

FEDERAL STATE AUTONOMOUS EDUCATIONAL INSTITUTION  
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Report  
on the practical task No. 1  
“Experimental time complexity analysis”

Performed by

*Cheng-Yuan and Ma*  
*Academic group*

J4133c

Petr Chunaev St.

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Language : python

Goal : Experimental study of the time complexity of different algorithms

Problem : Generate an n-dimensional random vector  $\mathbf{v} = [v, v, \dots, v]$  with non-negative elements.

For  $\mathbf{v}$ , implement the following calculations and algorithms:

## I.

Theory :

1.  $f(\mathbf{v}) = \text{const}$  (constant function);

Theory : when we create matrix , it cost  $O(\text{Row} * \text{Column})$  complexity

2.  $f(\mathbf{v}) = \sum v$  (the sum of elements);

Theory : when we create matrix , it cost  $O(\text{Row} * \text{Columns})$  complexity

and it cost another Row \* Columns to make calculation of sum

complexity will be  $2(\text{Row} * \text{Columns}) = O(\text{Row} * \text{Columns})$

3.  $f(\mathbf{v}) = \prod v$  (the product of elements)

Theory : when we create matrix , it cost  $O(\text{Row} * \text{Columns})$  complexity

and it cost another Row \* Columns to make calculation of product

complexity will be  $2(\text{Row} * \text{Columns}) = O(\text{Row} * \text{Columns})$

4. supposing that the elements of  $\mathbf{v}$  are the coefficients of a polynomial  $P$  of

degree  $n - 1$ , calculate the value  $P(1.5)$  by a direct calculation of  $P(x) = \sum v x^{(k-1)}$  (i.e. evaluating each term one by one) and by Horner's method

Theory : To understand the method, let us consider the example of  $2x^3 - 6x^2 + 2x - 1$ . The polynomial can be evaluated as  $((2x - 6)x + 2)x - 1$ . The idea is to initialize result as coefficient of  $x^n$  which is 2 in this case, repeatedly multiply result with  $x$  and add next coefficient to result. Finally return result.

## 5. Bubble Sort of the elements of $\nu$

Theory : Bubble sort is the simplest sorting algorithm that works by repeatedly swapping the adjacent elements if they are in the wrong order. This algorithm is not efficient for large data sets due to its average and worst-case time complexity is quite high.

Steps :

Run a nested for loop to traverse the input array using two variables  $i$  and  $j$ , such that  $0 \leq i < n-1$  and  $0 \leq j < n-i-1$

If  $\text{arr}[j]$  is greater than  $\text{arr}[j+1]$  then swap these adjacent elements, else move on

Print the sorted array

Time Complexity:  $O(N^2)$

Auxiliary Space:  $O(1)$

## 6. Quick Sort of the elements of $\nu$ ;

Theory : quick sort is one of sorting algorithms as well

Step :

The idea of Quick Sort is to first find a reference point

Then send two agents to search from both sides of the data to the middle. If a value is found on the right that is smaller than the reference point, and a value is found on the left that is smaller than the reference point big, let them swap.

Repeatedly find and exchange until the two meet. Then swap the meeting point with the reference point. The first round is over.

Time Complexity: average :  $O(n\log n)$  , best :  $O(n\log n)$  , worst :  $O(n^2)$

Auxiliary Space:  $O(x)$

7. Timsort of the elements of  $v$ .

Theory : Timsort is derived from merge sort and insertion sort , designed to perform well on many kinds of real-world data

Step :

We divide the Array into chunks called Run . We sort these runs one by one using insertion sort, and then combine the runs using the combine function used in merge sort. Only use Insertion Sort to sort the Array if its size is less than run.

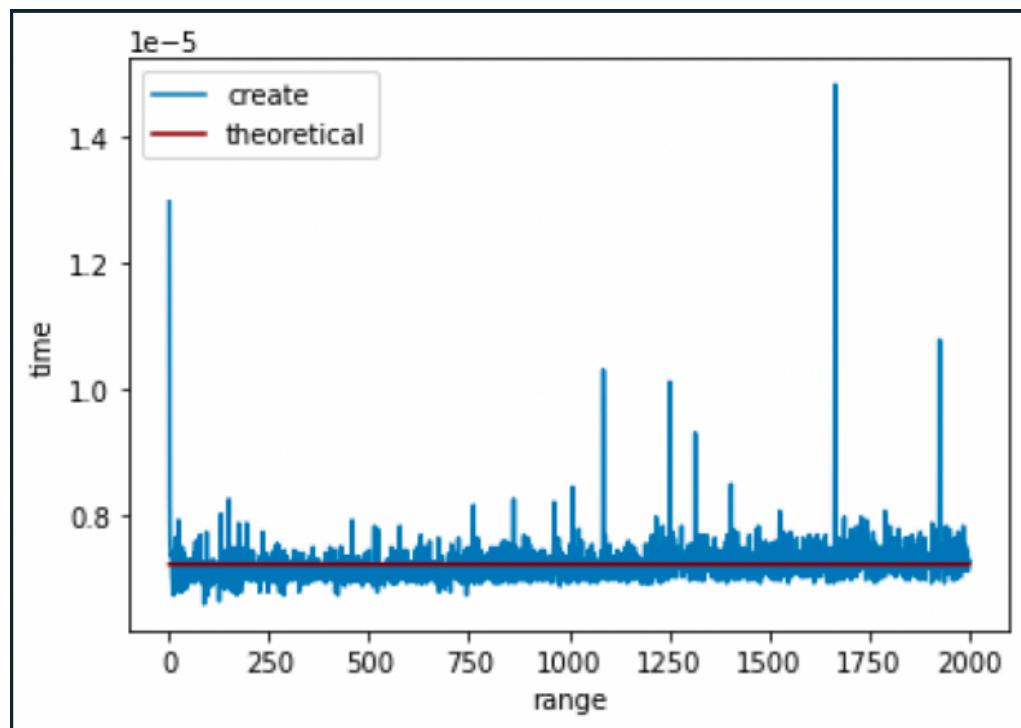
Depending on the size of the array, the run size may vary from 32 to 64. Note that the merge function performs well when the large and small subarrays are powers of 2. The idea is based on the fact that insertion sort performs well for small arrays.

Time Complexity:  $O(n\log n)$

Auxiliary Space:  $O(x)$

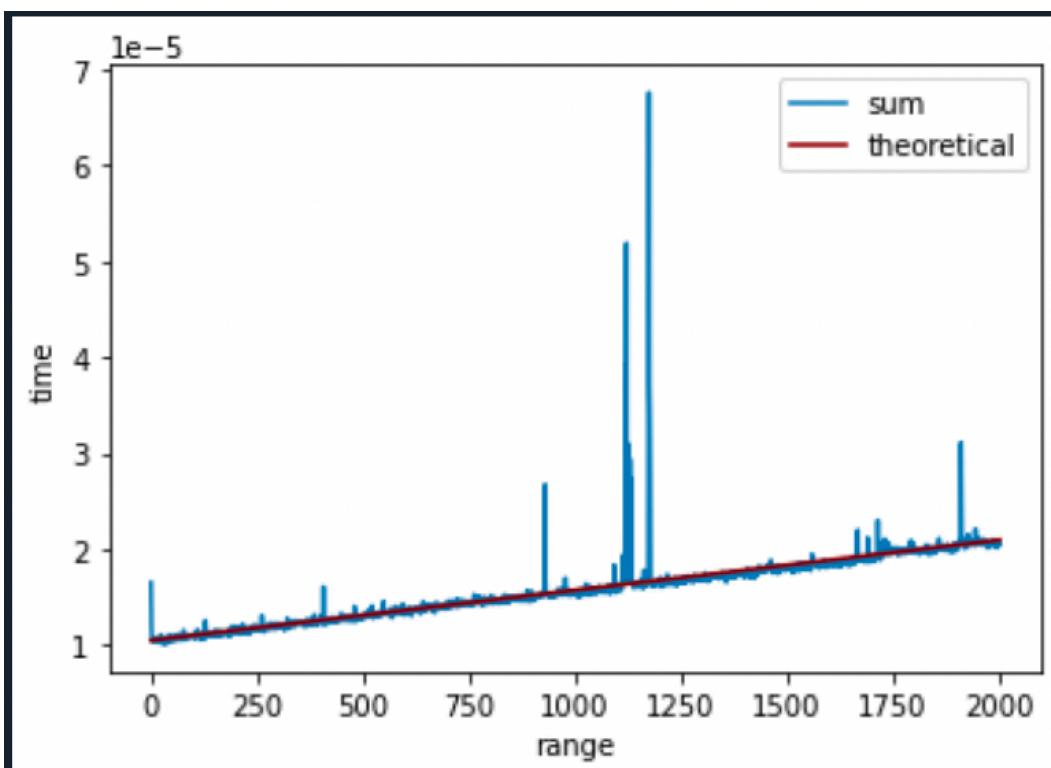
Result :

### Const



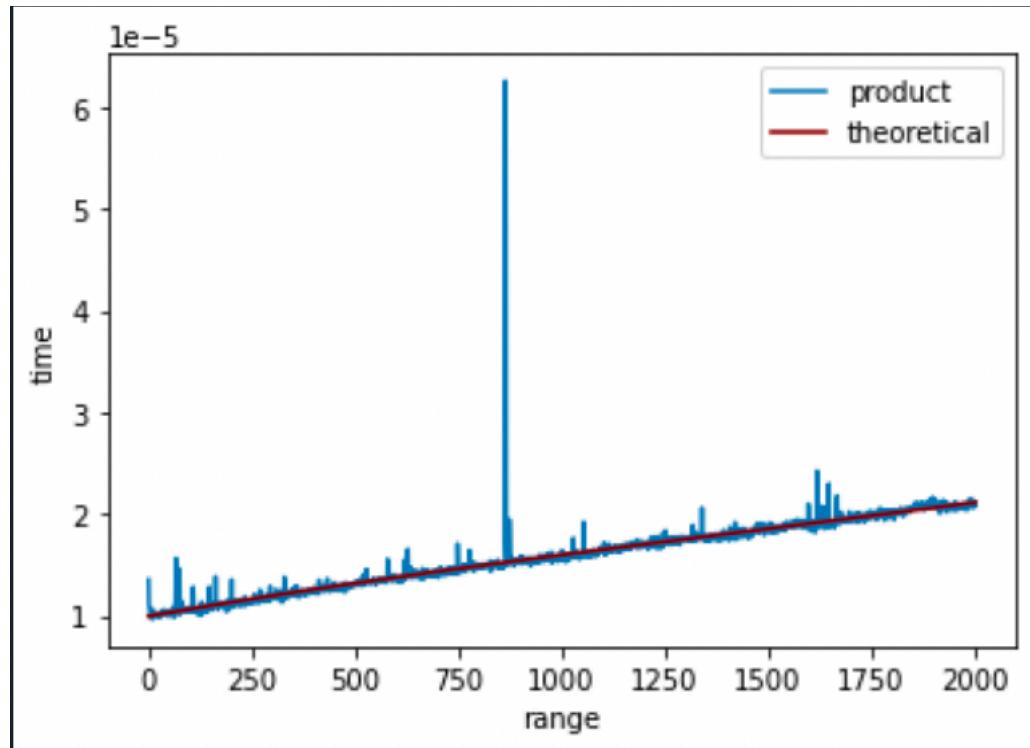
As you can see that wave of empirical is moving up and down through theoretical line but never goes too far away , except there are some noises , but on average they are typically identical

### Sum



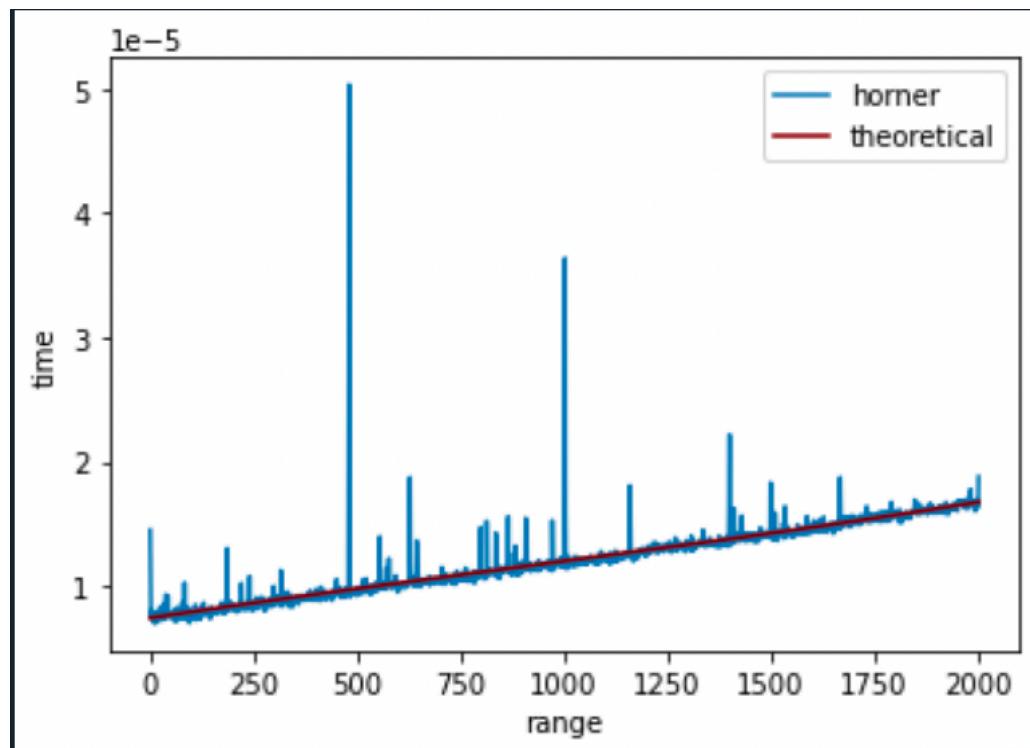
As you can see that wave of empirical is moving up and down of linear theoretical line , but it never goes far from it , except some noises

## Product



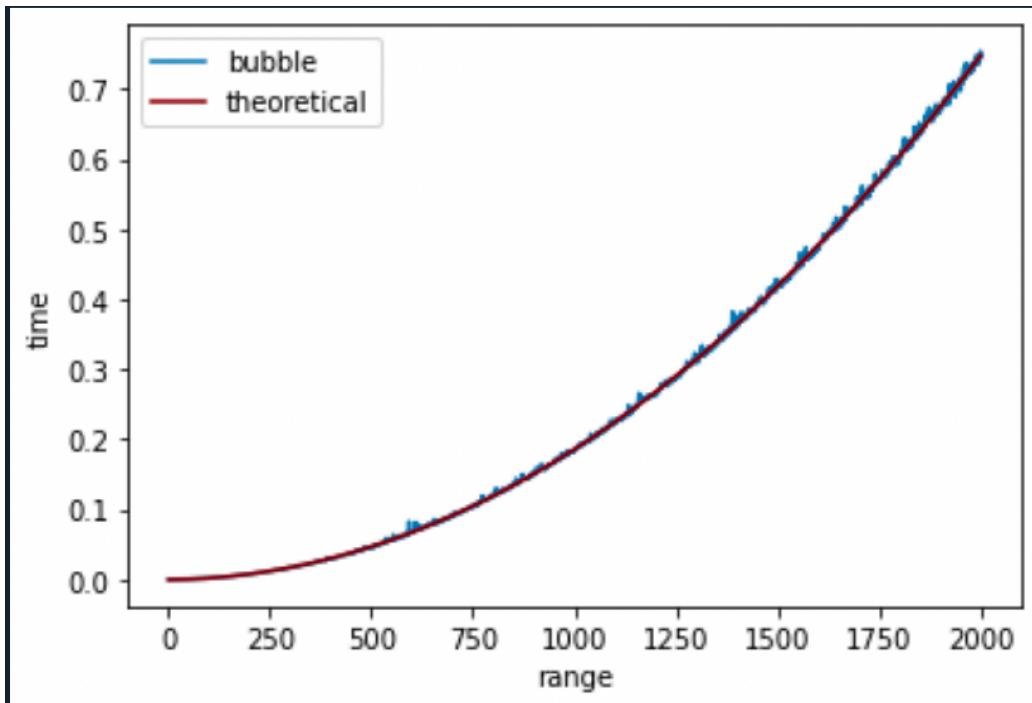
In the graph , empirical line is ascending with linear way , comparing with theoretical line , we can see that they both can match each other .

## Horner



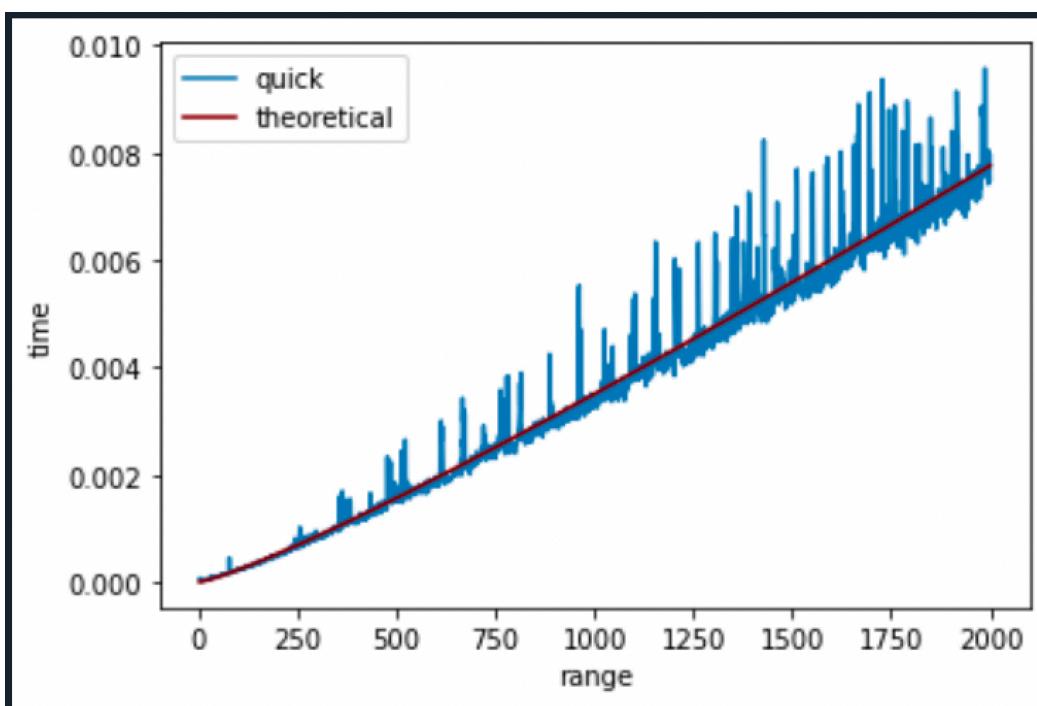
We can see that even empirical wave fluctuates , there is still a pattern in it . So when we compare with theoretical line to find the pattern , wave and theoretical line would be gorgeously combined together

### Bubble sort



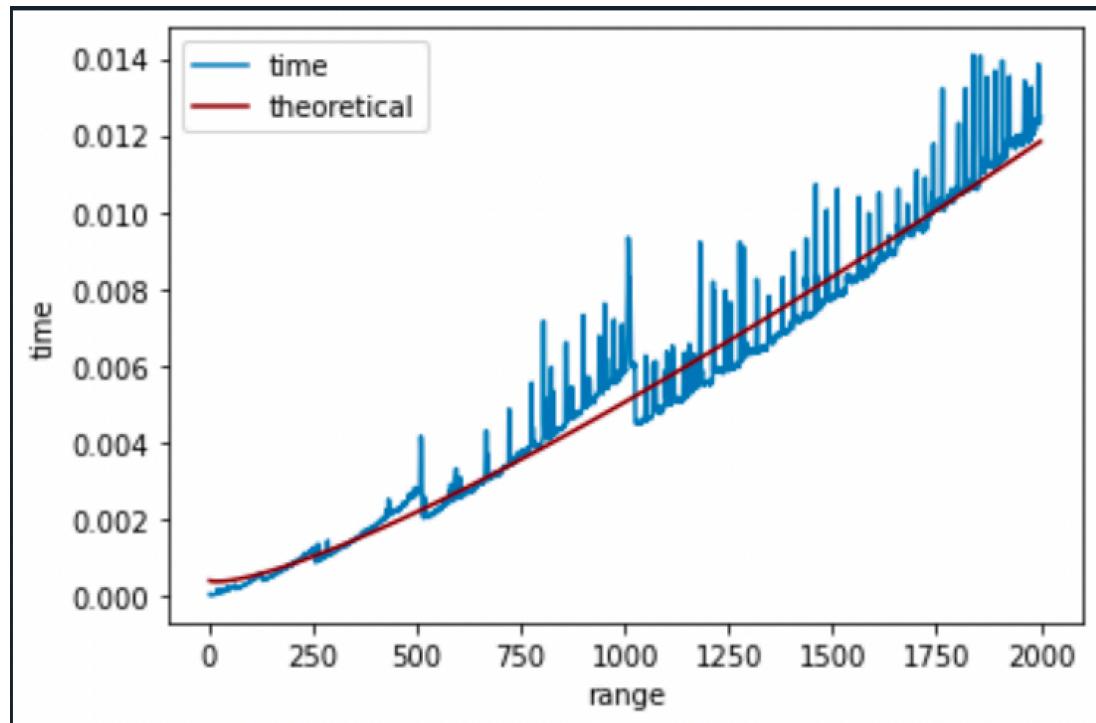
As we can see it is bubble sort cost much more execution time comparing than first 4 examples, time increases dramatically , and when we compare with theoretical pattern  $O(x^2)$  , it perfectly match .

### Quick sort



Above graph is for quick sort , we can see that there is huge fluctuation , maybe because of random array , so execution time could be more random . But when we take better look , we still can realize there is a concrete ascending rate . So when we combine empirical line with theoretical line  $O(x \cdot \log x)$  , it can show a much clear ascending pattern .

### Timesort



Timesort has complexity  $O(n \cdot \log n)$  , so ascending rate is not so much different to quick sort . When we use theoretical line to match empirical line , it show a very clear time complexity .

II. Generate random matrices  $A$  and  $B$  of size  $n \times n$  with non-negative elements. Find the usual matrix product for  $A$  and  $B$ .

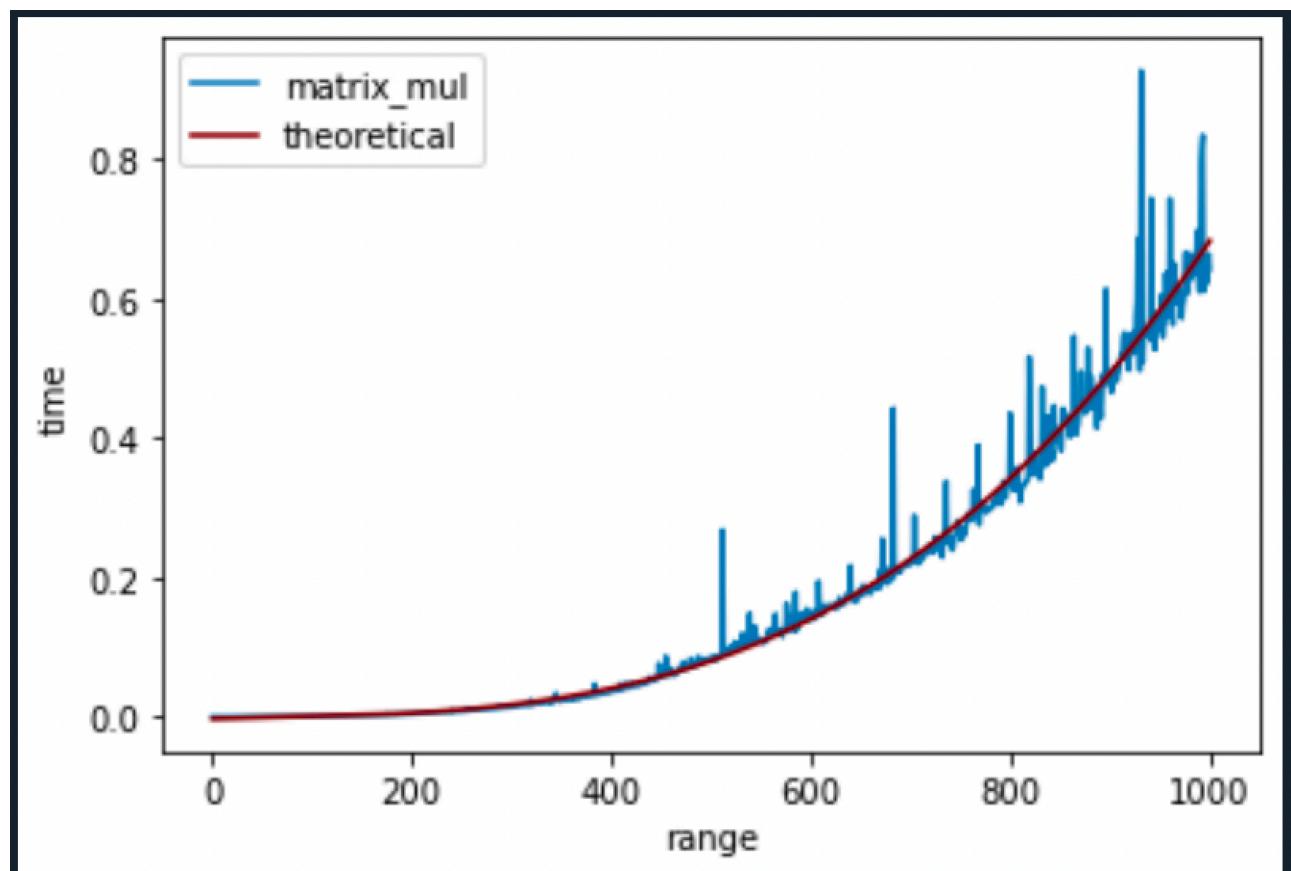
Theory :

Here I implemented numpy to use np.dot to do multiplication

Usually without implementing any API , the naive matrix multiplication and the Solvay Strassen algorithm are two most common way . There exist algorithms that achieve better complexity than the naive  $O(n^3)$ . Strassen algorithm achieves a complexity of  $O(n^{2.807})$  . Here is the graph where I use theoretical line to show more clear time complexity . As we can see that Matrix multiplication cost much more than other functions we tested above , even I only tried 1000 iterations .

Result :

I tried to run until range 2000 , but even after 2 hours , it still showed no outcome , so I tried until 1000 , below is the graph



### III. Describe the data structures and design techniques used within the algorithms.

I used python to complete this graph by applying numpy which is considered one of most useful implementations . I used numpy to create two matrix with the same size . Arrays from the NumPy library, called N-dimensional arrays or ndarray , are used as the primary data structure for representing data.

Due to property of ndarray , I can make multiplication with mathematical way . Therefore I use numpy.dot to make calculation to get product of two matrix

conclusion:

In the first section through graphs that I created , we can see that in each graph , it shows fluctuation in each empirical time complexity . But when we try to match with theoretical time complexity , they all can fit well . So we can conclude that time complexities of theoretical assumption are correct

In the second section , I used numpy instead of common algorithms such as naive matrix multiplication and the Solvay Strassen algorithm , it shows  $O(x^3)$  execute time .which can be tested with theoretical complexity as graph above .

### Appendix

<https://github.com/MaChengYuan/task1.git>