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## Week 1 assignment

Course:  
**HPC**

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31. März 2023

## Problem 1

Given an integer  $n$ , count the number of its divisors.

### Solution 1:

```
def count_divisors(n):
    count = 0
    d = 1
    while d <= n:
        if n % d == 0:
            count += 1
        d += 1
    return count
```

### Solution 2:

```
def count_divisors(n):
    count = 0
    d = 1
    while d * d <= n:
        if n % d == 0:
            count += 1 if n / d == d else 2
        d += 1
    return count
```

## Solution :

- Describing solution 1: The function `count_divisors` counts the number of divisors of a given integer  $n$  by looping over all possible divisors and using a counter variable to count the found divisors. since we iterate " $n$ " times for each value of " $n$ ", the number of operations performed is directly proportional to the value of " $n$ ". Hence the algorithm has a time complexity  $O(n)$ .
- Describing solution 2: This time we iterate over all possible divisors up to  $\sqrt{n}$  and we fill up a counter variable each time a divisor is found, considering whether we are dealing with multiples of  $n$ . The number of operations is proportional to the square root of  $n$ . This can be expressed as  $O(\sqrt{n})$ .
- Running the 2 programs for different values of  $n$  :

Value of $n$	Solution 1 timing	Solution 2 timing
100	0.000003	0.000003
1000	0.000003	0.000003
10000	0.002	0.000043
100000	0.031	0.0003
1000000	0.34	0.004

## Problem 2

Big-O notation:

- 
- |   |
|---|
| <p>a) <math>T(n) = 3n^3 + 2n^2 + \frac{1}{2}n + 7</math> Prove that : <math>T(n) = \mathbf{O}(n^3)</math></p> <p>b) Prove : <math>\forall k, n^k</math> is not <math>\mathbf{O}(n^{k-1})</math></p> |
|---|

**Solution**

- a) For  $n \geq 1$ , we have:

$$T(n) \leq n^3(3 + 2 + \frac{1}{2} + 7)$$

Thus :

$$T(n) \leq \frac{15}{2}n^3 + 7$$

For  $c = \frac{16}{2}$  and for all  $n \geq 1$  we have:

$$T(n) \leq \frac{15}{2}n^3 + 7 \leq cn^3$$

Hence finally :  $T(n) = \mathbf{O}(n^3)$

- b) We proceed with contradiction, assume that  $\forall k, n^k$  is  $\mathbf{O}(n^{k-1})$ . Then :  $\exists c, n_0$  such that  $\forall n \geq n_0, n^k \leq c.n^{k-1}$ .

Dividing both sides by  $n^{k-1}$ , we get  $n \leq c$  for all  $n \geq n_0$ . But this is a contradiction, since  $n$  can be arbitrarily large and  $c$  is a constant., Therefore, we have shown that  $\forall k \geq 1, n^k$  is not  $\mathbf{O}(n^{k-1})$ .

<b>Problem 3</b>
<p>a) Given two sorted arrays, write a function (with a language of your choice) that merge the two arrays into a single sorted array.</p> <p>b) Analyze the complexity of your func.on using Big-O notation.</p>






**Solution:**

- a) In python we proceed as follows

```
def merge(A, B):
    i, j = 0, 0
    C = []

    while i < len(A) and j < len(B):
        if A[i] <= B[j]:
            C.append(A[i])
            i += 1
        else:
            C.append(B[j])
            j += 1

    while i < len(A):
        C.append(A[i])
        i += 1

    while j < len(B):
        C.append(B[j])
        j += 1

    return C
```

```
A = np.array([2, 4, 6, 8, 10])
B = np.array([1, 3, 5, 7, 9])
print(A)
print(B)
```

```
[ 2  4  6  8 10]
[ 1  3  5  7  9]
```

```
merge(A, B)
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

- b) Two input sorted lists  $A = [a_1, \dots, a_\alpha]$  of size  $\alpha$  and  $B = [b_1, \dots, b_\beta]$  of size  $\beta$  can be merged into a sorted list  $C = [c_1, \dots, c_{\alpha+\beta}]$  of size  $\alpha + \beta$  in linear time.

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**Proof**

- Let pointers  $i$ ,  $j$ , and  $k$  to current positions in  $A$ ,  $B$ , and  $C$ , respectively, be initially at the first positions,  $i = j = k = 1$ .
- Each time the smaller of  $a_i$  and  $b_j$  is copied to  $c_k$ , and the pointers  $k$  and either  $i$  or  $j$  are incremented by 1:

$$\begin{cases} a_i \geq b_j \Rightarrow c_k = b_j, j \leftarrow j + 1, k \leftarrow k + 1 \\ a_i \leq b_j \Rightarrow c_k = a_i, i \leftarrow i + 1, k \leftarrow k + 1 \end{cases}$$

- After  $A$  or  $B$  is exhausted, the rest of the other list is copied to  $C$
- Each comparison advances  $k$  so that the maximum number of comparisons is  $n = \alpha + \beta$ , all other operations being linear, too  
Hence finally the time complexity is  $\mathbf{O}(\alpha + \beta)$

**Problem 4**

- Using the master method analyse the complexity of merge sort.
- Using the master method analyse the complexity of binary search

**Solution:**

- Let's assume that  $T(n)$  is the worst-case time complexity of merge sort for  $n$  integers. When  $n \geq 1$  (merge sort on single element takes constant time), We can break down the time complexities as follows:
  - Divide part: the time complexity of the divide part is  $\mathbf{O}(1)$ , because calculating the middle index takes constant time.
  - Conquer part: We are recursively solving two sub-problems. each of size  $\frac{n}{2}$ . So the time complexity of each sub-problem is  $T(n/2)$  and overall time complexity of conquer part is  $2T(n/2)$ .
  - Combine part: The worst case time complexity of the merging process is  $\mathbf{O}(n)$ :

To calculate  $T(n)$  we need to sum the time complexities of the divide ,conquer and combine part , thus getting the recursion :  $T(n) = \mathbf{O}(1) + 2T(n/2) + \mathbf{O}(n)$  Hence :  
 $T(n) = 2T(n/2) + c.n$

Now recall the 3 cases of complexity analysis using the master theorem :

- If  $f(n) = \mathbf{O}(n^k)$  where  $k \leq \log_b(a)$  then  $T(n) = \mathbf{O}(n^{\log_b(a)})$
- If  $f(n) = \mathbf{O}(n^k)$  where  $k = \log_b(a)$  then  $T(n) = \mathbf{O}(n^k \cdot \log n)$
- If  $f(n) = \mathbf{O}(n^k)$  where  $k \geq \log_b(a)$  then  $T(n) = \mathbf{O}(n^k)$

Comparing this with the merge sort algorithm lends us :

$$T(n) = 2T(n/2) + c.n$$

$$T(n) = aT(n/b) + \mathbf{O}(n^k)$$

where :  $a = 2$  and  $b = 2$

$$\mathbf{O}(n^k) = c.n = \mathbf{O}(n) \Rightarrow k = 1$$

$$\text{Also : } \log_b(a) = \log_2(2) = 1 = k$$

This falls under the 2nd case of the Master theorem , hence finally the time complexity of merge sort with the master theorem is given by :

$$T(n) = \mathbf{O}(n^k \cdot \log n) = \mathbf{O}(n^1 \cdot \log n) = \mathbf{O}(n \cdot \log n)$$

- Since the binary search time complexity satisfies the recurrence :  $T(n) = T(n/2) + \mathbf{O}(1)$   
For  $a=1$  and  $b=2$  we have :  $f(n) = \mathbf{O}(1)$   
Applying the master theorem we deduce that the time complexity for binary search is given by :  $\mathbf{O}(\log n)$

### Problem 5

- Write a function called merge sort (using a language of your choice) that takes two arrays as parameters and sort those two arrays using the merge sort algorithm.
- Analyse the complexity of your algorithm without using the master theorem.
- Prove the 3 cases of the master theorem.
- Choose an algorithm of your choice and analyse it's complexity using the Big-O notation.

### Solution:

```

1 def merge_sort ( arr1 , arr2 ) :
2     if len( arr1 ) <= 1 and len( arr2 ) <= 1 :
3         return sorted ( arr1 + arr2 )
4     mid1 = len ( arr1 ) // 2
5     mid2 = len ( arr2 ) // 2
6     left1 = arr1 [: mid1 ]

```

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```

7   right1 = arr1 [ mid1 :]
8   left2 = arr2 [: mid2 ]
9   right2 = arr2 [ mid2 :]
10  sorted_left = merge_sort ( left1 , left2 )
11  sorted_right = merge_sort ( right1 , right2 )
12  return merge ( sorted_left , sorted_right )
13 def merge ( left , right ) :
14     result = []
15     while left and right :
16
17         if left [0] <= right [0]:
18             result . append ( left . pop (0) )
19         else :
20             result . append ( right . pop (0) )
21         if left :
22             result . extend ( left )
23         if right :
24             result . extend ( right )
25     return result
26
27     A = [4 , 2 , 1 , 6 , 8]
28     B = [3 , 7 , 5 , 9]
29     sorted_array = merge_sort ( A , B )
30     print ( sorted_array )
31     Output : [1 , 2 , 3 , 4 , 5 , 6 , 7 , 8 , 9]

```

- let's analyse the time complexity of this algorithm without using the master theorem :  
we distinguish several levels to the tree our algorithm is based on :

- At the first level, there is one node with value  $n$ .
- At the second level, there are two nodes with value  $\frac{n}{2}$ .
- At the third level, there are four nodes with value  $\frac{n}{4}$ .
- At the  $k$ -th level, there are  $2^k$  nodes with value  $\frac{n}{2^k}$ .
- The last level will have nodes with value 1 , and there will be  $n$  of them.

We can compute the total number of nodes in the tree as follows:

$$1 + 2 + 4 + \dots + 2^{k-1} + n = 2^k - 1 + n$$

where  $k$  is the number of levels in the tree. Since the height of the tree is  $k$ , we have:  
 $2^k = n + 1 \implies k = \log_2(n + 1)$  Therefore, the tree has  $\log_2(n + 1)$  levels.

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To compute the time complexity of merge sort based on this tree, we can start at the bottom of the tree and work our way up. At each level  $k$ , the total work done is  $O(n)$  (since there are  $n$  nodes at that level, each of which takes constant time to sort).

Therefore, the total work done at all levels is:  $O(n \log_2(n+1))$

We deduce that the algorithm has time complexity :  $O(n \cdot \log(n))$

### Problem 6

- Write a function using python3 that multiply two matrices A,B (without the use of numpy or any external library).
- What's the complexity of your algorithm (using big-O notation)?
- Write the same function in C. (bonus)
- Optimize this multiplication and describe each step of your optimisation.

### Solution:

```
1 def matrix_multiply (A , B ) :  
2     # check the dim of each matrix  
3     if len( A [0]) != len( B ) :  
4         raise ValueError ( " Matrix dimensions do not match " )  
5  
6     # define the result matrix  
7     result = [[0 for j in range ( len( B [0]) ) ] for i in range ( len( A  
8         ) ) ]  
9  
10    # multiplication  
11    for i in range (len ( A ) ) :  
12        for j in range (len( B [0]) ) :  
13            for k in range (len ( B ) ) :  
14                result [ i ][ j ] += A [ i ][ k ] * B [ k ][ j ]  
15  
16    return result
```

- The complexity of this algorithm is  $O(n^3)$ . This is due to the fact that each element of the result matrix requires  $n$  multiplications and  $n$  additions, and there are  $n^2$  elements in total, leading to a total of  $n^3$  operations.
- Let's write the same function in C:



```

1 #include <stdio.h>
2 #include <stdlib.h>
3
4 int** matrix_multiplication(int** A, int** B, int m, int n, int nB) {
5     int i, j, k;
6     int** res = (int**)malloc(m * sizeof(int*));
7     for (i = 0; i < m; i++) {
8         res[i] = (int*)malloc(nB * sizeof(int));
9         for (j = 0; j < nB; j++) {
10             res[i][j] = 0;
11             for (k = 0; k < n; k++) {
12                 res[i][j] += A[i][k] * B[k][j];
13             }
14         }
15     }
16     return res;
17 }

```

- To optimize the multiplication we propose the following vectorization approach :

```

1 def py_matmul3(a, b):
2     ra, ca = a.shape
3     rb, cb = b.shape
4     assert ca == rb, f"{ca} != {rb}"
5
6     output = np.zeros(shape=(ra, cb))
7     for i in range(ra):
8         output[i] = np.dot(a[i], b)
9
10
11     return output

```

Using broadcasting, we can essentially remove the loop and using just a line `output[i] = np.dot(a[i], b)` we can compute entire value for the *i*th row of the output matrix. What numpy does is broadcasting the vector `a[i]` so that it matches the shape of matrix `b`. Then it calculates the dot product for each pair of vector. Broadcasting rules are pretty much same across major libraries like numpy, tensorflow, pytorch etc.

## Problem 7

### Quiz

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## Solution

- a) A
- b) D
- c) C