

Task 2:

Aicha cheridi : 23138371

```
# multithreading
%%timeit
threads = []
for n in nums:
    thread = Thread(target=approximate_pi, args=(n,))
    thread.start()
    threads.append(thread)

for thread in threads:
    thread.join()

✓ 3m 15.7s

24.5 s ± 62.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
# Multiprocessing
%%timeit
processes = []
for n in nums:
    process = multiprocessing.Process(target=approximate_pi, args = (n,))
    process.start()
    processes.append(process)

for process in processes:
    process.join()

✓ 2m 3.7s

15.4 s ± 178 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Task 3:

```
# multithreading
%%timeit
threads = []
for file_name in numpy_files_names:
    thread = Thread(target=load_array, args=(file_name,))
    thread.start()
    threads.append(thread)

for thread in threads:
    thread.join()

✓ 2.6s

292 ms ± 18.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
# Multiprocessing
%%timeit
processes = []
for file_name in numpy_files_names:
    process = multiprocessing.Process(target=load_array, args = (file_name,))
    process.start()
    processes.append(process)
# Wait for all processes to complete
for process in processes:
    process.join()

✓ 17.5s

2.2 s ± 88.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

The code for task 2 benefits from Multiprocessing because the pi approximation function is computations heavy task and benefit more from exploiting all the cpus core through a multiprocessing. It runs 37% faster than using Multithreading

The code for task 3 benefits from Multithreading because we are reading numpy arrays from the disk i.e I/O bound tasks that benefit more from multithreading since the threads run concurrently (when one thread is idle the other can run). It runs 86% faster than using Multiprocessing

Task 1:

I used the function cv2.resize with cv2.INTER_LANCZOS4 interpolation that is 91% faster than skimage:

