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Algorithm

step by step finite sequence of instruction to solve well defined computational problem.

- 1) Time Complexity
- 2) need for analyzing an algo
- 3) Big O
- 4) Merge Sort with eg.
- 5) Control abstraction for divide and Conquer - 3
- 6) measure performance of algo
- 7) algorithm to compute sum of n numbers and find its time and space complexity

- 8) ~~Time of algo~~
- 9) Dif. time and space complexity

Time of algoSpace of algoTime and space complexityLinear Search algorithm, best, worst, average case

- 1) Merge Sort 1. Worst case analysis,
- 2) Asymptotic Complexity of algo, 3 notations used for asymptotic
- 3) Divide and Conquer strategy is used in Merge Sort

divide and conquer strategy

- ① Input : 0 or more values
- ② Output : 1 or more values
- ③ Definiteness : Each instruction are clear and unambiguous
- ④ Effectiveness : do semi. avoid unnecessary steps
- ⑤ Finiteness : Step are finite

~~study of Algo requires 3 steps~~

- ① Algo design
- ② Proving correctness of algo.
- ③ Analysis of algorithm

(notes)

Time Complexity

Time Complexity of an algorithm is the amount of time it needs to run to completion.

Running time depends on

- ① I/O to program
- ② Compile,
- ③ Nature and Speed of instruction

Space Complexity

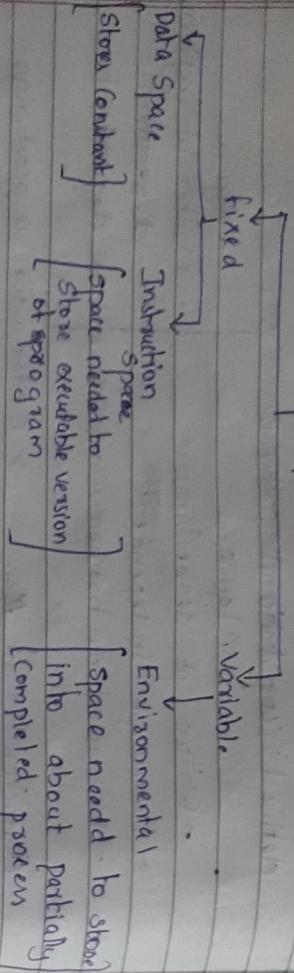
The amount of memory needs to run an algorithm for completion.

ProgramAlgorithmCodeImplementationExecutionOutput

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## Analyzing time and space complexity

### ① Frequency Count Method



Need for analysing an algorithm

- ① predict the behaviour of an algorithm without implementing it on a specific computer.
- ② compare performance of two algorithms to solve same problem
- ③ required to know the capability of the algorithm.

Time and Space Trade off

(Notes)

$$\text{Time complexity} = O(1)$$

$$\begin{array}{l} \text{cost} \\ \text{frequency} \\ \hline a = 10 & c_1 \\ b = 10 & c_2 \\ c = a + b & c_3 \\ \text{Print}(c) & c_4 \end{array}$$

$$S(n) = O(1)$$

B. Sum of n numbers

$$S = 0$$

$$\text{for } (\text{int } i=0; i < n; i++)$$

$$\begin{array}{l} \text{cost} \\ \text{frequency} \\ \hline c_1 \\ c_2 \\ n+1 \end{array}$$

$$S = S + A[i]$$

$$\begin{array}{l} c_3 \\ n \end{array}$$

Time Complexity

def

return S

$c_4$

1

- calculates the time needed

- counts time for all statements

- depends mostly on input data size.

→ Depends mostly on auxiliary variables

Time complexity of mergesort : Space :-  $O(n)$  is  $O(\log n)$

$$S(n) = O(n)$$

(2) Another way of finding time complexity of Main polynomial form using 2 rules

(1) drop low order terms (because it is not significant)

(2) drop constant multiplier

$$\text{eg:- } ① \quad 2n^3 + 3n^2 + 4n + 6$$

$$\text{Time Complexity} = O(n^3)$$

$$② \quad 17n^4 + 3n^2 + 4n + 8 \rightarrow O(n^4)$$

$$③ \quad 16n + \log n \rightarrow O(n)$$

### Time and Space Complexity Analysis of Loops

① Addition of  $n \times n$  matrix

Code

Diagram

return

1

	Cost	Frequency
add(A, B, n);	1	1
for(i=0; i<n; i++)	$n+1$	1
for(j=0; j<n; j++)	$n(n+1)$	$n+1$
c[i][j] = a[i][j] + b[i][j]	$n^2$	$n(n+1)$
}	1	$n+1$
return c;	1	1

$$\text{Time Complexity} = C_1(n+1) + C_2(n^2+n) + C_3(n^2) + C_4$$

$$= n^2(C_2 + C_3) + n(C_1 + C_2)$$

$$\propto O(n^2)$$

Space Complexity:

$$A \rightarrow n^2$$

$$B \rightarrow n^2$$

$$C \rightarrow n^2$$

$$i \rightarrow 1$$

$$j \rightarrow 1$$

$$n \rightarrow 1$$

(2) Multiplication of 2 square matrix

$\text{mul}(A, B, n, m);$

for(i=0; i<m; i++)

  for(j=0; j<n; j++)

    for(k=0; k<n; k++)

      c[i][j] += A[i][k] \* B[k][j]

return

1

$$T(n) = n+1 + n^2 + n + n^3 + n^2 + n^3 + 1$$

$$T(n) \Rightarrow O(n^3)$$

Space Complexity:

$$A \rightarrow n^2$$

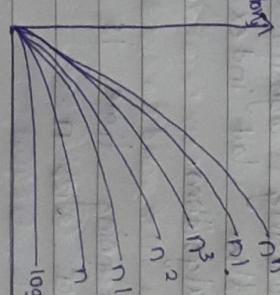
condition swap like  $B \rightarrow n^2 \rightarrow 3n^2 + 1 \approx O(n^2)$

$$\text{swap } C \rightarrow n^2$$

$$i, j, k, n \rightarrow 1$$

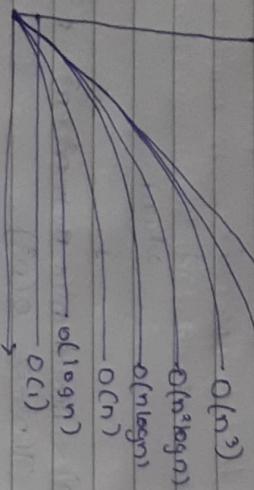
Growth Rate graph

No. of iterations



- Arrange & illustrate the following growth rates in increasing order  $O(n^4), O(n), O(n), O(n\log n), O(n^2 \log n), O(\log n), O(n!)$

$$\begin{aligned} O(1) &< O(\log n) < O(n) < O(n\log n) < O(n^2 \log n) < O(n^4) \\ &< O(n!) < O(n^n) \end{aligned}$$



### Worst Case

In this case, the algorithm will take maximum running time for input size  $n$  to execute.

e.g:- We are searching an element in an array using a searching algorithm then if an element is found at the last index then it's worst case for the algorithm.

→ or not in the arr

Worst case running time is the longest running time for any input of size  $n$ .

### Average Case

In this case, the algorithm will take the ~~average~~ minimum running time for input size.

e.g:- Element found in middle

Average case running time assume that all inputs of a given size are equally likely.

Best Case  
In this case, the algorithm will take the minimum running time for an input size.  
e.g:- a first element of array

In the best case analysis, we calculate lower bound on running time of an algorithm.

### Amortized running time

It refers to the time required to perform a sequence of related operations averaged over all the operations performed.

### Linear Search Algorithm

```
int search (int arr[], int n, int x)
```

```
{  
    for (int i=0; i<n; i++)  
        if (arr[i] == x)  
            return i;  
    return -1;  
}
```

Worst case time complexity:  $O(n)$   
Average Case " " "  $O(1)$   
Best Case " " "  $O(n)$

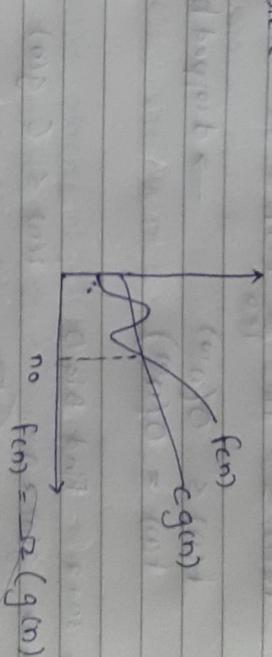
## Asymptotic notation

Answer paper

To enable us to make meaningful statements about time and space complexity of an algorithm, asymptotic notations are used. It describes behavior of time and space complexity of large instance characteristics.

Asymptotic notations are mathematical tool to represent the time complexity of algorithms for asymptotic analysis.

- ↓ measure the efficiency of algorithms that -
- don't depend on machine specific constant
- don't require algorithms to be implemented



### Asymptotic notations:

#### (1) Big O

- used to express the upperbound of an algorithm running time
- measure longest time possibly taken for algorithm to complete.

-  $f(n)$  and  $g(n)$  are non-negative function, if there exist an integer  $n_0$  and a constant  $c > 0$ , such that for integer  $n > n_0$

$$f(n) \leq c \cdot g(n)$$

$f(n) = O(g(n))$

+ Big O gives worst case running time of an algo.

$$f(n) = O(g(n))$$

$$\log(n)$$

$$f(n) = O(n^2)$$

$$f(n) = O(1)$$

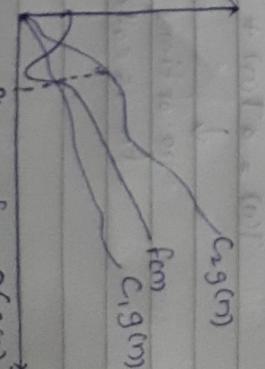
#### (2) Theta ( $\Theta$ )

If the function is b/w the lower and upper bound, the function is denoted as  $\Theta$  notation.

For any non negative function  $f(n)$  and  $g(n)$ , if there exist an integer  $n_0$  and positive constant  $C_1$  &  $C_2$ ,  $C_1 > 0$  and  $C_2 > 0$ , such that for every integer  $n > n_0$

$$C_1 g(n) \geq f(n) \geq C_2 g(n)$$

which is denoted as  $f(n) = \Theta(g(n))$



(3) Omega ( $\Omega$ )

Used to represent lower bound of an algorithm

- if  $f(n)$  and  $g(n)$  be non-negative integers, if there exists an integer  $n_0$  and a constant  $c > 0$ , such that for integers  $n > n_0$
- $f(n) \geq c \cdot g(n)$

$$f(n) \geq c \cdot g(n)$$

↑

- It provides best case complexity of an algorithm.
- measure of minimum time taken for algorithm to complete

Proof:

$$\text{If } f(n) = a_m n^m + a_{m-1} n^{m-1} + \dots + a_1 n^1 + a_0$$

$$f(n) = O(g(n))$$

$f(n) \rightarrow$  function or a statement!

$a_m > 0 \rightarrow$  mean value of  $n$  is greater than zero

$$f(n) \geq \sum_{i=0}^m |a_i| n^i$$

$$f(n) \geq n^m \geq \prod_{i=0}^m |a_i| n^{i-m}$$

$$f(n) \leq O(n^m)$$

$\rightarrow$  dropped low order term

$$f(n) = O(n^m)$$

Q.

$$f(n) = 3n + a \quad \text{Find Big O}$$

$$\text{Assume } f(n) = n \quad f(n) \leq C g(n)$$

(Note)

Recursive Equations

Substitution Method  
Substitution method we mathematical induction to find the constant and show that the solution works. The substitution method can be used to establish either upper or lower bound on a recurrence.

- A recurrence equation is an equation or inequality that describes a function in terms of its values of smaller inputs.
- Useful for expressing the running time of recursive algorithms.

General form:

$$T(n) = a T(n) + g(n) \rightarrow \text{time required for doing other operations}$$

$\downarrow$

no. of times recursive operation  $T(n)$  is called

e.g.: Recurrence eqn for factorial

$$T(n) = 0 \quad \text{if } n = 0$$

$$T(n) = 1 \cdot T(n-1) + b \quad \text{for } n > 0$$

Constant

### Solving Recurrence Equations

Three methods for solving recurrence are

- ① Substitution method
- ② Recursion Tree Iteration Method
- ③ Masters Theorem

Divide and Conquer  
 It is a top-down approach to designing algorithm that consist of dividing the problem into smaller sub problems hoping that the solution of sub problems are easier to find.

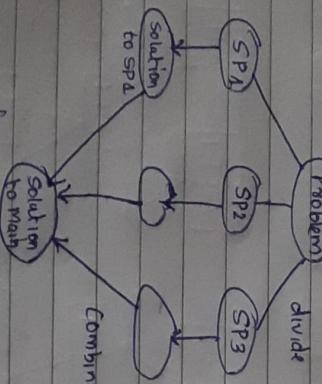
The composing the partial solutions into the solution of the original problem.

- ④ Divide  
 Dividing the problem into number of sub problem that are smaller instances of same problem

- ⑤ Conquer  
 Conquer(solve) the subproblems by solving them recursively.

- ⑥ Combine

Combining the solutions of sub problems into solution of the original problem.



→ Control Abstraction for divide and conquer algorithm.

divide\_and\_conquer(P)

{

  if small( $P$ ) //  $P$  is very small, soln is trivial

    return solution( $S$ );

  else;

    divide the problem  $P$  in to  $k$  instances  $P_1, P_2, \dots, P_k$

}

    divide\_and\_conquer( $P_i$ )

}

### Merge Sort

- uses divide and conquer strategy
- The basic idea is to divide the list into sublist
- sort each sublist
- finally merge them to get a single sorted list

Merge( $A[P_1, q]$ )

$$n_1 = q - p + 1$$

$$n_2 = 30 - q$$

$$L_1 = [1, \dots, n_1]$$

$$R = [1, 2, \dots, n_2]$$

} be new arrays

for ( $i = 1$  to  $n_1$ )

$L[i] = A[p+i-1]$

for ( $j = 1$  to  $n_2$ )

$R[j] = A[q+j-1]$

$$L[n_1+1] = \infty$$

$$R[n_2+1] = \infty$$

$i=1$      $j=1$

for ( $R = p$  to  $q$ )

  if ( $L[i] \leq R[j]$ )

$A[k] = L[i]$

$i = i + 1$

  else:

$A[k] = R[j]$

$j = j + 1$

  divide the problem  $P$  in to  $k$  instances  $P_1, P_2, \dots, P_k$

}

## Merge Sort ( $A, P, Q$ )

$\frac{P}{3} < Q$

$$Q = P + \frac{Q}{2}$$

Merge Sort ( $A, P, Q$ )  $\rightarrow T(n/2)$

Merge Sort ( $A, P+1, Q$ )  $\rightarrow T(n/2)$

Merge ( $A, P, Q$ )  $\rightarrow O(n)$

For eg:

1 5 4 8 2 4 6 9

$n_1$   $n_2$

Step 1:  
Create two new list  
 $L = [1, 5, 7, 9]$   $R = [2, 4, 6, 8]$

and place  $\alpha$  at  $n$

$$L = [1, 5, 7, 8, \infty] \quad R = [2, 4, 6, 9, \infty]$$

Step 2:  
Compare and fill  $A$ .

Create another array  $A[k]$

$$A[k] = [1, 5, 7, 8, 9]$$

Step 3:  
Compare and fill  $A[k]$

Compare and fill  $A[k]$

$$\begin{array}{|c|c|c|c|c|c|c|} \hline 11 & 5 & 17 & 8 & 12 & 4 & 9 & 6 \\ \hline \end{array}$$

$$\begin{array}{|c|c|} \hline 12 & 4 \\ \hline \end{array}$$

## Quick Sort

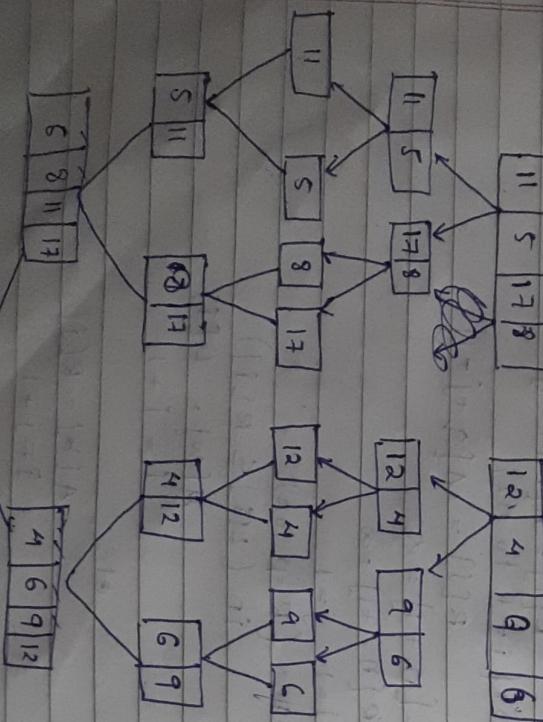
using Master's Theorem

$$a = 2$$

$$b = 2$$

$$k = 1$$

$$\begin{aligned} T(n) &= b(n \log_b^a \log^{P+1} n) \text{ for } O(n) \\ &= b(n \log n) \end{aligned}$$



The total time taken for merge sort is  $O(n \log n)$

Additional notes:

→ Recursive algorithm that follows divide and conquer approach.  
→ The best case and average case time complexity is  $O(n \log n)$ .  
→ Worst case time complexity is  $O(n^2)$ .  
→ Given an array, take any element from the array call it as pivot value and put value in the position in such a way that elements less than the pivot value comes on left-hand side and elements greater than the pivot value comes on right hand side.

Quick-Sort(A, P, R)

{

if {P < R}

{

q = PARTITION(A, P, R)

QUICK-SORT(A, P, q-1)

QUICK-SORT(A, q+1, R)

{

2. Sort the subarray with total size  
 $(R - P + 1) - 1 = Q$

### Matrix Multiplication

Matrix Multiplication Rule

3 methods

(1) Naive Method

Time Complexity -  $O(n^3)$  - 3 loops

(2) Divide and Conquer Approach

Cost =  $(n)^3$

Time

Space

Time

Space