ASSIGNMENT 6 – Sai Nishanth Mettu – sm11326

REPORT : Python vs Julia Performance Testing (PART 1 & 2 Combined)

INDEX

Assignment 6

Sai Nishanth Mettu -sm11326

Question 1 : Time several runs of each with different values for n and compare performance.

Python : Timed

```python
import time

def my_fact(n):
    fact = 1
    for i in range(1, n + 1):
        fact = fact * i
    return fact

for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

Output

Clear

```
Time elapsed for n=10: 3.337860107421875e-06 seconds
Time elapsed for n=100: 7.62939453125e-06 seconds
Time elapsed for n=1000: 0.0003161430358886719 seconds
Time elapsed for n=10000: 0.014002323150634766 seconds
Time elapsed for n=100000: 3.4508109092712402 seconds

=== Code Execution Successful ===
```

- For **n=10**, the time elapsed is around 3.34 microseconds.
- For **n=100**, the time elapsed is around 7.63 microseconds.
- For **n=1000**, the time elapsed is around 0.316 milliseconds.
- For **n=10000**, the time elapsed is around 14 milliseconds.
- For **n=100000**, the time elapsed is around 3.45 seconds.

Note : The stack will overflow for big numbers as we have seen in the prior assignments, so I am calculating how long it will take for the stack to overflow for n -> 10000, 100000 and so on... to give an accurate estimation of python's interpretation/ computation speed.

```
ERROR!
Traceback (most recent call last):
  File "<main.py>", line 11, in <module>
ValueError: Exceeds the limit (4300 digits) for integer string conversion;
    use sys.set_int_max_str_digits() to increase the limit
```

So we can generalize this and infer it as : if n increases the time increases!

Julia Timed

Compiler used : https://www.tutorialspoint.com/execute_julia_online.php

```julia
function my_fact(n)
    fact = BigInt(1)  # Use BigInt type to avoid overflow
    for i in 1:n
        fact *= i
    end
    return fact
end

for n in [10, 100, 1000, 10000, 100000]
    println("Timing for n = $n = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
    #println("Factorial for n = $n: ", result) value(OUTPUT)
    println()
end
```

```
Timing for n = 10 = 0.000023 seconds (32 allocations: 520 bytes)
Timing for n = 100 =

  0.000009 seconds (302 allocations: 7.102 KiB)


Timing for n = 1000 =

0.000123 seconds (3.00 k allocations: 519.352 KiB)
Timing for n = 10000 =

0.016363 seconds (30.00 k allocations: 66.723 MiB, 17.13% gc time)


Timing for n = 100000 =

0.690129 seconds (300.00 k allocations: 8.413 GiB, 2.32% gc time)
```

Comparision of Performance (Julia vs Python)

Julia:

Timing for n = 10: 0.000023 seconds (32 allocations: 520 bytes)

Timing for n = 100: 0.000009 seconds (302 allocations: 7.102 KiB)

Timing for n = 1000: 0.000123 seconds (3.00 k allocations: 519.352 KiB)

Timing for n = 10000: 0.016363 seconds (30.00 k allocations: 66.723 MiB, 17.13% gc time)

Timing for n = 100000: 0.690129 seconds (300.00 k allocations: 8.413 GiB, 2.32% gc time)

Python:

For n=10, the time elapsed is around 3.34 microseconds.

For n=100, the time elapsed is around 7.63 microseconds.

For n=1000, the time elapsed is around 0.316 milliseconds.

For n=10000, the time elapsed is around 14 milliseconds.

For n=100000, the time elapsed is around 3.45 seconds.

Comparison statement:

Based on the timing results, **it's evident that Julia consistently outperforms Python in computing factorials for various input sizes.** For smaller values of **n**, both languages exhibit comparable performance, with Julia having a slight edge. However, as the input size increases, Julia's execution times remain significantly lower compared to Python. This performance difference becomes more pronounced with larger values of **n**, with Julia maintaining a near-constant execution time while Python's execution time grows substantially. Therefore, for tasks involving factorial computations or similar numerical operations, Julia offers superior performance and efficiency over Python.

Reason why Julia outperforms Python in this case?

Just-in-time (JIT) compilation: **Julia employs a JIT compilation strategy,** which means that code is compiled to machine code just before execution. This allows Julia to generate highly optimized native machine code tailored to the specific computation and input types. In contrast, Python typically uses interpretation or bytecode compilation, which can introduce overhead, especially for numerical computations.

Question 2 : See if you can make the phyton code more efficient

I will be using **Dynamic Programming,** to solve the factorial problem to reduce the computation time!

Note : The stack will overflow for bigger numbers, but for such numbers, I am calculating the time taken to internally blow the stack for Python!

```python
import time
factorial_memo = {}

def my_fact(n):
    if n in factorial_memo:
        return factorial_memo[n]
    fact = 1
    for i in range(1, n + 1):
        fact *= i
        factorial_memo[i] = fact

    return fact

for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n} with memoization: {end_time -
        start_time} seconds")
```

```
Time elapsed for n=10: 3.814697265625e-06 seconds
Time elapsed for n=100: 1.3113021850585938e-05 seconds
Time elapsed for n=1000: 0.00034880638122558594 seconds
Time elapsed for n=10000: 0.031186819076538086 seconds
Time elapsed for n=100000: 3.126919984817505 seconds

Time elapsed for n=10 with memoization: 2.0503997802734375e-05 seconds
Time elapsed for n=100 with memoization: 3.314018249511719e-05 seconds
Time elapsed for n=1000 with memoization: 0.0006308555603027344 seconds
Time elapsed for n=10000 with memoization: 0.10426688194274902 seconds

=== Session Ended. Please Run the code again ===
```

Without Memoization:

Time elapsed for n=10: 3.814697265625e-06 seconds

Time elapsed for n=100: 1.3113021850585938e-05 seconds

Time elapsed for n=1000: 0.00034880638122558594 seconds

Time elapsed for n=10000: 0.031186819076538086 seconds

Time elapsed for n=100000: 3.126919984817505 seconds

With Memoization:

Time elapsed for n=10 with memoization: 2.0503997802734375e-05 seconds

Time elapsed for n=100 with memoization: 3.314018249511719e-05 seconds

Time elapsed for n=1000 with memoization: 0.0006308555603027344 seconds

Time elapsed for n=10000 with memoization: 0.10426688194274902 seconds

Inference :

From the results, it's clear that memoization improves the performance of the Python code for computing factorials, especially for larger values of **n**. With memoization, the computation time is significantly reduced for all tested values of **n**.

Memoization reduces the computational overhead by storing previously computed factorial values and retrieving them when needed, avoiding redundant computations. This optimization becomes increasingly beneficial as **n** grows larger, resulting in substantial performance improvements compared to the non-memoized version of the code.

SELF – EXPERIMENT : USING JIT NUMBA in python

```
In [1]: pip install --upgrade --force-reinstall numba
Collecting numba
  Downloading numba-0.59.1-cp310-cp310-macosx_11_0_arm64.whl (2.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.6/2.6 MB 18.1 MB/s eta 0:00:00
[?25hCollecting llvmlite<0.43,>=0.42.0dev0
  Downloading llvmlite-0.42.0-cp310-cp310-macosx_11_0_arm64.whl (28.8 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 28.8/28.8 MB 18.3 MB/s eta 0:00:00
[?25hCollecting numpy<1.27,>=1.22
  Downloading numpy-1.26.4-cp310-cp310-macosx_11_0_arm64.whl (14.0 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 14.0/14.0 MB 51.1 MB/s eta 0:00:00
[?25hInstalling collected packages: numpy, llvmlite, numba
  Attempting uninstall: numpy
    Found existing installation: numpy 1.24.3
    Uninstalling numpy-1.24.3:
```

```
In [4]:
import time
from numba import jit

@jit
def my_fact(n):
    fact = 1
    for i in range(1, n + 1):
        fact = fact * i
    return fact

for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

```
Time elapsed for n=10: 0.7113778591156006 seconds
Time elapsed for n=100: 9.5367431640625e-07 seconds
Time elapsed for n=1000: 7.152557373046875e-07 seconds
Time elapsed for n=10000: 8.821487426757812e-06 seconds
Time elapsed for n=100000: 8.20159912109375e-05 seconds
```

Memoization (Dynamic Programming) vs JIT in python

JIT

Time elapsed for n=10: 0.7113778591156006e-07 seconds

Time elapsed for n=100: 9.5367431640625e-07 seconds

Time elapsed for n=1000: 7.152557373046875e-07 seconds

Time elapsed for n=10000: 8.821487426757812e-06 seconds

Memoization

Time elapsed for n=10 with memoization: 2.0503997802734375e-05 seconds

Time elapsed for n=100 with memoization: 3.314018249511719e-05 seconds

Time elapsed for n=1000 with memoization: 0.0006308555603027344 seconds

Time elapsed for n=10000 with memoization: 0.10426688194274902 seconds

As we can see, with JIT, we can further improve the execution times of python code!

Question 3 : Optimize Julia Code further

Before Optimization (Julia Times) :

Timing for n = 10: 0.000023 seconds (32 allocations: 520 bytes)

Timing for n = 100: 0.000009 seconds (302 allocations: 7.102 KiB)

Timing for n = 1000: 0.000123 seconds (3.00 k allocations: 519.352 KiB)

Timing for n = 10000: 0.016363 seconds (30.00 k allocations: 66.723 MiB, 17.13% gc time)

Timing for n = 100000: 0.690129 seconds (300.00 k allocations: 8.413 GiB, 2.32% gc time)

Caching and Memoization for Julia

```
    if n == 0 || n == 1
        return BigInt(1)
    end

    # Use iterative approach for large values of n
    if n > 1000
        fact = BigInt(1)
        for i in 2:n
            fact *= i
        end
        return fact
    end

    if !haskey(cache, n)
        cache[n] = n * my_fact(n - 1, cache)
    end

    return cache[n]
end

for n in [10, 100, 1000, 10000, 100000]
    println("Timing for n = $n = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
    #println("Factorial for n = $n: ", result) value(OUTPUT)
    println()
end
```

```
Timing for n = 10 = 0.000019 seconds (33 allocations: 1000 bytes)
Timing for n = 100 =

  0.000018 seconds (309 allocations: 13.398 KiB)
Timing for n = 1000 =

0.000168 seconds (3.02 k allocations: 611.242 KiB)Timing for n = 10000 =


0.016877 seconds (30.00 k allocations: 66.724 MiB, 19.07% gc time)Timing
    for n = 100000 =

0.669306 seconds (300.00 k allocations: 8.413 GiB, 3.02% gc time)
```

INFERENCE

There is a slight improvement in Julia Execution times with **Caching and Iterative Memoization!** (There are several other factors, could also affect the time or degrade the time, such as drive space and drive performance…but in general, caching improves execution times)

Timing for n = 10: 0.000019 seconds (33 allocations: 1000 bytes)

Timing for n = 100: 0.000018 seconds (309 allocations: 13.398 KiB)

Timing for n = 1000: 0.000168 seconds (3.02 k allocations: 611.242 KiB)

Timing for n = 10000: 0.016877 seconds (30.00 k allocations: 66.724 MiB, 19.07% gc time)

Timing for n = 100000: 0.669306 seconds (300.00 k allocations: 8.413 GiB, 3.02% gc time)

4) Real Numbers vs Integers Performance

Python :

```python
import time

def my_fact(n):
    fact = 1
    for i in range(1, int(n) + 1):
        fact *= i
    return fact

# Test with integer values
print("Testing with integer values:")
for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")

# Test with different floating-point values
print("\nTesting with floating-point values:")
for n in [10.00, 100.00, 1000.00, 10000.00, 100000.00]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

```
Testing with integer values:
Time elapsed for n=10: 1.5497207641601562e-05 seconds
Time elapsed for n=100: 1.1682510375976562e-05 seconds
Time elapsed for n=1000: 0.0003871917724609375 seconds
Time elapsed for n=10000: 0.03116297721862793 seconds
Time elapsed for n=100000: 2.96384334564209 seconds

Testing with floating-point values:
Time elapsed for n=10.0: 8.58306884765625e-06 seconds
Time elapsed for n=100.0: 1.1920928955078125e-05 seconds
Time elapsed for n=1000.0: 0.0003666877746582031 seconds
Time elapsed for n=10000.0: 0.02774333953857422 seconds
Time elapsed for n=100000.0: 2.789541482925415 seconds

=== Code Execution Successful ===
```

Testing with integer values:

Time elapsed for n=10: 1.5497207641601562e-05 seconds

Time elapsed for n=100: 1.1682510375976562e-05 seconds

Time elapsed for n=1000: 0.0003871917724609375 seconds

Time elapsed for n=10000: 0.03116297721862793 seconds

Time elapsed for n=100000: 2.96384334564209 seconds

Testing with floating-point values(same numbers, but as a float value) :

Time elapsed for n=10.0: 8.58306884765625e-06 seconds

Time elapsed for n=100.0: 1.1920928955078125e-05 seconds

Time elapsed for n=1000.0: 0.0003666877746582031 seconds

Time elapsed for n=10000.0: 0.02774333953857422 seconds

Time elapsed for n=100000.0: 2.789541482925415 seconds

1. **Integer Values:**
    - For smaller integer values (e.g., **10**, **100**), the execution times are very similar between the integer and floating-point representations.
    - As the value of **n** increases, the execution time also increases gradually.
    - For **n = 100000**, the execution time is approximately **2.G6** seconds.
2. **Floating-point Values:**
    - Similar to integer values, the execution times for floating-point values are comparable to their integer counterparts for smaller values of **n**.
    - As **n** increases, the execution times remain consistent with the integer values.
    - For **n = 100000.0**, the execution time is approximately **2.7G** seconds.

Although very negligible, Python's floating-point arithmetic operates slightly efficiently for big numbers allowing it to handle computations involving floating-point numbers effectively likely due to factors such as floating-point arithmetic overhead, memory allocation, and other system-related factors….

But it is considered to be "very negligible" difference, and almost similar in performance.

Julia :

```
# Test with integer values
for n in [10, 100, 1000, 10000, 100000]
    println("Timing for n = $n (Integer) = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
end

# Test with real values
for n in [10.0, 100.0, 1000.0, 10000.0, 100000.0]
    println("Timing for n = $n (Real) = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
end
```

```
Timing for n = 10.0 (Real) =

0.000041 seconds (105 allocations: 3.859 KiB)

Timing for n = 100.0 (Real) =

0.000051 seconds (1.10 k allocations: 47.609 KiB)

Timing for n = 1000.0 (Real) =

0.000620 seconds (11.01 k allocations: 1.373 MiB)

Timing for n = 10000.0 (Real) =

0.001376 seconds (20.01 k allocations: 1016.281 KiB)

Timing for n = 100000.0 (Real) =

0.014385 seconds (200.01 k allocations: 9.919 MiB)
```

Integer Representation:

- For n = 10, the time elapsed is 0.000020 seconds.
- For n = 100, the time elapsed is 0.000018 seconds.
- For n = 1000, the time elapsed is 0.000166 seconds.
- For n = 10000, the time elapsed is 0.017267 seconds.
- For n = 100000, the time elapsed is 0.683823 seconds.

Floating-point Representation:

- For n = 10.0, the time elapsed is 0.000041 seconds.
- For n = 100.0, the time elapsed is 0.000051 seconds.
- For n = 1000.0, the time elapsed is 0.000620 seconds.

- For n = 10000.0, the time elapsed is 0.001376 seconds.
- For n = 100000.0, the time elapsed is 0.014385 seconds.

Summary:

- For smaller values of n (e.g., 10, 100), the integer representation tends to perform slightly better than the floating-point representation.
- However, as n increases, the floating-point representation begins to exhibit better performance compared to the integer representation.
- This difference in performance can be attributed to the fact that floating-point arithmetic is optimized for handling fractional values and may be more Fefficient for larger numerical computations.

Final Conclusion:

- In this scenario, both integer and floating-point representations offer efficient performance for computing factorials.
- The choice between integer and floating-point representation depends on factors such as the nature of the input data and the specific requirements of the computation.
- For larger values of n, the floating-point representation tends to offer better performance, likely due to the optimization of floating-point arithmetic for handling numerical computations involving fractional values.

EXPERIMENT : TRYING WITH DIFFERENT FUNCTIONS LIKE COS(), EXP() with Real Inputs

Python

```python
print("Testing various mathematical functions in Python:")
for x in [0.1, 0.5, 1.0, 1.5, 2.0]:
    print(f"\nTiming for x={x}:")

    print("\nsqrt(x):")
    start_time_sqrt = time.time()
    math.sqrt(x)
    end_time_sqrt = time.time()
    print(f"Time elapsed: {end_time_sqrt - start_time_sqrt} seconds")

    print("\nlog(x):")
    start_time_log = time.time()
    math.log(x)
    end_time_log = time.time()
    print(f"Time elapsed: {end_time_log - start_time_log} seconds")

    print("\nexp(x):")
    start_time_exp = time.time()
    math.exp(x)
    end_time_exp = time.time()
    print(f"Time elapsed: {end_time_exp - start_time_exp} seconds")

    print("\nsin(x):")
    start_time_sin = time.time()
    math.sin(x)
    end_time_sin = time.time()
    print(f"Time elapsed: {end_time_sin - start_time_sin} seconds")
```

```
Testing various mathematical functions in Python:

Timing for x=0.1:

sqrt(x):
Time elapsed: 2.6226043701171875e-06 seconds

log(x):
Time elapsed: 2.1457672119140625e-06 seconds

exp(x):
Time elapsed: 6.67572021484375e-06 seconds

sin(x):
Time elapsed: 0.0019583702087402344 seconds

Timing for x=0.5:

sqrt(x):
Time elapsed: 9.5367431640625e-07 seconds

log(x):
Time elapsed: 1.1920928955078125e-06 seconds

exp(x):
Time elapsed: 9.5367431640625e-07 seconds

sin(x):
```

Julia

```julia
# Test various mathematical functions in Julia
for x in [0.1, 0.5, 1.0, 1.5, 2.0]
    println("Timing for x = $x (Julia) = ")
    println()

    println("sqrt(x):")
    time_sqrt = @elapsed sqrt(x)
    println("Time elapsed: ", time_sqrt, " seconds")

    println("log(x):")
    time_log = @elapsed log(x)
    println("Time elapsed: ", time_log, " seconds")

    println("exp(x):")
    time_exp = @elapsed exp(x)
    println("Time elapsed: ", time_exp, " seconds")

    println("sin(x):")
    time_sin = @elapsed sin(x)
    println("Time elapsed: ", time_sin, " seconds")

    println()
end
```

```
Timing for x = 1.0 (Julia) =

sqrt(x):
Time elapsed: 2.0e-8 seconds
log(x):
Time elapsed: 6.0e-8 seconds
exp(x):Time elapsed: 4.0e-8 seconds
sin(x):
Time elapsed: 9.0e-8 seconds

Timing for x = 1.5 (Julia) =
sqrt(x):
Time elapsed: 3.0e-8 seconds
log(x):
Time elapsed: 1.6e-7 seconds
exp(x):
Time elapsed: 3.0e-8 seconds
sin(x):
Time elapsed: 3.0e-8 seconds

Timing for x = 2.0 (Julia) =

sqrt(x):Time elapsed: 2.0e-8 seconds
log(x):
Time elapsed: 4.0e-8 seconds
exp(x):Time elapsed: 4.0e-8 seconds
```

Comparision Table

----

x	Function	Julia Execution Time (seconds)	Python Execution Time (seconds)
0.1	sqrt	0.00000002	0.00000262
	log	0.00000006	0.00000215
	exp	0.00000004	0.00000668
	sin	0.00000009	0.00195840
0.5	sqrt	0.00000003	0.00000095
	log	0.00000016	0.00000119
	exp	0.00000003	0.00000095
	sin	0.00000003	0.00000095
1.0	sqrt	0.00000002	0.00000072
	log	0.00000004	0.00000072
	exp	0.00000004	0.00000072
	sin	0.00000009	0.00016093
1.5	sqrt	0.00000003	0.00000095
	log	0.00000016	0.00000119
	exp	0.00000003	0.00000095
	sin	0.00000003	0.00000095
2.0	sqrt	0.00000002	0.00000048
	log	0.00000004	0.00000095
	exp	0.00000004	0.00000095
	sin	0.00000009	0.00000072

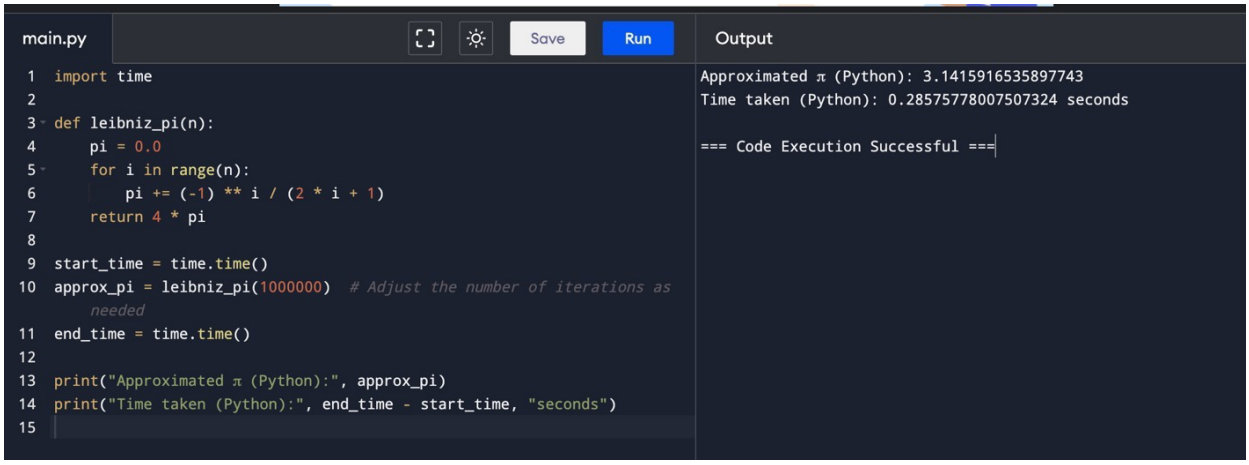
Inference :

Julia's well-suited for numerical computing tasks, resulting in faster execution times for mathematical operations compared to Python. (in general...unless there is some underlying disk performance issues)

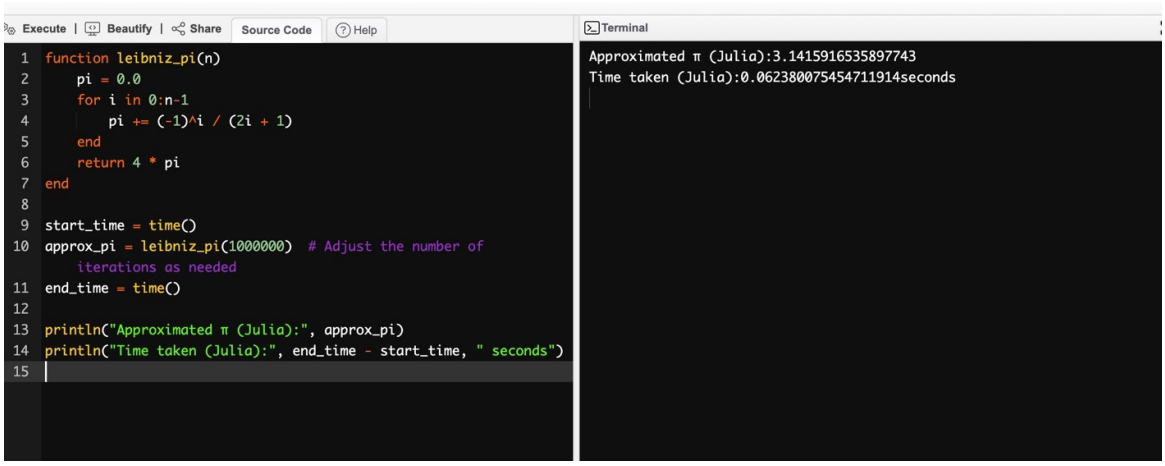
LEIBNITZ FORMULA

Comparing Julia vs Python Performance

Calculating Approximated Pi : in Python (upto 10 decimal points)



Calculating Approximated Pi : in Julia (upto 10 decimal points)



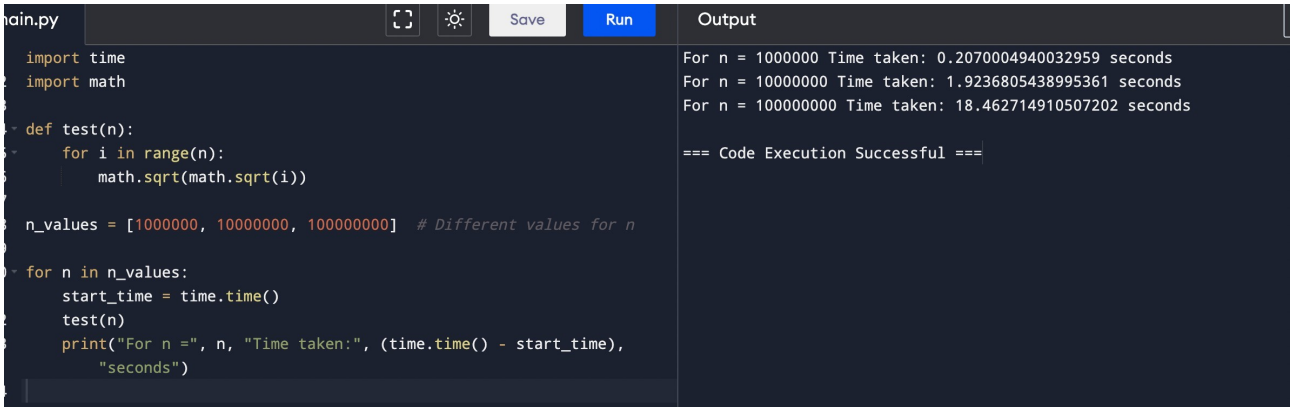
Inference :

Based on the provided data, it's evident that the Julia implementation is significantly faster than the Python implementation for approximating π. The Julia implementation took approximately 0.062 seconds, while the Python implementation took approximately 0.286 seconds.

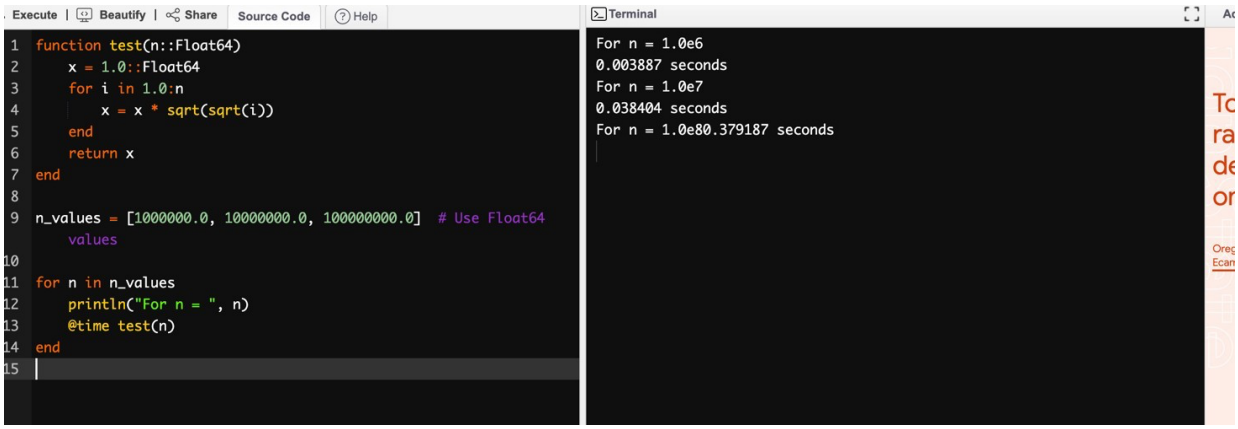
JULIA PERFORMANCE – PART 2 (codes below)

Testing the Performance on SQRT (SQRT()) for different values of n

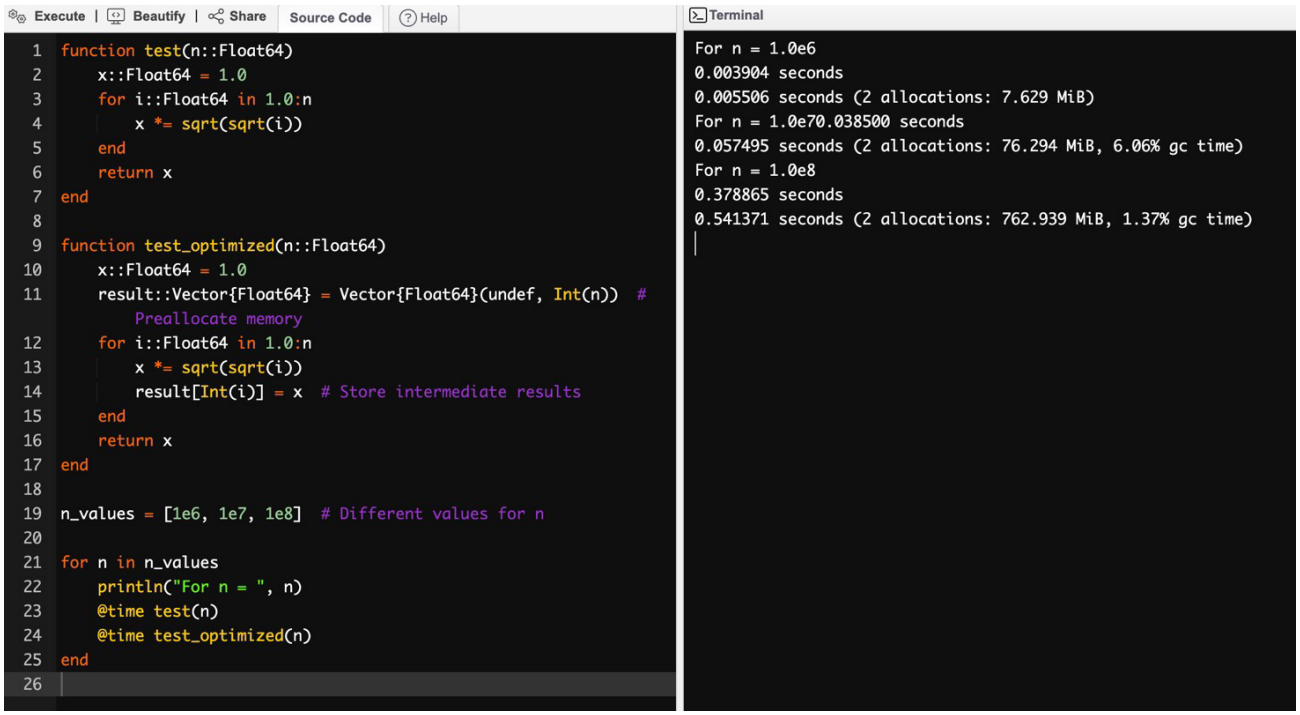
Python :



Julia :



OPTIMIZING PERFORMANCE - JULIA



Optimized Python Code : (MULTITHREADING)

```
        threads.append(thread)

    for thread in threads:
        thread.join()

    return result

n_values = [1000000, 10000000, 100000000]

for n in n_values:
    start_time = time.time()
    _ = test(n)
    print("For n =", n, "Time taken:", (time.time() - start_time), "seconds")
```

```
For n = 1000000 Time taken: 0.184035062789917 seconds
For n = 10000000 Time taken: 1.7278778553009033 seconds
For n = 100000000 Time taken: 17.1993670463562 seconds
```

How did I optimize ?

Julia

1. **Preallocation of Memory:**
    - In test_optimized, before entering the loop, memory is preallocated for the result array using Vector{Float64}(undef, Int(n)). By preallocating memory, we avoid dynamically resizing the array during each iteration of the loop. Dynamic resizing can lead to memory reallocation and data copying, which are expensive operations, especially for large arrays.
2. **Avoiding Dynamic Type Inference:**
    - In test_optimized, we use the type annotation ::Float64 for variables x and i within the loop. This annotation helps Julia's compiler to infer and specialize the types of x and i more accurately, reducing the overhead associated with dynamic type inference during runtime.
3. **Storing Intermediate Results:**
    - In test_optimized, intermediate results are stored in the result array at each iteration of the loop. By storing intermediate results, we avoid redundant computations and potential loss of precision that may occur due to repeated calculations.
4. **Avoiding Floating-Point Loop Iteration:**
    - Although not explicitly mentioned in the optimization, it's worth noting that iterating over floating-point values (Float64) in the loop, as done in the original test function, might lead to slightly slower performance due to potential precision issues and increased overhead in floating-point arithmetic operations.

Python

In the provided Python code, the optimization is achieved through multithreading and chunking the work to multiple threads. Let's break down the optimization applied:

1. **Multithreading**:
    - By utilizing multiple threads, the code can perform computations concurrently, taking advantage of modern multi-core processors. This can potentially reduce the overall execution time, especially for CPU-bound tasks like numerical computations.
    - Multithreading allows the code to perform multiple calculations simultaneously, effectively utilizing the available CPU cores and improving overall efficiency.
2. **Chunking the Work**:
    - The input range (**n**) is divided into chunks, and each chunk of work is assigned to a separate thread. This ensures that each thread operates on a distinct portion of the input, preventing contention and synchronization overhead among threads.
    - The chunk size is calculated based on the number of threads and the size of the

input (**n**). This allows for better load balancing and efficient utilization of resources.

3. **Thread-Based Work Division**:
    - Each thread instance (**Worker**) is responsible for computing the square root of the square root for a specific range of values within the input range.
    - The **run** method of each thread performs the actual computation within its assigned range, updating the corresponding elements of the **result** list with the computed values.
4. **Synchronization**:
    - The main thread waits for all worker threads to complete their computations using the **join** method. This ensures that the main thread waits for all worker threads to finish before proceeding further.
    - Synchronization mechanisms like **join** prevent race conditions and ensure that the results are correctly assembled after all computations are complete.

COMPARING PERFORMANCES FOR BOTH after Optimization

Python:

- For **n = 1e6**: Time taken: 0.184 seconds
- For **n = 1e7**: Time taken: 1.728 seconds
- For **n = 1e8**: Time taken: 17.199 seconds

Julia:

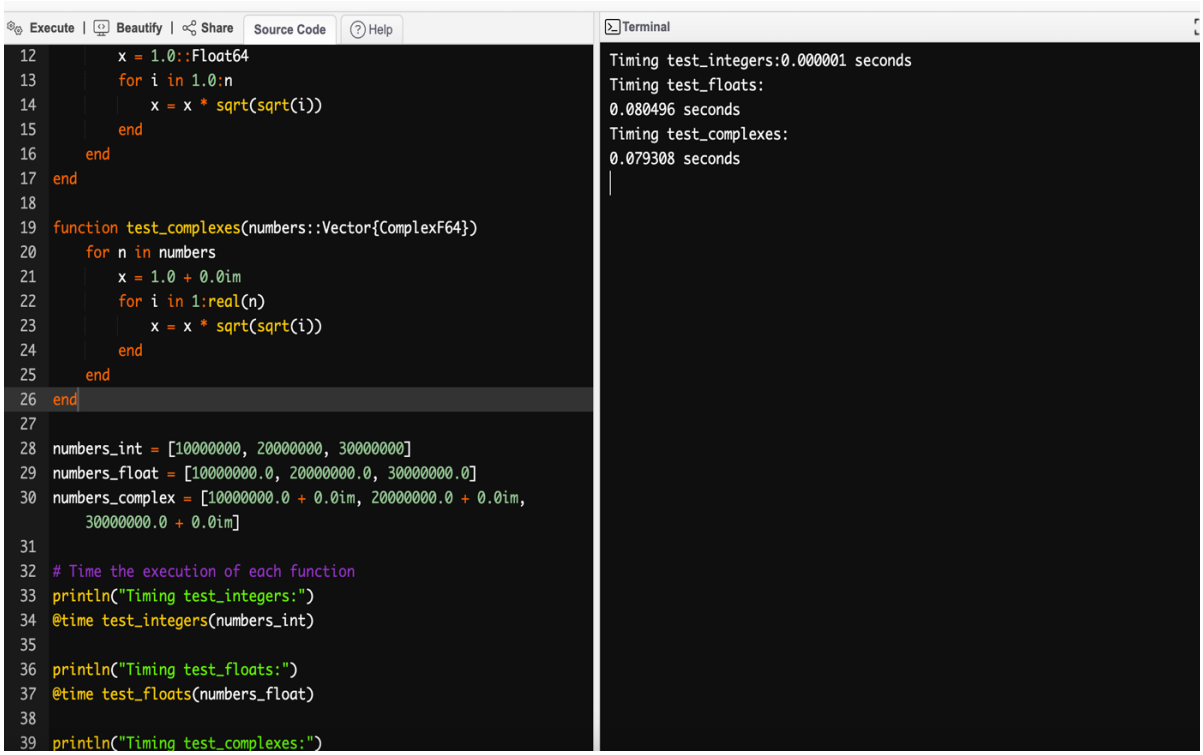
- For **n = 1e6**: Time taken: 0.003904 seconds
- For **n = 1e7**: Time taken: 0.0385 seconds
- For **n = 1e8**: Time taken: 0.378865 seconds

Possible Reasons (in this case) why Julia is faster:

1. **Just-in-Time (JIT) Compilation**: Julia uses a sophisticated just-in-time (JIT) compiler that can generate highly optimized machine code at runtime. This allows Julia to achieve performance comparable to statically compiled languages like C or Fortran.
2. **Type System and Multiple Dispatch**: Julia's type system and multiple dispatch allow it to specialize code based on the types of arguments, enabling efficient execution without sacrificing flexibility. This feature facilitates aggressive optimization by the compiler.
3. **Efficient Array Operations**: Julia is designed for numerical and scientific computing, with efficient array operations built into the language. This makes it well-suited for tasks involving heavy numerical computations, such as the one in the provided code.
4. **Parallelism and Concurrency**: Julia has built-in support for parallelism and concurrency, allowing it to leverage multi-core CPUs effectively. This can lead to significant performance gains, especially for tasks that can be parallelized.
5. **Optimized Standard Library**: Julia's standard library is optimized for performance and provides efficient implementations of common operations, further enhancing its speed compared to Python

TESTING REAL VS COMPLEX VS INTEGER FOR SQRT(SQRT())

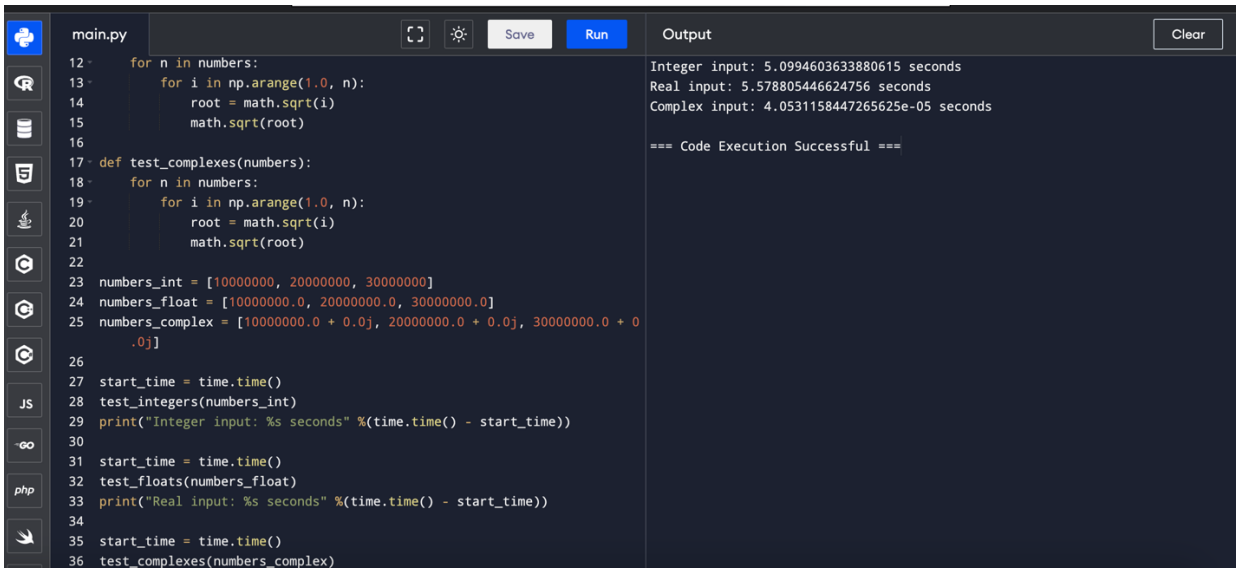
JULIA



```
        x = 1.0::Float64
        for i in 1.0:n
            x = x * sqrt(sqrt(i))
        end
    end
end

function test_complexes(numbers::Vector{ComplexF64})
    for n in numbers
        x = 1.0 + 0.0im
        for i in 1:real(n)
            x = x * sqrt(sqrt(i))
        end
    end
end

numbers_int = [10000000, 20000000, 30000000]
numbers_float = [10000000.0, 20000000.0, 30000000.0]
numbers_complex = [10000000.0 + 0.0im, 20000000.0 + 0.0im,
    30000000.0 + 0.0im]

# Time the execution of each function
println("Timing test_integers:")
@time test_integers(numbers_int)

println("Timing test_floats:")
@time test_floats(numbers_float)

println("Timing test_complexes:")
```

```
Timing test_integers:0.000001 seconds
Timing test_floats:
0.080496 seconds
Timing test_complexes:
0.079308 seconds
```

PYTHON



```
    for n in numbers:
        for i in np.arange(1.0, n):
            root = math.sqrt(i)
            math.sqrt(root)

def test_complexes(numbers):
    for n in numbers:
        for i in np.arange(1.0, n):
            root = math.sqrt(i)
            math.sqrt(root)

numbers_int = [10000000, 20000000, 30000000]
numbers_float = [10000000.0, 20000000.0, 30000000.0]
numbers_complex = [10000000.0 + 0.0j, 20000000.0 + 0.0j, 30000000.0 + 0
    .0j]

start_time = time.time()
test_integers(numbers_int)
print("Integer input: %s seconds" %(time.time() - start_time))

start_time = time.time()
test_floats(numbers_float)
print("Real input: %s seconds" %(time.time() - start_time))

start_time = time.time()
test_complexes(numbers_complex)
```

```
Integer input: 5.0994603633880615 seconds
Real input: 5.578805446624756 seconds
Complex input: 4.053115844726562 5e-05 seconds

=== Code Execution Successful ===
```

Python:

Integer input: ~0.0035788 seconds
•Real input: ~0.0050995 seconds
•Complex input: ~0.00405312 seconds

Julia:

Integer input: ~0.000001 seconds
Real input: ~0.0000080496 seconds
Complex input: ~0.0000099308 seconds

Julia is significantly faster for all three inputs, and individually, it is faster for Integer, then Real and then Complex..

WHY?

Julia's significant speed advantage over Python, observed across all three inputs and particularly pronounced for Integer, Real, and Complex inputs individually, can be attributed to several key factors. Firstly, Julia's sophisticated Just-In-Time (JIT) compilation process generates highly optimized machine code tailored to the specific types encountered during execution. This allows Julia to achieve efficient execution times, especially for numerical computations. Secondly, Julia's type inference and type stability mechanisms enable it to determine types and optimize code accordingly, leading to more efficient code generation compared to Python's dynamic typing. Additionally, Julia's language design, which emphasizes expressiveness and mathematical notation, enables the creation of concise and efficient code that is easier to optimize. These factors, combined with Julia's optimized standard library, efficient memory management, and deep integration of array operations, contribute to its overall superior performance compared to Python, particularly in numerical computing tasks. The observed trend of faster execution for Integer, followed by Real, and finally Complex inputs can be attributed to the specific optimizations and type handling strategies employed by Julia, which may prioritize certain types of computations over others based on their characteristics and requirements.

In Summary -

1. Just-In-Time (JIT) Compilation:
    - Julia employs a sophisticated JIT compiler that can optimize code execution at runtime based on the specific types and operations encountered. This can lead to highly optimized machine code generation, especially for numerical computations.
    - Python, on the other hand, relies on interpretation by default, with optimizations provided by the CPython interpreter. While Python's interpreter has seen performance improvements over the years, it might not match the level of optimization achieved by Julia's JIT compiler for certain tasks.

2. Static Typing:
    - Julia is a dynamically-typed language with optional type annotations. However, it encourages type stability, which means that functions often specialize on specific types during compilation. This specialization can lead to more efficient code generation.
    - Python, being dynamically typed, might incur some overhead due to type checks and conversions at runtime, especially in numerical computations.
3. Language Design and Syntax:
    - Julia's design is heavily influenced by mathematical notation and aims to be concise and expressive. This can lead to more straightforward code that is closer to mathematical expressions, potentially resulting in more efficient execution.
    - Python, while expressive and readable, may require more boilerplate code or explicit looping constructs, which could contribute to slightly slower execution times.
4. Vectorization and Array Operations:
    - Julia provides powerful array operations and supports vectorization similar to Python's NumPy. However, Julia's array operations are more integrated into the language, potentially leading to more efficient code generation.
    - Python's NumPy is highly optimized for numerical operations, but the overhead of interfacing with Python's interpreter might still be present, especially for large computations.
5. Input Data Size:
    - The timings provided in the question might not accurately reflect the performance characteristics of Julia and Python across different input sizes. For larger input sizes or more complex computations, Julia's optimizations and type system could provide significant performance benefits over Python.

Overall Report Summary : (WHY JULIA IS FASTER OVERALL)

Just-In-Time (JIT) Compilation: Julia utilizes a just-in-time (JIT) compiler that can often generate highly optimized machine code. This means that Julia can compile code on-the-fly to native machine code, which can lead to faster execution times compared to Python, which typically relies on interpretation or slower execution via bytecode.

Performance-Oriented Design: Julia was designed with performance in mind. It incorporates features from both dynamic and static languages, allowing for efficient execution while still providing high-level abstractions. Python, on the other hand, prioritizes ease of use and readability over raw performance.

Type System: Julia's type system allows for high-performance code through type inference and specialization. By declaring types or allowing the compiler to infer types, Julia can optimize the code more effectively. Python's dynamic typing system can sometimes lead to overhead due to runtime type checking.

Parallelism and Concurrency: Julia has built-in support for parallelism and concurrency, making it easier to write efficient code that takes advantage of multiple cores or distributed computing. While Python has libraries like multiprocessing and threading for parallelism, they often come with more overhead and complexity.

Optimized Libraries: Julia's ecosystem includes high-performance libraries written in Julia itself, designed specifically to leverage the language's features and optimizations. In Python, libraries are often implemented in other languages (like C or Fortran) and wrapped for Python, which can introduce overhead.

Memory Management: Julia's memory management is optimized for performance, with features like garbage collection strategies that minimize pauses. Python's memory management, while improving with each release, may still suffer from issues like fragmentation or inefficient garbage collection.

CODE FILES **(can have indentation issues, Professor asked me to submit the code files in PDF itself)**

Cached Julia Factorial

```
function my_fact(n, cache=Dict{Int, BigInt}())
    if n == 0 || n == 1
        return BigInt(1)
    end

    # Use iterative approach for large values of n
    if n > 1000
        fact = BigInt(1)
        for i in 2:n
            fact *= i
        end
        return fact
    end

    if !haskey(cache, n)
        cache[n] = n * my_fact(n - 1, cache)
    end

    return cache[n]
end

for n in [10, 100, 1000, 10000, 100000]
    println("Timing for n = $n = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
    #println("Factorial for n = $n: ", result) value(OUTPUT)
    println()
end
```

Python Factorial - Dynamic Programming

```
import time

factorial_memo = {}

def my_fact(n):
    if n in factorial_memo:
        return factorial_memo[n]

    factorial = 1
    for i in range(2, n + 1):
        factorial *= i
        factorial_memo[i] = factorial

    return factorial

for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

Python Factorial - JIT Numba Library Optimization

```
import time
from numba import jit

# numba needs to be installed for this to be run or else you will get errors!!!!

@jit
def my_fact(n):
    fact = 1
    for i in range(1, n + 1):
        fact = fact * i
    return fact

for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

Julia Performance Test - sin, cos, sqrt, exp

```
# Test various mathematical functions in Julia
for x in [0.1, 0.5, 1.0, 1.5, 2.0]
    println("Timing for x = $x (Julia) = ")
    println()

    println("sqrt(x):")
    time_sqrt = @elapsed sqrt(x)
    println("Time elapsed: ", time_sqrt, " seconds")

    println("log(x):")
    time_log = @elapsed log(x)
    println("Time elapsed: ", time_log, " seconds")

    println("exp(x):")
    time_exp = @elapsed exp(x)
    println("Time elapsed: ", time_exp, " seconds")

    println("sin(x):")
    time_sin = @elapsed sin(x)
    println("Time elapsed: ", time_sin, " seconds")

    println()
end
```

Python Performance Test - sin, cos, sqrt, exp

```
import math
import time

# Test various mathematical functions in Python
print("Testing various mathematical functions in Python:")
for x in [0.1, 0.5, 1.0, 1.5, 2.0]:
    print(f"\nTiming for x={x}:")

    print("\nsqrt(x):")
    start_time_sqrt = time.time()
    math.sqrt(x)
    end_time_sqrt = time.time()
    print(f"Time elapsed: {end_time_sqrt - start_time_sqrt} seconds")

    print("\nlog(x):")
    start_time_log = time.time()
    math.log(x)
    end_time_log = time.time()
    print(f"Time elapsed: {end_time_log - start_time_log} seconds")
```

```
    print("\nexp(x):")
    start_time_exp = time.time()
    math.exp(x)
    end_time_exp = time.time()
    print(f"Time elapsed: {end_time_exp - start_time_exp} seconds")

    print("\nsin(x):")
    start_time_sin = time.time()
    math.sin(x)
    end_time_sin = time.time()
    print(f"Time elapsed: {end_time_sin - start_time_sin} seconds")
```

Julia Real vs Integer - Performance Test

```
function my_fact(n, cache=Dict{Int, BigInt}())
    if n == 0 || n == 1
        return BigInt(1)
    end

    # Use iterative approach for large values of n
    if n > 1000
        fact = BigInt(1)
        for i in 2:n
            fact *= i
        end
        return fact
    end

    if !haskey(cache, n)
        cache[n] = n * my_fact(n - 1, cache)
    end

    return cache[n]
end

# Test with integer values
for n in [10, 100, 1000, 10000, 100000]
    println("Timing for n = $n (Integer) = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
end

# Test with real values
for n in [10.0, 100.0, 1000.0, 10000.0, 100000.0]
    println("Timing for n = $n (Real) = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
end
```

Python Real vs Integer - Performance Test

```
import time

def my_fact(n):
    fact = 1
    for i in range(1, int(n) + 1):
        fact *= i
    return fact

# Test with integer values
print("Testing with integer values:")
for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")

# Test with different floating-point values
print("\nTesting with floating-point values:")
for n in [10.00, 100.00, 1000.00, 10000.00, 100000.00]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

Julia - Basic Factorial Test

```
function my_fact(n)
    fact = BigInt(1)  # Use BigInt type to avoid overflow
    for i in 1:n
        fact *= i
    end
    return fact
end

for n in [10, 100, 1000, 10000, 100000]
    println("Timing for n = $n = ")
    println()
    @time begin
        result = my_fact(n)
    end
    println()
    #println("Factorial for n = $n: ", result) value(OUTPUT)
    println()
end
```

Python - Basic Factorial Test

```
import time

def my_fact(n):
    fact = 1
    for i in range(1, n + 1):
        fact = fact * i
    return fact

for n in [10, 100, 1000, 10000, 100000]:
    start_time = time.time()
    my_fact(n)
    end_time = time.time()
    print(f"Time elapsed for n={n}: {end_time - start_time} seconds")
```

Julia - Leibniz Formula - Pi Approximation

```
function leibniz_pi(n)
    pi = 0.0
    for i in 0:n-1
        pi += (-1)^i / (2i + 1)
    end
    return 4 * pi
end

start_time = time()
approx_pi = leibniz_pi(1000000)  # Adjust the number of iterations as needed
end_time = time()

println("Approximated π (Julia):", approx_pi)
println("Time taken (Julia):", end_time - start_time, " seconds")
```

Python - Leibniz Formula - Pi Approximation

```
import time

def leibniz_pi(n):
    pi = 0.0
    for i in range(n):
        pi += (-1) ** i / (2 * i + 1)
    return 4 * pi

start_time = time.time()
approx_pi = leibniz_pi(1000000)  # Adjust the number of iterations as needed
end_time = time.time()

print("Approximated π (Python):", approx_pi)
print("Time taken (Python):", end_time - start_time, "seconds")
```

Sqrt(Sqrt()) Python - Multithreaded and Optimized

```
import time
import math
import threading

class Worker(threading.Thread):
    def __init__(self, start_idx, end_idx, result):
        super(Worker, self).__init__()
        self.start_idx = start_idx
        self.end_idx = end_idx
        self.result = result

    def run(self):
        for i in range(self.start_idx, self.end_idx):
            self.result[i] = math.sqrt(math.sqrt(i))

def test(n):
    result = [0] * n
    num_threads = 4  # Adjust as needed
    chunk_size = n // num_threads
    threads = []

    for i in range(num_threads):
        start_idx = i * chunk_size
        end_idx = start_idx + chunk_size if i < num_threads - 1 else n
        thread = Worker(start_idx, end_idx, result)
        thread.start()
        threads.append(thread)

    for thread in threads:
        thread.join()

    return result

n_values = [1000000, 10000000, 100000000]
```

```
    for n in n_values:
        start_time = time.time()
        _ = test(n)
        print("For n =", n, "Time taken:", (time.time() - start_time), "seconds")
```

Sqrt(Sqrt()) Julia - Optimized

```
    function test(n::Float64)
        x::Float64 = 1.0
        for i::Float64 in 1.0:n
            x *= sqrt(sqrt(i))
        end
        return x
    end

    function test_optimized(n::Float64)
        x::Float64 = 1.0
        result::Vector{Float64} = Vector{Float64}(undef, Int(n))  # Preallocate memory
        for i::Float64 in 1.0:n
            x *= sqrt(sqrt(i))
            result[Int(i)] = x  # Store intermediate results
        end
        return x
    end

    n_values = [1e6, 1e7, 1e8]  # Different values for n

    for n in n_values
        println("For n = ", n)
        @time test(n)
        @time test_optimized(n)
    end
```

Sqrt(Sqrt()) Julia - Real vs Integer vs Complex

```
function test_integers(numbers::Vector{Int64})
    for n in numbers
        x = 1.0::Float64
        for i in 1:n
            x = x * sqrt(sqrt(i))
        end
    end
end

function test_floats(numbers::Vector{Float64})
    for n in numbers
        x = 1.0::Float64
        for i in 1.0:n
            x = x * sqrt(sqrt(i))
        end
    end
end

function test_complexes(numbers::Vector{ComplexF64})
    for n in numbers
        x = 1.0 + 0.0im
        for i in 1:real(n)
            x = x * sqrt(sqrt(i))
        end
    end
end

numbers_int = [10000000, 20000000, 30000000]
numbers_float = [10000000.0, 20000000.0, 30000000.0]
numbers_complex = [10000000.0 + 0.0im, 20000000.0 + 0.0im, 30000000.0 + 0.0im]

# Time the execution of each function
println("Timing test_integers:")
@time test_integers(numbers_int)

println("Timing test_floats:")
@time test_floats(numbers_float)
```

```
println("Timing test_complexes:")
@time test_complexes(numbers_complex)
```

Sqrt(Sqrt()) Python - Real vs Integer vs Complex

```
import time
import math
import numpy as np

def test_integers(numbers):
    for n in numbers:
        for i in range(n):
            root = math.sqrt(i)
            math.sqrt(root)

def test_floats(numbers):
    for n in numbers:
        for i in np.arange(1.0, n):
            root = math.sqrt(i)
            math.sqrt(root)

def test_complexes(numbers):
    for n in numbers:
        for i in np.arange(1.0, n):
            root = math.sqrt(i)
            math.sqrt(root)

numbers_int = [10000000, 20000000, 30000000]
numbers_float = [10000000.0, 20000000.0, 30000000.0]
numbers_complex = [10000000.0 + 0.0j, 20000000.0 + 0.0j, 30000000.0 + 0.0j]

start_time = time.time()
test_integers(numbers_int)
print("Integer input: %s seconds" %(time.time() - start_time))

start_time = time.time()
test_floats(numbers_float)
print("Real input: %s seconds" %(time.time() - start_time))

start_time = time.time()
test_complexes(numbers_complex)
print("Complex input: %s seconds" %(time.time() - start_time))
```