DAA – Unit II

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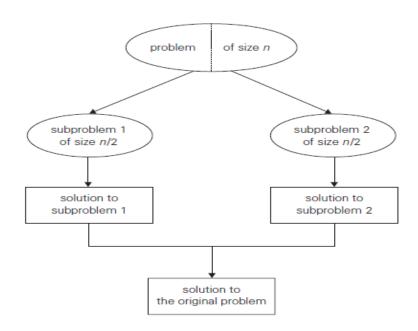
SYLLABUS

Duration (hour) 15		15	15	15	15	15	
	SLO-1	Introduction-Algorithm Design Introduction-Divide and Conquer		Introduction-Greedy and Dynamic Programming	Introduction to backtracking - branch and bound	Introduction to randomization and approximation algorithm	
S-1	SLO-2	Fundamentals of Algorithms	Maximum Subarray Problem	Examples of problems that can be solved by using greedy and dynamic approach	N queen's problem - backtracking	Randomized hiring problem	
SLO-1	SLO-1	Correctness of algorithm	Binary Search	Huffman coding using greedy approach	Sum of subsets using backtracking	Randomized quick sort	
S-2	SLO-2	Time complexity analysis	Complexity of binary search	Comparison of brute force and Huffman method of encoding	Complexity calculation of sum of subsets	Complexity analysis	
S-3	SLO-1	Insertion sort-Line count, Operation count Merge sort Knapsack problem using greedy approach Graph introduction		String matching algorithm			
•••	SLO-2	Algorithm Design paradigms	Time complexity analysis	Complexity derivation of knapsack using greedy	Hamiltonian circuit - backtracking	Examples	
\$ 4-5	SLO-1 SLO-2	Lab 1: Simple Algorithm-Insertion sort	Lab 4: Quicksort, Binary search	Lab 7: Huffman coding, knapsack and using greedy	Lab 10: N queen's problem	Lab 13: Randomized quick sort	
SLO-1 SLO-2	SLO-1	Designing an algorithm	Quick sort and its Time complexity analysis	Tree traversals	Branch and bound - Knapsack problem	Rabin Karp algorithm for string matching	
	And its analysis-Best, Worst and Average case	Best case, Worst case, Average case analysis	Minimum spanning tree - greedy Kruskal's algorithm - greedy	Example and complexity calculation. Differentiate with dynamic and greedy	Example discussion		
S-7	SLO-1	Asymptotic notations Based on growth functions.	Strassen's Matrix multiplication and its recurrence relation	Minimum spanning tree - Prims algorithm	Travelling salesman problem using branch and bound	Approximation algorithm	
5	SLO-2	0,0,θ, ω, Ω	Time complexity analysis of Merge sort	Introduction to dynamic programming	Travelling salesman problem using branch and bound example	Vertex covering	
S-8	SLO-1	Mathematical analysis	Largest sub-array sum	0/1 knapsack problem	Travelling salesman problem using branch and bound example	Introduction Complexity classes	
O-0	SLO-2	nduction, Recurrence relations Time complexity analysis of Largest sub- array sum		Complexity calculation of knapsack problem	Time complexity calculation with an example	P type problems	
S 9-10	SLO-2	Lab 2: Bubble Sort	Lab 5: Strassen Matrix multiplication	Lab 8: Various tree traversals, Krukshall's MST	Lab 11: Travelling salesman problem	Lab 14: String matching algorithms	

S-11		SLO-1	Solution of recurrence relations	Master Theorem Proof	Matrix chain multiplication using dynamic programming	Graph algorithms	Introduction to NP type problems	
		SLO-2	Substitution method	Master theorem examples	Complexity of matrix chain multiplication	Depth first search and Breadth first search	Hamiltonian cycle problem	
S-1		SLO-1	Solution of recurrence relations	Finding Maximum and Minimum in an array	Longest common subsequence using dynamic programming	Shortest path introduction	NP complete problem introduction	
	_	SLO-2	Recursion tree	Time complexity analysis-Examples	Explanation of LCS with an example	Floyd-Warshall Introduction	Satisfiability problem	
S-	SLO-1 Solution of recurrence relations		Solution of recurrence relations	Algorithm for finding closest pair problem	Optimal binary search tree (OBST)using dynamic programming	Floyd-Warshall with sample graph	NP hard problems	
	-	SLO-2	Examples	Convex Hull problem	Explanation of OBST with an example.	Floyd-Warshall complexity	Examples	
14-			Lab 3: Recurrence Type-Merge sort, Linear search	Lab 6: Finding Maximum and Minimum in an array, Convex Hull problem	Lab 9: Longest common subsequence	Lab 12: BFS and DFS implementation with array	Lab 15: Discussion over analyzing a real time problem	

Introduction to Divide and Conquer

$$a_0 + \ldots + a_{n-1} = (a_0 + \ldots + a_{-1}) + (a_0 + \ldots + a_{n-1}).$$

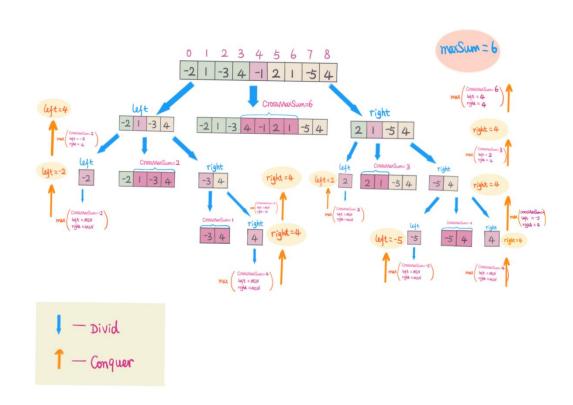


Maximum Sub-array problem

Maximum-subarray problem – divideand-conquer algorithm

- What is the time complexity?
- FindMaxSubarray:
- 1. if(j<=i) return (A[i], i, j);
- mid = floor(i+j);
- (sumCross, startCross, endCross) = FindMaxCrossingSubarray(A, i, j, mid);
- (sumLeft, startLeft, endLeft) = FindMaxSubarray(A, i, mid);
- 5. (sumRight, startRight, endRight) = FindMaxSubarray(A, mid+1, j);
- 6. Return the largest one from those 3

$$T(n) = 2T\left(\frac{n}{2}\right) + \Theta(n)$$



Binary Search & Complexity

```
Algorithm R Binary Search (I, h, key)
      if(l==h)
               if (a[l]=key)
               return I;
                else
               return 0;
      else
             mid = (I+h)/2;
             if (a[mid] = key)
             return mid;
               if (\text{key} < a[\text{mid}])
               return R Binary Search(I, mid-1, key)
                else
               return R Binary Search(mid+1, h, key)
```

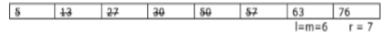
First m is determined and the element at index m is compared to x.

5	13	27	30	50	57	63	76
I=0 m=3							r=7

As x > numbers[3], the element may reside in numbers[4...7]. Hence, the first half is discarded and the values of I, m and r are updated as shown below.

5	13	27	30	50	57	63	76
				L=4	m=5		r = 7

Now the element \mathbf{x} needs to be searched in numbers[4...7]. As \mathbf{x} > numbers[5], new values of I, m and r are updated in a similar way.



Now, comparing \mathbf{x} with numbers[6], we get the match. Hence, the position of $\mathbf{x} = 63$ have been determined.

Analysis

Linear search runs in O(n) time. Whereas binary search produces the result in $O(\log n)$ time Let T(n) be the number of comparisons in worst-case in an array of n elements. Hence,

$$T(n) = \begin{cases} 0 & if \ n = 1 \\ T(\frac{n}{2}) + 1 & otherwise \end{cases}$$

Using this recurrence relation T(n) = log n .

Therefore, binary search uses $O(\log n)$ time.

Merge Sort and Time Complexity

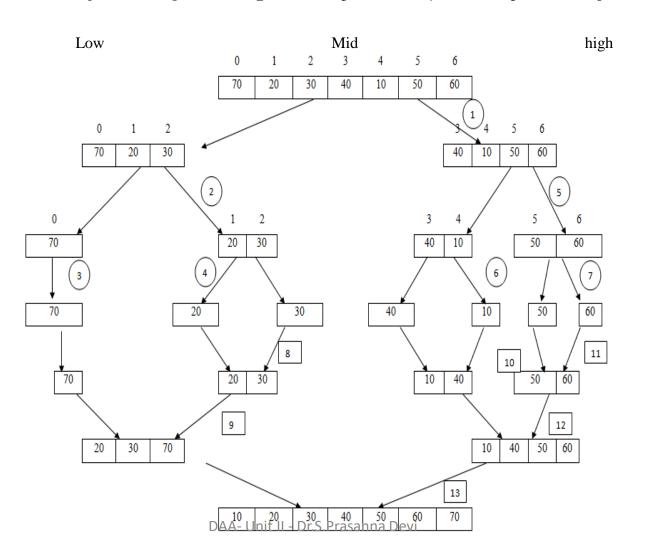
```
ALGORITHM Mergesort(A[0..n - 1])
//Problem Description:Sorts array A[0..n - 1] by recursive
    mergesort
//Input: An array A[0..n - 1] of orderable elements
//Output: Array A[0..n - 1] sorted in nondecreasing order
if n > 1
        copy A[0.. Floor(n/2) to B[0.. n- 1]
        copy A[ ceil(n/2)... n-1] to C[0.. n - 1]
        Mergesort(B[0.. - 1])
        Mergesort(C[0.. - 1])
        Merge(B, C, A)
```

```
ALGORITHM Merge(B[0..p-1], C[0..q-1], A[0..p+q-1])
//Problem Description: Merges two sorted arrays into one sorted
array
//Input: Arrays B[0..p - 1] and C[0..q - 1] both sorted
//Output: Sorted array A[0..p + q - 1] of the elements of B and C
i \leftarrow 0; i \leftarrow 0; k \leftarrow 0
while i < p and j < q do
                  if B[i]≤ C[j ]
                                    A[k] \leftarrow B[i]; i \leftarrow i + 1
                  else A[k] \leftarrow C[j]; j \leftarrow j + 1
                  k \leftarrow k + 1
if i = p
                  copv C[i..q - 1] to A[k..p + q - 1]
else copy B[i..p - 1] to A[k..p + q - 1]
Analysis:
Assuming for simplicity that n is a power of 2, the recurrence
relation for the number of key comparisons C(n) is
C(n) = 2C(n/2) + Cmerge(n) for n > 1,
C(1) = 0.
As per Master theorem
                                                       T(n) = \Theta(n^d \log n) if
Given data
                                     f(n) = cn
                                                       therefore n^d = n^1
a = 2, b = 2
                  => d = 1
a = b^d = 2 = 2^1
so T(n) = \Theta(n \log n)
Time complexity of merge sort for all cases is \Theta(n \log n)
```

Merge Sort and Time Complexity

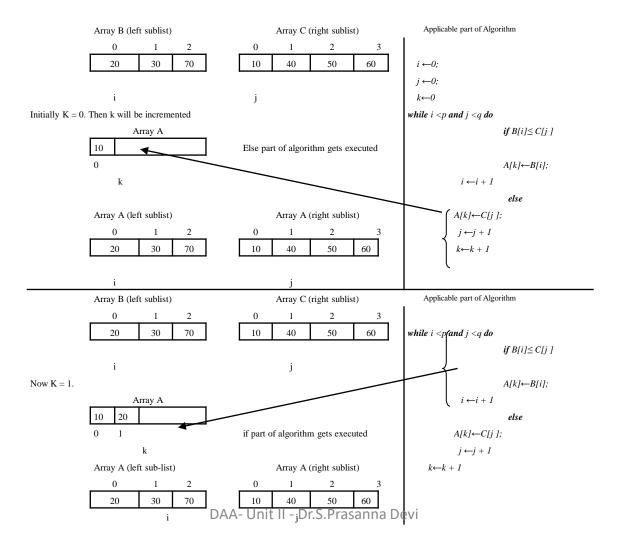
Sort the following set of elements using merge sort: 70, 20, 30, 40, 10, 50, 60.

bott the following set of elements using merge sort. 70, 20, 50, 10, 10, 50, 00.									
Consider the list of elements as	70	20	30	40	10	50	60		
	0	1	2	3	4	5	6	_	



Merge Sort and Time Complexity

Let us see the **combine** operation more closely with the help of some example. Consider that at some instance we have got two sub-lists 20, 30, 40, 70 and 10, 50, 60. then



Quick Sort & Time Complexity

```
Quicksort (A, p, r)

1 if p < r

2   q = \text{Partition}(A, p, r)

3   Quicksort (A, p, q - 1)

4   Quicksort (A, q + 1, r)

5   i = p - 1

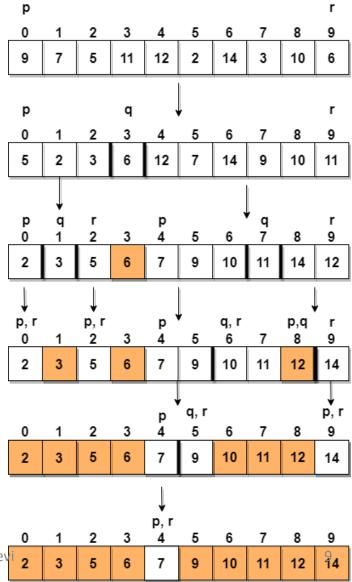
6   i = i + 1

6   exchange A[i] with A[j]

7   exchange A[i + 1] with A[r]

8 return i + 1
```

- Quickest recognized sorting algorithm in practice:
- T(n) = 2T(n/2) + O(n)
- Average case: O(N log N)
- Worst case: O(N^2)

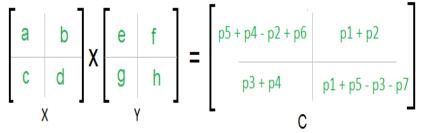


Strassen's Matrix Multiplication & Time Complexity

$$p1 = a(f - h)$$
 $p2 = (a + b)h$
 $p3 = (c + d)e$ $p4 = d(g - e)$
 $p5 = (a + d)(e + h)$ $p6 = (b - d)(g + h)$
 $p7 = (a - c)(e + f)$

The A \boldsymbol{x} B can be calculated using above seven multiplications.

Following are values of four sub-matrices of result C



X, Y and C are square metrices of size N x N

a, b, c and d are submatrices of A, of size N/2 x N/2

e, f, g and h are submatrices of B, of size N/2 x N/2

p1, p2, p3, p4, p5, p6 and p7 are submatrices of size N/2 x N/2

Analysis

$$T(n) = \left\{ egin{array}{ll} c & if \ n=1 \ 7 \ x \ T(rac{n}{2}) + d \ x \ n^2 & otherwise \end{array}
ight.$$
 where c and d are constants

Using this recurrence relation, we get $\ T(n) = O(n^{log7})$

```
procedure MatrixMultiplication(A, B)
 input A, B n*n matrix
 output C, n*n matrix
begin
 for (i = 0; i < n; i++)
  for (j = 0; j < n; j++)
   C[i,j] = 0;
  end for
 end for
 for (i = 0; i < n; i++)
  for (j = 0; j < n; j++)
   for(k = 0; k < n; k++)
    C[i,j] = C[i,j] + A[i,k] * B[k,j]
   end for
  end for
 end for
end MatrixMultiplication
```

Analysis using Naive Method: $T(n) = O(n^3)$

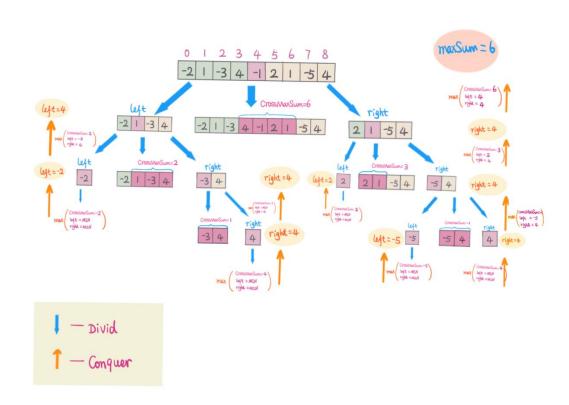
Largest Sub-array sum & its complexity

Same as Max sub array problem

Maximum-subarray problem – divideand-conquer algorithm

- What is the time complexity?
- FindMaxSubarray:
- if(j<=i) return (A[i], i, j);
- mid = floor(i+j);
- (sumCross, startCross, endCross) = FindMaxCrossingSubarray(A, i, j, mid);
- 4. (sumLeft, startLeft, endLeft) = **FindMaxSubarray**(A, i, mid);
- 5. (sumRight, startRight, endRight) = FindMaxSubarray(A, mid+1, j);
- 6. Return the largest one from those 3

$$T(n) = 2T\left(\frac{n}{2}\right) + \Theta(n)$$



Masters Theorem and Examples

```
T(n) = aT(n/b) + f(n) where a >= 1 and b > 1There are following three cases:

1. If f(n) = \Theta(n^c) where c < Log_b a then T(n) = \Theta(n^{Log}_b a)

2. If f(n) = \Theta(n^c) where c = Log_b a then T(n) = \Theta(n^c Log n)

3. If f(n) = \Theta(n^c) where c > Log_b a then T(n) = \Theta(f(n))

Case 2 can be extended for f(n) = \Theta(n^c Log^p n)

If f(n) = \Theta(n^c Log^p n) for some constant k >= 0 and c = Log_b a, then T(n) = \Theta(n^c Log^{p+1} n)
```

- Examples of some standard algorithms whose time complexity can be evaluated using Master Method
 - Merge Sort: $T(n) = 2T(n/2) + \Theta(n)$. It falls in case 2 as c is 1 and $Log_b a$ is also 1. So the solution is $\Theta(n Log n)$
- Binary Search: $T(n) = T(n/2) + \Theta(1)$. It also falls in case 2 as c is 0 and $Log_b a$ is also 0. So the solution is $\Theta(Logn)$

Masters Theorem and Examples

```
1. T (n) = 3T (n/2) + n 2 = \Rightarrow T (n) = \Theta(n 2) (Case 3)
2. T (n) = 4T (n/2) + n 2 = \Rightarrow T (n) = \Theta(n 2 log n) (Case 2)
3. T (n) = T (n/2) + 2n = \Rightarrow \Theta(2n) (Case 3)
4. T (n) = 2nT(n/2) + n n \Rightarrow Does not apply (a is not constant)
5. T (n) = 16T (n/4) + n = \Rightarrow T (n) = \Theta(n 2) (Case 1)
6. T (n) = 2T (n/2) + n log n =\Rightarrow T (n) = n log2 n (Case 2)
7. T (n) = 2T (n/2) + n/ \log n \Rightarrow Does not apply (non-polynomial difference between f(n) and n \log b a)
8. T (n) = 2T (n/4) + n 0.51 = \Rightarrow T (n) = \Theta(n 0.51) (Case 3)
9. T (n) = 0.5T (n/2) + 1/n = \Rightarrow Does not apply (a < 1)
10. T (n) = 16T (n/4) + n! = \Rightarrow T (n) = \Theta(n!) (Case 3)
11. T (n) = \sqrt{2}T (n/2) + log n = \Rightarrow T (n) = \Theta(\sqrt{n}) (Case 1)
12. T (n) = 3T (n/2) + n = \Rightarrow T (n) = \Theta(n lg 3) (Case 1)
13. T (n) = 3T (n/3) + \sqrt{n} = ⇒ T (n) = \Theta(n) (Case 1)
 14. T (n) = 4T (n/2) + cn = \Rightarrow T (n) = \Theta(n 2) (Case 1)
 15. T (n) = 3T (n/4) + n log n = ⇒ T (n) = \Theta(n log n) (Case 3)
16. T (n) = 3T (n/3) + n/2 = \Rightarrow T (n) = \Theta(n log n) (Case 2)
 17. T (n) = 6T (n/3) + n 2 log n =\Rightarrow T (n) = \Theta(n 2 log n) (Case 3)
18. T (n) = 4T (n/2) + n/ \log n \Rightarrow T (n) = \Theta(n \ 2) (Case 1)
19. T (n) = 64T (n/8) – n 2 log n =\Rightarrow Does not apply (f(n) is not positive)
20. T (n) = 7T (n/3) + n 2 = \Rightarrow T (n) = \Theta(n 2) (Case 3)
21. T (n) = 4T (n/2) + log n = \Rightarrow T (n) = \Theta(n 2) (Case 1)
 22. T(n) = T(n/2) + n(2 - \cos n) = \Rightarrow Does not apply I - Dr.S. Prasanna Devi
```

Find Max and Min of an array & its complexity Algorithm: Max - Min(x, y)

Naive Method Algorithm: Max-Min-Element (numbers[])

max := numbers[1]
min := numbers[1]

for i = 2 to n do

if numbers[i] > max

then max := numbers[i]

if numbers[i] < min

then min := numbers[i]

return (max, min)

T(n) = O(n)

```
Algorithm: Max - Min(x, y)
if y - x ≤ 1 then
  return (max(numbers[x], numbers[y]), min((numbers[x], numbers[y]))
else
  (max1, min1):= maxmin(x, [((x + y)/2)])
  (max2, min2):= maxmin([((x + y)/2) + 1)],y)
return (max(max1, max2), min(min1, min2))
```

Analysis

Let $\emph{T(n)}$ be the number of comparisons made by $\mathit{Max}-\mathit{Min}(x,y)$, where the number of eleme n=y-x+1 .

If T(n) represents the numbers, then the recurrence relation can be represented as

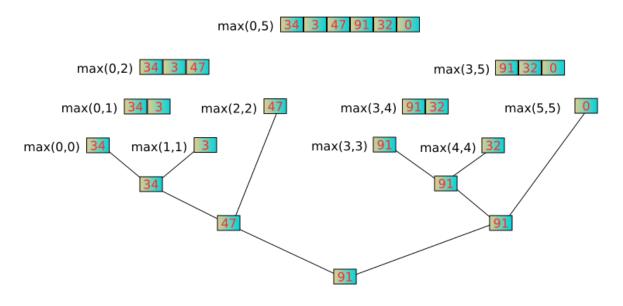
$$T(n) = egin{cases} T\left(\lfloor rac{n}{2}
floor
ight) + T\left(\lceil rac{n}{2}
ceil
ight) + 2 & for \, n > 2 \ 1 & for \, n = 2 \ 0 & for \, n = 1 \end{cases}$$

Let us assume that n is in the form of power of 2. Hence, $n = 2^k$ where k is height of the recursion tree. So,

$$T(n) = 2.T(\frac{n}{2}) + 2 = 2.\left(2.T(\frac{n}{4}) + 2\right) + 2.\ldots = \frac{3n}{2} - 2$$

Compared to Naïve method, in divide and conquer approach, the number of comparisons is less. Howevering the asymptotic notation both of the approaches are represented by **O(n)**.

Find Max and Min of an array & its complexity



```
Algorithm: Max - Min(x, y)

if y - x ≤ 1 then

return (max(numbers[x], numbers[y]), min((numbers[x], numbers[y]))

else

(max1, min1):= maxmin(x, [((x + y)/2)])

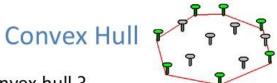
(max2, min2):= maxmin([((x + y)/2) + 1)],y)

return (max(max1, max2), min(min1, min2)) anna Devi
```

Finding Closest Pair problem & its complexity

```
• Closest-Pair (S).
• If |S| = 1, output \delta = \infty. If |S| = 2, output \delta = |p2 - p1|.
Otherwise, do the following steps:
1. Let m = median(S).
2. Divide S into S1, S2 at m.
3. \delta 1 = Closest-Pair(S1).
4. \delta 2 = Closest-Pair(S2).
5. \delta12 is minimum distance across the cut.
6. Return \delta = \min(\delta 1, \delta 2, \delta 12).
Recurrence is T(n) = 2T(n/2) + O(n), which solves to T(n) = O(n \log n).
                                                         Problem: Refer CW
```

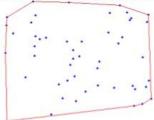
Convex Hull Problem & complexity



What is the convex hull?

It is the smallest convex set containing the points. Or we can also say it is a rubber band wrapped around the "outside" points.

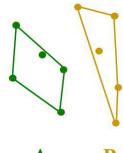
In the example below, the convex hull of the blue points is the red line that contains them.



- In divide and conquer, method we divide the set of n points in O(n) time into two subsets, one containing the leftmost [n/2] points, and one containing the right most [n/2] points, recursively compute the convex hull of the subsets, and then combine the hulls in O(n) time. The running time is described by the familiar recurrence
- T(n) =2T(n/2) +o(n),
 so the divide and conquer method runs in o(n log n) time.

Convex Hull: Divide & Conquer

- Preprocessing: sort the points by x-coordinate
- Divide the set of points into two sets A and B:
 - A contains the left $\lfloor n/2 \rfloor$ points,
 - B contains the right $\lceil n/2 \rceil$ points
- Recursively compute the convex hull of A
- Recursively compute the convex hull of B
- Merge the two convex hulls



Problem: Refer CW

Question Bank

- 1.(i) Write a pseudo code for divide and conquer algorithm for merging two sorted arrays into a single sorted one. Explain with an example.
 - (ii) Set up and solve a recurrence relation for the number of key comparisons made the above pseudo code.
- 2. Design a recursive decrease by-one algorithm for sorting the n real numbers in an array with an examples and also determine the number of key comparisons and time efficiency of an algorithm.
- 3. Write a simple example to explain quick sort algorithm.
- 4.(i) Write an algorithm to sort a set of N numbers using insertion sort.
 - (ii) Trace the algorithm for the following set of numbers:20,35,18,8,14,41,3,39. 85.
- 5. (i) Write an algorithm to sort a set of N numbers using quick sort.
 - (ii) Trace the algorithm for the following set of numbers:20,35,18,8,14,41,3,39. 8 5.
- 6. Explain Strassen's Matrix multiplication algorithm with an example.
- 7. Explain Convex Hull problem and derive its complexity.
- 8. Write a recursive algorithm to find the max and min of an array. Derive its complexity.
- 9. Explain algorithm to find the closest pair problem and derive its complexity.
- 10. Write an algorithm to find the sum of a sub-array and to get the least element of a given sub array. What is the time complexity?
- 11. Problems on application of Master's Theorem to find the time complexity.