

### Problem Set 3

**Due date:** Electronic submission of the pdf file of this homework is due on **2/10/2023 before 11:59pm** on ecampus.

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**Resources.** Below resources were used for reference -

- <https://www.calculator.net/log-calculator.html>
- Cormen, Leiserson, Rivest, Stein: Introduction to Algorithms, 3rd edition, The MIT Press, 2009 (or 4th edition)
- <https://opensa-server.cs.vt.edu/ODSA/Books/CS3/html/RecurrenceIntro.html>
- <https://www.programiz.com/dsa/master-theorem>

On my honor, as an Aggie, I have neither given nor received any unauthorized aid on any portion of the academic work included in this assignment. Furthermore, I have disclosed all resources (people, books, web sites, etc.) that have been used to prepare this homework.

**Signature:**

A handwritten signature in blue ink, appearing to read 'Ajain' with a stylized flourish at the end.

**Problem 1** (20 points).

**Solution.** To use mathematical induction, we need to have a base case, hypothesis step and then induction step. Let's get our base case first. It is given that  $T(2) = 2$ , we can multiply right hand side by  $\log_2 2$  since it evaluates to 1. So,  $T(2) = 2 \log_2 2$  is our base case.

Let's assume that if  $n = 2^k$  for some integer  $k > 0$  then  $T(n) = n \log_2 n$  is true. Substituting the value of  $n$ , we get  $T(2^k) = 2^k \log_2 2^k$ .

Now we need to prove that this holds true for some  $n = 2^{k+1}$ . We know that  $T(n) = 2T(n/2) + n$  if  $n = 2^k$  for  $k > 1$ ,

Substituting  $n = 2^{k+1}$ , we get

$$T(2^{k+1}) = 2T(2^{k+1}/2) + 2^{k+1} = 2T(2^k) + 2^{k+1}$$

Replacing  $T(2^k)$  by the value which we got before, we get

$$T(2^{k+1}) = 2 * 2^k \log_2 2^k + 2^{k+1} = 2^{k+1} \log_2 2^k + 2^{k+1} = 2^{k+1}(\log_2 2^k + 1)$$

We can now replace 1 with  $\log_2 2$  on right hand side, we will get  $2^{k+1}(\log_2 2^k + \log_2 2)$ . Using logarithm rule of addition, we can simplify it as  $2^{k+1}(\log_2(2^k * 2)) = 2^{k+1}(\log_2(2^{k+1}))$ .

Therefore our equation becomes -

$$T(2^{k+1}) = 2^{k+1}(\log_2(2^{k+1})).$$

We have proved that our assumption holds true for  $k + 1$ , hence by mathematical induction we can say that the solution of the given recurrence relation is  $T(n) = n \log_2 n$ .

**Problem 2** (20 points).

**Solution.** In the proposed recursive procedure for insertion sort, there are two steps. First is to sort a sub-array  $A[1..n-1]$  and then insert  $A[n]$  into the sorted array  $A[1..n-1]$ . We need a base case which is easy to derive. When we only have 1 element in array, then it is already sorted. So,  $T(1) = 1 = \Theta(1)$  becomes our base case. For arrays which have more than  $n$  elements, we will recursively sort the first  $n-1$  elements and then insert the  $n^{th}$  element into this sorted array. In worst case, inserting this element will take  $\Theta(n)$  time because we will need to look into entire array to find the position for inserting the element. Assuming array is of size  $n$ , let  $T(n)$  denote running time for this version of insertion sort. Then the recurrence relation for  $T(n)$  can be expressed as:

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1, \\ T(n-1) + \Theta(n) & \text{if } n > 1 \end{cases}$$

**Problem 3** (20 points).

**Solution.** We know that to multiply two matrices A and B of size  $2 \times 2$  using divide and conquer matrix multiplication algorithm, we will need 8 multiplications and some more evaluations (additions). In that case, we write our recurrence relation as  $T(n) = 8T(n/2) + \Theta(n^2)$  and  $T(2) = \Theta(1)$  is our base case. When we solve it, we get the time complexity as  $T(n) = \Theta(n^{\log_2 8}) = \Theta(n^3)$ . So, in general we can say that in case of divide and conquer matrix multiplication algorithm if

we have  $m$  sub problems with  $k$  multiplications each then time complexity can be written as  $T(n) = \Theta(n^{\log_m k})$ . Using the above logic, the time complexity for the 3 ways discovered by V. Pan can be calculated as -

$68 \times 68$  matrix, 132464 multiplications :  
 $T(n) = \Theta(n^{\log_{68} 132464}) = \Theta(n^{2.7951284873614})$

$70 \times 70$  matrix, 143640 multiplications :  
 $T(n) = \Theta(n^{\log_{70} 143640}) = \Theta(n^{2.7951226897483})$

$72 \times 72$  matrix, 155424 multiplications :  
 $T(n) = \Theta(n^{\log_{72} 155424}) = \Theta(n^{2.7951473910934})$

Clearly, the best asymptotic running time among the 3 methods is for  $70 \times 70$  matrix =  $\Theta(n^{2.7951226897483})$ .

In Strassen's algorithm, 7 multiplications are used and its time complexity is  $T(n) = \Theta(n^{\log_2 7}) = \Theta(n^{2.8073549220576})$ . As we can see  $\Theta(n^{2.8073549220576})$  is bigger than  $\Theta(n^{2.7951226897483})$ , therefore the method discovered by V. Pan for  $70 \times 70$  matrices is better than Strassen's algorithm.

**Problem 4** (20 points).

**Solution.** If we go with the basic process of multiplying two complex numbers, we will end up doing 4 multiplications :  $(a + bi)(c + di) = ac + adi + bci + bdi^2 = ac + i(ad + bc) - bd = (ac - bd) + i(ad + bc)$ . Multiplying two complex numbers using 3 multiplications can be tricky. However, it is clear that the real component will contain  $ac - bd$  and imaginary will contain  $ad + bc$ . If we do  $(a + b)(c + d)$ , we get  $ac + ad + bc + bd = X$  using 1 multiplication. Looking at our real component, let's do 2 more multiplications,  $ac = Y$  and  $bd = Z$ . We can combine these 3 using addition and subtraction to get our required values. Our real component will then become  $Y - Z = ac - bd$  and imaginary component will become  $X - Y - Z = ac + ad + bc + bd - ac - bd = ad + bc$ . Below is the algorithm:

given input : a, b, c, d

$X = (a + b)(c + d)$  # 1<sup>st</sup> multiplication

$Y = ac$  # 2<sup>nd</sup> multiplication

$Z = bd$  # 3<sup>rd</sup> multiplication

real =  $Y - Z$

imaginary =  $X - Y - Z$

return real & imaginary

**Problem 5** (20 points).

**Solution.** According to master method, if there is a recurrence relation  $T(n) = aT(n/b) + f(n)$  such that  $a \geq 1, b > 1$  and  $f(n)$  is eventually positive then,

the time complexity can be written in simpler terms for 3 cases :

$$T(n) = \begin{cases} \Theta(n^{\log_b a}) & \text{if } f(n) = O(n^{\log_b a - \epsilon}), \\ \Theta(n^{\log_b a} \log n) & \text{if } f(n) = \Theta(n^{\log_b a}), \\ \Theta(f(n)) & \text{if } f(n) = \Omega(n^{\log_b a + \epsilon}) \text{ and } f(n) \text{ is regular,} \end{cases}$$

Given the recurrence relation  $T(n) = T(n/2) + \Theta(1)$ ,  $a = 1$ ,  $b = 2$  and  $f(n) = \Theta(1)$ ,  $n^{\log_b a} = n^{\log_2 1} = n^0 = 1$ .

$f(n) = \Theta(1) = \Theta(n^0) = \Theta(n^{\log_2 1})$ . Therefore,  $2^{nd}$  case of master method is applicable here. Thus,  $T(n) = \Theta(n^{\log_b a} \log n) = \Theta(n^{\log_2 1} \log n) = \Theta(\log n)$ . Since base of logarithm can be anything as it won't affect the result, so we can finally conclude that  $T(n) = \Theta(\log_2 n) = \Theta(\lg n)$  ( $\log_2 x$  is written as  $\lg x$ ).