000	new_grid
[i][j] = grid[i][j] + D * (grid_xx + grid_yy) * dt				
16	96.344 MiB	-4354.141 MiB	100	return new_grid

Filename: diffusion_profile.py

Line #	Mem usage	Increment	Occurences	Line Contents
18	49.234 MiB	49.234 MiB	1	@profile
19				def run_experiment(num_iter
ations):				
20				# Setting up initial co
nditions				
21	49.234 MiB	0.000 MiB	1	xmax, ymax = grid_shape
22	52.328 MiB	3.094 MiB	643	grid = [[0.0] * ymax fo
r x in range(xmax)]				
23				
24				# These initial conditi
ons are simulating a drop of dye in the middle of our				
25				# simulated region
26	52.328 MiB	0.000 MiB	1	block_low = int(grid_sh
ape[0] * 0.4)				
27	52.328 MiB	0.000 MiB	1	block_high = int(grid_s
hape[0] * 0.5)				
28	52.328 MiB	0.000 MiB	65	for i in range(block_lo
w, block_high):				
29	52.328 MiB	0.000 MiB	4160	for j in range(bloc
k_low, block_high):				
30	52.328 MiB	0.000 MiB	4096	grid[i][j] = 0.
005				
31				
32				# Evolve the initial co
nditions				
33	91.344 MiB	-3787.469 MiB	101	for i in range(num_ite


```

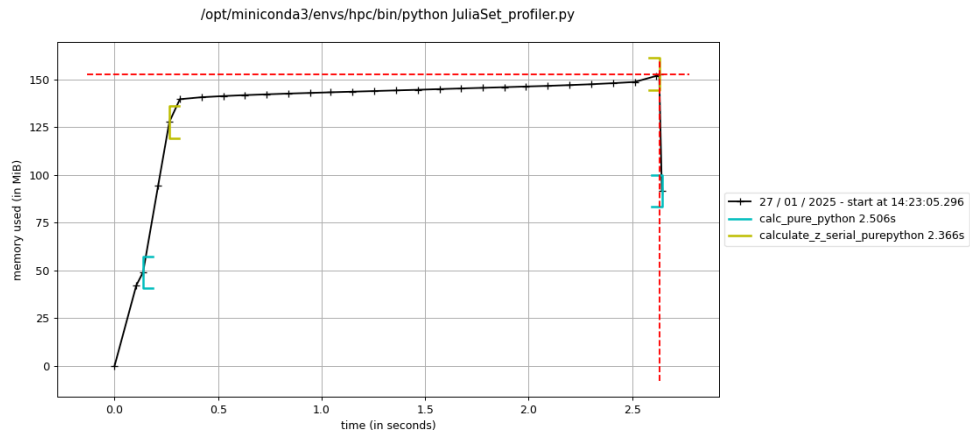
rations):
    34    91.344 MiB 5241.969 MiB          100          grid = evolve(grid,
0.1)

```

In [51]: `!python -m mprof run diffusion_profile.py`

mprof.py: Sampling memory every 0.1s
 running new process
 running as a Python program...

In [52]: `!python -m mprof plot -o memory_profile_task2.png mprofile_20250127142305`



Bonus Exercise

```

In [61]: import psutil
import time
import threading
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

class CPUProfiler:
    def __init__(self):
        self.cpu_data = []
        self.start_time = None
        self._stop_event = threading.Event()
        self._thread = None

    def start(self):
        self.cpu_data = []
        self.start_time = time.time()
        self._stop_event.clear()
        self._thread = threading.Thread(target=self._record_cpu_usage)
        self._thread.start()

    def stop(self):
        self._stop_event.set()
        self._thread.join()
        end_time = time.time()
        elapsed_time = end_time - self.start_time
        print(f"Profiling took {elapsed_time:.4f} seconds.")

```

```

def _record_cpu_usage(self):
    while not self._stop_event.is_set():
        self.record()
        time.sleep(0.1)

def record(self):
    cpu_percent = psutil.cpu_percent(interval=None, percpu=True)
    current_time = time.time() - self.start_time
    self.cpu_data.append((current_time, cpu_percent))

def profile(self, func, *args, **kwargs):
    self.start()
    start_exec = time.time()
    result = func(*args, **kwargs)
    end_exec = time.time()
    self.stop()
    exec_time = end_exec - start_exec
    print(f"Execution took {exec_time:.4f} seconds.")
    return result

def plot(self, filename="cpu_profile.png"):
    if not self.cpu_data:
        print("No profiling data recorded.")
        return

    df = pd.DataFrame(self.cpu_data, columns=["Time", "CPU Usage"])
    num_cores = len(df["CPU Usage"][0])
    plt.figure(figsize=(10, 6))
    for core in range(num_cores):
        core_usage = [usage[core] for usage in df["CPU Usage"]]
        plt.plot(df["Time"], core_usage, label=f"Core {core}")

    plt.xlabel("Time (s)")
    plt.ylabel("CPU Usage (%)")
    plt.title("CPU Usage per Core")
    plt.legend()
    plt.grid(True)
    plt.savefig(filename)
    plt.show()

def summary(self):
    if not self.cpu_data:
        print("No profiling data recorded.")
        return

    df = pd.DataFrame(self.cpu_data, columns=["Time", "CPU Usage"])
    num_cores = len(df["CPU Usage"][0])
    summary_data = []
    for core in range(num_cores):
        core_usage = [usage[core] for usage in df["CPU Usage"]]
        summary_data.append({"Core": core, "Average Usage": np.mean(core_usage)})
    summary_df = pd.DataFrame(summary_data)
    print(summary_df)

# Example usage:
profiler = CPUProfiler()

```

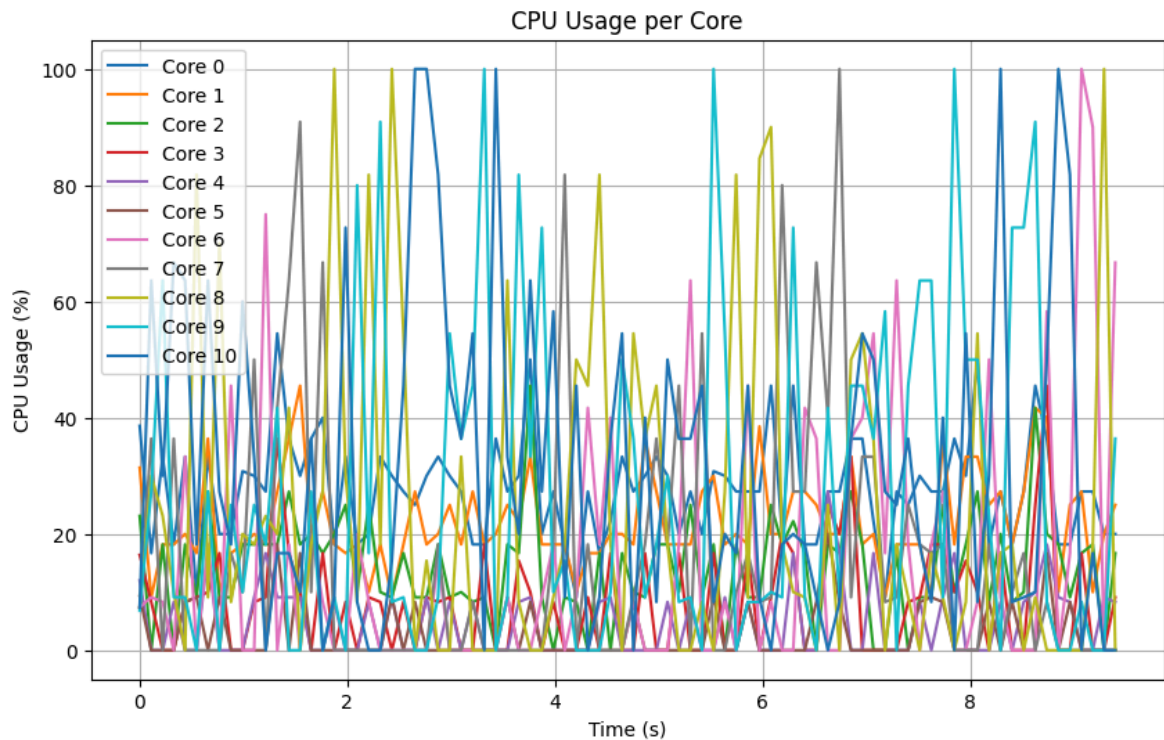
This creates a CPUProfiler class to measure and visualize CPU usage. It uses psutil to sample CPU usage over time, storing the time and per-core usage in cpu_data. The

profile method runs a given function while recording CPU usage. The plot method then creates a graph showing CPU usage per core over time using matplotlib, and the summary method calculates and prints average and maximum CPU usage per core using pandas. Essentially, it observe how much CPU a function uses and how that usage is distributed across CPU cores.

```
In [62]: from diffusion import run_experiment

num_iterations = 100
grid = profiler.profile(run_experiment, num_iterations)
profiler.plot()
profiler.summary()
```

Profiling took 9.5005 seconds.
Execution took 9.4527 seconds.



	Core	Average Usage	Max Usage
0	0	27.706977	54.5
1	1	22.110465	45.5
2	2	14.155814	45.5
3	3	8.108140	45.5
4	4	4.667442	27.3
5	5	2.733721	20.0
6	6	15.543023	100.0
7	7	15.884884	100.0
8	8	24.202326	100.0
9	9	27.280233	100.0
10	10	31.543023	100.0

```
In [63]: from JuliaSet import calc_pure_python

profiler2 = CPUProfiler()
desired_width = 1000
max_iterations = 300
grid = profiler2.profile(calc_pure_python, desired_width, max_iterations)
profiler2.plot()
profiler2.summary()
```

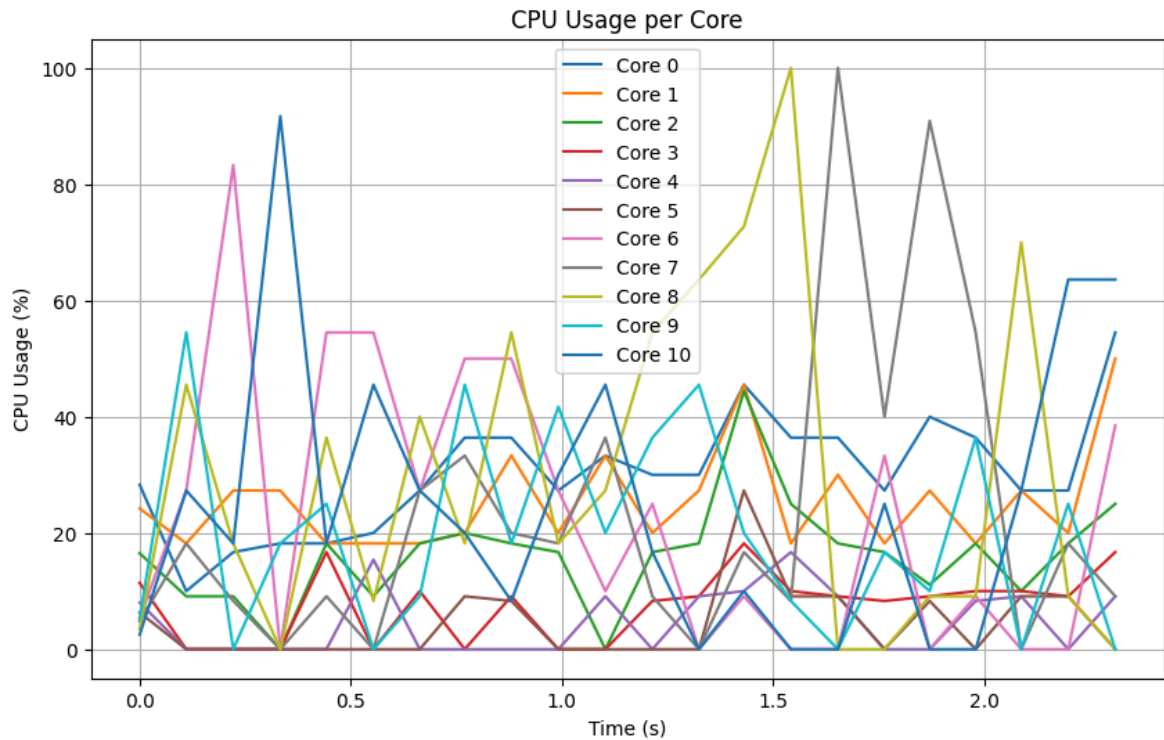
Length of x: 1000

Total elements: 1000000

calculate_z_serial_purepython took 2.189697027206421 seconds

Profiling took 2.4161 seconds.

Execution took 2.3394 seconds.



	Core	Average Usage	Max Usage
0	0	30.145455	54.5
1	1	25.463636	50.0
2	2	16.218182	44.4
3	3	7.504545	18.2
4	4	4.722727	16.7
5	5	4.350000	27.3
6	6	22.931818	83.3
7	7	23.745455	100.0
8	8	29.918182	100.0
9	9	19.809091	54.5
10	10	24.577273	91.7